Stock Market Concentration and the Distributional Impact of Financialization

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Abstract

Our paper investigates the long-term implications of stock market concentration for income distribution, using a panel dataset of 46 countries between 1989 and 2016. We find that greater stock market concentration — measured by the market capitalization share of the top 10 firms — is positively associated with rising income inequality. This relationship is robust across multiple measures of inequality, including the Gini coefficient, the income shares of the top 1% and top 10%, and the declining share of the bottom 50%. The results hold after controlling for macroeconomic factors, financial development, and both country and time fixed effects. Our findings indicate that equity market structures have important distributive implications. Concentrated markets appear to disproportionately benefit top-income groups, reflecting unequal ownership of financial assets and the excess gains of dominant firms. At the same time, stock market concentration is associated with declining income shares for the bottom half of the population, suggesting a redistribution of economic gains from the bottom to the top. We also explore the role of financial development and uncover a non-linear, U-shaped relationship with inequality: while financial expansion reduces inequality at early stages, more advanced financial systems tend to reinforce it. This pattern, which contrasts with earlier literature on the finance-inequality nexus, may reflect recent trends in financialization and capital market dynamics that increasingly favor high-income groups.

Keywords: inequality, stock market concentration, financial development.

JEL classification: E44, G15, O16

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1 Motivation and Research Question

Stock market concentration has emerged as one of the defining structural features of global financial markets today. In the U.S., the top ten firms now account for more than 34% of the S&P 500's market capitalization—levels not seen since the dot-com era (Stern et al., 2024; Lamont et al., 2024). Industry experts increasingly warn that this extreme concentration could amplify systemic risk, reduce diversification, and distort capital allocation (Aliaga, 2024; Lakos-Bujas, 2024). Yet, a critical dimension of this trend has received considerably less attention: its long-term implications for income inequality.

Capital markets are not passive intermediaries—they shape who gets financed, who grows, and who falls behind. In concentrated equity markets, dominant firms benefit from cheaper capital, preferential investor flows, and policy influence, while smaller firms face persistent barriers to entry. Over time, these dynamics undermine competition and reduce economic mobility. Bae et al. (2021) show that stock market concentration reduces IPO activity, slows innovation, and distorts capital allocation toward incumbent firms. Neuhann and Sockin (2024) offer a theoretical model in which concentration generates investment misallocation, endogenous illiquidity, and long-run inefficiency. These findings suggest that the concentration of capital not only erodes market dynamism but may also entrench inequality by limiting access to opportunity and suppressing upward mobility. Theoretical frameworks from the political economy of finance (Rajan & Zingales, 2003) and creative destruction (Aghion et al., 2005) suggest that such structures may entrench inequality by locking in the advantages of incumbent firms and their shareholders. Yet, despite this theoretical foundation, there is little cross-country empirical work that directly examines this relationship.

Our paper fills an important gap in the finance-inequality nexus by exploring how stock market concentration affects income distribution across a panel of 46 countries from 1989 to 2016. Utilizing a variety of income inequality measures, while controlling for financial development, macroeconomic fundamentals, and institutional factors, we find that higher stock market concentration is significantly associated with rising income inequality. Our results are robust among different specifications for income inequality and financial development measures.

As policymakers, economists, and institutional investors confront the interconnected challenges of rising inequality and expanding corporate dominance, this paper offers timely evidence on the importance of capital market design. In that sense, our work provides evidence that the architecture of financial markets — not just their depth, access or efficiency — constitutes a critical channel through which financial systems shape distributive outcomes. Even in well-capitalized markets, the degree of concentration plays a key role in determining who gains and who is left behind.

2 Literature Review

2.1 Financial Development and Inequality

Early theoretical work established ambiguous predictions for how financial development affects income inequality. Classical models by Greenwood and Jovanovic (1990) and others suggested an inverted-U "Kuznets curve" relationship, where inequality first rises then falls as finance expands. In contrast, many empirical studies find monotonic effects. For example, Beck, Demirguc-Kunt and Levine (2004) document in a broad cross-country sample that deeper financial intermediary development reduces inequality by disproportionately boosting incomes of the poor. Their evidence of finance's pro-poor growth impact supports the view that improved credit access helps equalize opportunities. Consistent with this, Claessens and Perotti (2007) emphasize that greater financial inclusion – via credit and insurance access – can narrow inequality, while also noting that entrenched elites might stifle financial development to preserve rents (a political economy channel). Not all evidence aligns with a benign view of finance. Some research finds that beyond a point, finance may exacerbate inequality. Jauch and Watzka (2016), using panel data for 138 countries with 2SLS techniques, find that higher private credit-to-GDP is associated with increases in income inequality. Similarly, Roine, Vlachos, and Waldenström (2009) show that financial development is "pro-rich": expansions of stock markets tended to raise top income shares in advanced economies over the 20th century. These divergent findings hint at nonlinearities or structural differences. Recent work attempts to reconcile them. Brei, Ferri, and Gambacorta (2023) examine 97 economies and report a non-monotonic pattern: up to a point, financial deepening lowers inequality, but at high levels of financial development, further expansion via capital markets increases inequality whereas bank-based expansion does not. In other words, who benefits from finance depends on the structure: deeper stock markets vs. banking sector growth can have opposite distributional effects. This resonates with Hsieh, Chen and Lin's (2019) finding that a more market-oriented financial system (relative to bank-dominated) correlates with less inequality, while greater banking concentration worsens it. Overall, the literature underscores that financial development's impact on inequality is nuanced – it may lift the poor and reduce inequality in earlier stages , but past a threshold, further financialization (especially via securities markets) can concentrate income and wealth at the top. This motivates more granular inquiry into which aspects of finance drive inequality under different conditions. Key gaps remain in pinning down causality (beyond correlations) and in distinguishing channels (e.g. credit access for the poor vs. rent extraction by the wealthy).

These gaps set the stage for examining specific facets of finance – such as the composition of finance or institutional context – in shaping inequality.

2.2 Finance and Inequality: Equity Participation, Returns to Capital, and Income Dynamics

A complementary strand of literature focuses on the mechanisms linking financial markets to household income dynamics – for instance, who owns financial assets and how returns on those assets are distributed. One important theme is stock market participation. Only a subset of households own equities, and this limited participation means that asset price booms may widen wealth inequality. Using an overlapping-generations asset-pricing model, Favilukis (2013) demonstrates that the rise in stock ownership rates alongside greater income inequality can explain several macro trends (a stock boom, declining risk-free rates) and, crucially, that stock market participation played a "major role in increasing wealth inequality" in recent decades. Intuitively, when only higher-income households hold stocks, any excess returns accrue primarily to them. Melcangi and Sterk (2024) further show that the degree of stock participation materially alters macroeconomic outcomes: in their monetary business-cycle model, a low participation rate amplifies the differential impacts of monetary policy on rich vs. poor, affecting inequality. This line of work highlights that the distribution of financial asset ownership is a key parameter governing inequality dynamics. Indeed, Gans et al. (2019) combine theory and microdata to argue that when shareholding is far more concentrated than consumption, increases in corporate profits or monopoly mark-ups will favor the wealthy. In the United States, they note the top 20% of households consume roughly the same total as the bottom 60%, yet hold 13 times as much corporate equity – implying that any rise in profit shares disproportionately rewards the rich. This mechanism can exacerbate inequality when market power increases, a point we revisit below. Another body of research examines how the source of inequality – whether it comes from labor income or capital income – influences asset returns and macrofinancial stability. Markiewicz and Raciborski (2022) find that changes in the equity risk premium depend on the source of rising inequality. Their work, set in a calibrated general equilibrium model, suggests that an inequality increase driven by greater capital income (profits, dividends) may have different implications for asset pricing than one driven by wage dispersion. These nuances matter for understanding feedback loops between inequality and finance. Relatedly, theoretical research has started to integrate long-run inequality trends into growth models. For example, Bretschger et al. (2012) develop a unified growth model (spanning decades if not centuries) where technological change and even environmental policy can shape inequality outcomes. While not centered on financial markets per se, such models provide insight into how economic forces (like innovation or climate policy) might have distributional effects that interact with financial factors (e.g. through returns to new vs. old capital). In summary, this second strand emphasizes that financial markets are not a neutral conduit – who participates and how returns are allocated are central to inequality. Equity markets exhibit extreme positive skewness in returns, as documented by Bessembinder (2018): in the U.S. from 1926–2016, just 4% of listed firms accounted for the entire net wealth creation of the stock market, while the other 96% collectively barely matched the return on Treasury bills. This skew implies that investors fortunate or wealthy enough to hold the "superstar" stocks realize outsized gains, contributing to wealth concentration. Together, these studies point to a potential vicious cycle: high inequality can alter asset price dynamics , and conversely, the structure of asset ownership and returns can amplify inequality. However, much of this work is theoretical or based on stylized models – there remains a need for empirical analysis connecting these mechanisms to real-world data, especially in emerging contexts.

2.3 Bank Competition, Concentration, and Inequality

A large literature explores how the structure of the banking sector – the degree of competition or concentration – impacts economic opportunities and income distribution. The classic hypothesis is that more competitive banking (less concentration) improves access to credit for smaller firms and lower-income borrowers, thereby leveling the playing field. Empirical evidence generally supports this. Pioneering work by Cetorelli and Strahan (2006) showed that concentrated local banking markets act as a barrier to entry for new firms: when a few banks dominate, they tend to favor established (typically larger) firms, limiting credit to startups. Conversely, increased competition through bank deregulation in the U.S. spurred entry of new firms and boosted small business activity, effects that likely enhanced income mobility and reduced regional inequality. Along similar lines, Bonaccorsi di Patti and Dell'Ariccia (2004) found in Italian data that higher banking concentration correlates with fewer new firm creations, whereas competition facilitates entrepreneurship. Cornaggia et al. (2015) provide complementary evidence that U.S. banking deregulation (which intensified competition) relaxed credit constraints on small and young firms, resulting in more innovation. This suggests bank competition can indirectly reduce inequality by enabling more widespread innovation and job creation at new firms (rather than rents accruing only to incumbents). Household-level and aggregate studies likewise indicate that bank competition has egalitarian effects. Delis et al. (2014) report that banking system reforms which improve efficiency – e.g. easing entry barriers, strengthening competition – are associated with decreases in income inequality. The mechanism is that competitive banking lowers borrowing costs and expands financial services to previously credit-rationed groups. A recent within-country analysis by Coccorese and Dell'Anno (2024) corroborates this: studying 103 Italian provinces over 2000–2018, they find that greater local banking development (more branches and lending relative to population) reduces income inequality. Notably, they adjust inequality measures for tax evasion and use instrumentation to address endogeneity, lending credibility to a causal interpretation. There is also evidence that excessive concentration in banking can worsen inequality. Using cross-country panel methods, Hsieh, Chen and Lin (2019) show that less banking competition (higher concentration) is linked to significantly higher inequality, especially in advanced economies and in times of crisis. However, some findings complicate the picture. Cetorelli (2004) noted that in some cases banking concentration might facilitate relationship lending that promotes growth of certain industries (paradoxically, higher concentration was associated with larger firm size in those sectors). Similarly, Bonaccorsi di Patti and Dell'Ariccia observed a positive link between concentration and industrial growth in sectors most dependent on external finance. These results align with an older "information hypothesis" that a concentrated banking sector with monopolistic rents might have greater capacity to invest in costly screening/monitoring, potentially benefiting some borrowers. But from an inequality standpoint, those benefits seem to accrue to a narrow set of firms/individuals (likely not the financially excluded). Indeed, Brei et al. (2023) reconcile these contrasts by distinguishing how finance grows: when credit expansion occurs via a few large banks, the gains may bypass the broader population, whereas fostering competition or stock market access tends to spread benefits more evenly. On net, the evidence tilts toward the view that bank competition is inequality-reducing. It expands credit to underserved borrowers, encourages new firm entry, and lowers the cost of finance for small businesses – all of which can raise incomes in lower segments of the distribution. The policy implication is that measures to prevent excessive bank concentration (e.g. anti-trust enforcement in banking, encouraging new entrants or fintech alternatives) could have social benefits in terms of equity. A caveat is that banking competition must be balanced with prudential oversight; extremely fierce competition might erode lending standards and lead to crises, which themselves often hurt the poor the most. Some studies indeed find that financial crises shrink top incomes (the rich lose capital income), temporarily compressing inequality, though crises clearly are not a desirable method of redistribution.

2.4 Market Concentration and Inequality in the Real Economy

Beyond the financial sector, increasing concentration in product markets and industries has raised concerns about its impact on inequality. The past few decades have seen many industries become dominated by a handful of "superstar" firms, which often enjoy high profit margins. This trend can affect inequality through multiple channels: by shifting income from labor to capital, by creating winners-take-most dynamics among firms, and by influencing the spatial or skill distribution of jobs. Autor et al. (2020) have documented the declining labor share of income in concentrated industries, suggesting that monopoly/oligopoly power allows firms to capture more value at the expense of workers. In terms of individual incomes, a concentrated market may result in outsized rewards for the owners and executives of dominant firms, widening the gap between top earners and the rest. Formal analysis by Gans et al. (2019) lends support to these concerns. They point out that while monopoly pricing hurts consumers broadly, the benefits of those higher prices (in the form of profits) accrue to shareholders – who are typically wealthier. Because share ownership is far more unequally distributed than consumption, market concentration tends to increase inequality. Their empirical calculations for the US indicate that the top 1% and top 20% wealth groups stand to gain disproportionately from increases in markups, whereas the bottom 80% lose more in consumer surplus than they gain in any equity holdings. In effect, concentrated markets act like a regressive transfer: money flows from a dispersed base of consumers/workers to a concentrated set of owners. Hotchin and Leigh (2024) provide new evidence consistent with this in the Australian context. They examine the industries in which Australia's richest individuals acquired their fortunes and find these industries have markedly higher concentration ratios than the economy-wide average. Moreover, as Australian product markets have consolidated from 1990 to 2020, an increasing share of top fortunes are being made in highly concentrated sectors. This suggests that market power and wealth accumulation at the top are closely linked. Their results imply that rising industry concentration can contribute to the surge in top wealth shares – a pattern likely mirrored in other countries with similar "winner-take-all" dynamics. In addition to these distributional effects, market concentration can have indirect effects on inequality via innovation and growth. On one hand, dominant firms with large profits might invest heavily in RD, potentially spurring growth and new technologies that benefit society. On the other hand, Hou and Robinson (2006) find that firms in more concentrated industries actually earn lower average stock returns (even controlling for risk factors) , consistent with the idea that such firms face less uncertainty and enjoy entrenched rents. Lower required returns mean investors are willing to pay a premium for these firms' stable profits, essentially capitalizing the expectation of persistent monopoly rents. This reflects a transfer of wealth to incumbent firm owners, and it can also signal less dynamism. If high concentration stifles entry of new competitors, it may slow job creation and wage growth for middle-class workers. Indeed, there is evidence that periods of rising concentration coincide with fewer startups and less labor market fluidity (e.g. fewer opportunities for workers to switch jobs for higher pay), which can entrench income inequality. The work of Cornaggia et al. (2015) indirectly speaks to this: by showing that greater banking competition leads to more innovation by small firms, it implies that lowering barriers (financial or otherwise) allows more competitors to challenge incumbents, likely yielding more widely shared gains. Conversely, a concentrated real economy without competitive pressure could lead to unequal outcomes – high gains for a few, stagnation for others. In sum, the literature on industry concentration suggests it is a contributing factor to inequality, primarily through rent concentration and reduced labor share. Empirical research is still catching up to recent trends – many studies are underway to quantify how much of rising inequality can be explained by increased market power of firms. The consensus emerging is that while globalization and technology matter, market concentration and reduced competition have materially tilted the distribution of income toward capital owners. From a policy perspective, this raises the importance of competition policy (antitrust enforcement, regulation of monopolies) as a tool not just for efficiency but for equity.

2.5 Stock Market Concentration and Inequality

The question of stock market concentration – meaning the degree to which a national stock market's capitalization or returns are dominated by a few mega-firms – has only recently gained attention. This issue ties together elements of the prior sections: it reflects real-economy concentration (since big firms dominate market cap) but also encapsulates financial factors like investor portfolios and asset returns. A highly concentrated stock market could have several inequality-relevant consequences. First, if a handful of firms account for most stock market wealth and gains, then the benefits of equity ownership will accrue mainly to those holding those particular stocks. Given that richer investors tend to hold more diversified portfolios (and a larger share of stock wealth overall), they are more likely to own the "winners" in a concentrated market. In contrast, small investors with index funds or undiversified holdings might miss out. Bessembinder (2018) quantifies the extreme skew: over the long run, the best-performing 4% of listed companies generated the entire net wealth increase in the U.S. stock market, whereas the other 96% of stocks collectively just matched the return of short-term Treasury bills. This finding implies that owning even an average slice of the stock market (let alone missing the top 4%) yields modest gains, whereas capturing the big winners delivers massive wealth growth. Such dynamics naturally favor those investors with substantial equity exposure and professional management – typically affluent households and institutional investors. It underscores how stock market concentration can translate into wealth concentration. Recent empirical work has started to examine macro-level effects of stock market concentration. Bae et al. (2021) assemble data from 47 countries over three decades and document that stock markets dominated by a few star firms tend to perform worse on broader economic metrics. Specifically, greater stock market concentration is associated with less efficient capital allocation, fewer IPOs, lower innovation, and slower overall growth. These findings, published in the Journal of Financial Economics, suggest a paradox: even in competitive economies, a very concentrated stock market (where a few firms attract most investor capital) can undermine competition and dynamism in the real economy. Although Bae et al. do not directly measure inequality, the implications are clear – a sluggish IPO market and suppressed innovation could mean fewer new firms and jobs, harming income growth for the broader population. In other words, stock market concentration may entrench the dominance of incumbent firms, mirroring the inequality-increasing effects of product market concentration discussed earlier. On the theoretical side, Neuhann and Sockin (2024) develop a general equilibrium model to investigate financial market concentration. They show that when trading and ownership of equities become concentrated among a small group of investors, it can lead to misallocation of capital in the economy. In their model, "crowding" of investment into a few assets/firms with price impact distorts efficient investment decisions. While their focus is allocative efficiency, one can infer distributional consequences: misallocation often means foregone growth or employment that would have benefited wider segments of society. If capital chases the same few firms, smaller firms (which might employ more middle-class labor or be owned by middle-class entrepreneurs) struggle to obtain financing. Thus, the model of Neuhann and Sockin provides a mechanism by which stock market concentration could harm equality of opportunity and outcomes. It is instructive to put current U.S. stock market concentration in historical perspective. Fears about today's "FAANG"-dominated market (with five to seven tech giants comprising 25–30% of S&P 500 capitalization) are often voiced. Yet, Schlingemann and Stulz (2022) show that mid-20th century markets were even more top-heavy. In the 1950s–60s, just the top 3 stocks comprised roughly 28% of total market cap – about equivalent to the top 7 stocks' share today. The largest single stock (AT&T) was 13% of the market in 1960, compared to 7% for Apple recently. They also find that the largest public firms of earlier eras had far larger employment footprints (e.g. GM in 1953 employed over 1.3% of the US workforce, whereas Apple in 2019 was only 0.1%). This historical comparison suggests that while current concentration is high by recent standards, the economic dominance of superstar firms (and hence potential inequality effects) was substantial in the past as well. One difference, however, is in the role of public corporations in the economy. Kahle and Stulz (2017) document that the number of U.S. public companies has fallen by 50% since 1997, and those that remain are older, larger, and more profitable on average. Strikingly, the top 200 public firms by profits now earn as much as all the other public firms combined. This profit concentration indicates that public equity markets have become a venue where a small set of firms capture enormous value. For inequality, this means the gains from equity (dividends, capital gains) are coming disproportionately from a narrow set of firms – again likely accruing to a narrow set of shareholders. The shrinking number of listings also implies fewer opportunities for broad-based wealth creation through new public offerings. Kahle and Stulz discuss several reasons for these trends (technology, globalization, M&A, the rise of private equity), but an implicit consequence is the intensification of stock market concentration and its attendant distributional implications. In summary, stock market concentration is an emerging focal point linking finance and inequality. The literature so far (Bae et al., 2021; Bessembinder, 2018; Schlingemann & Stulz, 2022) suggests that when equity markets become highly concentrated, it can reflect and reinforce broader inequalities – by skewing wealth gains to a few firms/investors and by dampening the competitive, growth-generating function of capital markets. However, direct empirical evidence on the inequality impact of stock market concentration remains sparse. This is a gap our study aims to fill. We have assembled new data on stock market concentration across countries and time, and we employ a formal econometric strategy to estimate its effect on income and wealth inequality. By bridging the above strands of literature, our work will clarify whether a concentration of market capitalization in a few firms indeed translates into greater income and wealth gaps (and through what channels). In doing so, we connect the insights from financial development, banking, and industrial organization research to provide a more complete picture of how the evolving structure of capital markets influences economic inequality – the core empirical contribution of our paper.

3 Methodology

3.1 Data

Our paper examines a panel dataset of 46 countries[1] over the period 1989-2016. Table 1 provides definitions and data sources for the main variables used in the empirical analysis. The dataset includes key measures of income inequality (Gini, top 1% [P99], top 10% [P90], and bottom 50% [P50] income shares), as well as, stock market concentration among the top 10 firms (SMC), stock market capitalization as a percentage of GDP (SMCap), the asset share of the largest banks (BC), and the stock market turnover ratio (SMT). We also include the IMF's Financial Development Index (FD), which serves as a comprehensive indicator of financial depth, access, and efficiency. Lastly, we control for macroeconomic factors: gross domestic savings, inflation (GDP deflator), trade openness, and per capita GDP growth. Most variables are sourced from the World Bank's World Development Indicators (WDI) and the World Federation of Exchanges, while income inequality measures are drawn from the World Inequality Database (WID) and financial development indices are drawn from the IMF database.

[INSERT Table 1]

Table 2 reports the aggregate summary statistics for the full sample of country-year observations. The average Gini index across the sample is 36.4, with a range from 22.9 to 64.8, capturing a wide spectrum of income inequality levels across advanced and developing economies. The income shares of the top 1% (P99) and top 10% (P90) populations average 14.2% and 41.4%, respectively,

[1] List of countries in the sample: Argentina, Australia, Austria, Bangladesh, Belgium, Brazil, Canada, China, Colombia, Denmark, Egypt, Arab Rep., Finland, France, Germany, Greece, Hong Kong SAR, China, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Korea, Dem. People's Rep., Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Turkiye, United Kingdom, United States.

while the bottom 50% (P50) holds an average of 17.1%. These figures reflect persistent disparities in income distribution across countries and time. Stock market concentration (SMC), measured by the share of market capitalization held by the top 10 firms, averages 49.4%, with a range from 3.2% to 91.0%. Stock market capitalization as a share of GDP (SMCap) has a mean of 82.2% but a maximum of over 1,700%, likely driven by financial centers such as Hong Kong or Singapore where global firms are listed relative to a small domestic economy.

Financial development and market size indicators also display large disparities. Stock market capitalization as a share of GDP (SMCap) has a mean of 82.2% but a maximum of over 1,700%, likely driven by financial centers such as Hong Kong or Singapore where global firms are listed relative to a small domestic economy. Stock market turnover (SMT) also exhibits extreme outliers, with a mean of 206% and a maximum exceeding 165,000%, potentially reflecting short-term speculative activity, or extreme liquidity events in small or offshore markets. Inflation ranges from -6.0% to over 6,200%, implying episodes of hyperinflation.

[INSERT Table 2]

Panel A of Table 3 presents the average values by country for the main variables in our dataset.

We observe substantial cross-country variation in income inequality, with Gini coefficients ranging from around 26 (e.g., Denmark, Norway) to over 60 (e.g., South Africa, Brazil). This is consistent with the documented differences between more egalitarian advanced economies and highly unequal developing countries. The income shares of the top 1% (P99) and top 10% (P90) are generally higher in countries with high Gini coefficients, as expected. For instance, Brazil and South Africa show both high Gini indices and top-income shares, pointing to persistent elite income capture. In contrast, countries like Austria, Finland, and Sweden have lower Gini and top-share values, consistent with their stronger redistributive institutions.

Panel B of Table 3 reports Pearson correlation coefficients among the main variables. Several interesting relationships emerge. First, the correlation between stock market concentration (SMC) and inequality measures is positive but relatively weak (e.g., 0.05 with Gini, 0.07 with P99 and P90), and not statistically significant at the 5% level. In countries like the U.S., China, and India, where concentration is high and Gini is elevated, there may be reinforcing mechanisms at play: dominant firms controlling access to capital markets, commanding wage premiums at the top, and lobbying for policies that entrench inequality. Theoretically, this aligns with the political economy view of concentration, where powerful firms accumulate both economic and political capital, affecting distributional outcomes beyond what market forces alone would predict. Interestingly, stock market concentration (SMC) is only weakly correlated with market capitalization (SMCap) (0.22) and turnover ratio (SMT) (-0.01), suggesting that market concentration is not directly related to market size or liquidity.

[INSERT Table 3]

Bank concentration (BC) is negatively correlated with inequality (-0.31), in contrast to the effect of stock market concentration. This could reflect the stabilizing role of dominant banks in certain countries. Trade openness, highly correlated with SMCap and FD, also correlates negatively with Gini (-0.41), suggesting that integration into global markets may constrain domestic rent-seeking and enhance competition. GDP per capita growth is weakly correlated with Gini (0.04, not significant), reinforcing findings from literature that growth alone does not guarantee a reduction in inequality without attention to structural and institutional factors.

In terms of the financial development index (FD), it is negatively correlated with Gini (-0.41), supporting the view that more advanced financial markets can reduce inequality by improving access to credit and investment opportunities. Similarly, savings rates and trade openness show negative correlations with inequality, consistent with standard growth and development theories. Inflation is positively correlated with Gini (0.20), suggesting that macroeconomic instability may disproportionately hurt lower-income households, either through erosion of real wages or reduced access to hedging mechanisms. This aligns with results from empirical literature showing that inflation is often regressive.

3.2 Model

We estimate the effect of stock market concentration on income inequality by regressing various inequality measures for the country c in year t on lagged values of stock market concentration and other indicators of financial development from year $(t-1)$. Lagging all key explanatory variables by one period (t–1) helps reduce the simultaneity bias and allows for a more credible interpretation of the relationship between stock market concentration and income inequality. Since inequality evolves gradually and reflects cumulative institutional and market forces, using lagged regressors ensures that market structure precedes observed distributional outcomes. This timing structure also helps to address potential reverse causality, where rising inequality could, in turn, influence stock market concentration or financial development.

To address potential omitted variable bias, we include both country- and time- fixed effects in our benchmark specification. Country-fixed effects control for time-invariant characteristics such as legal institutions, political history, or social norms that might jointly affect inequality and financial structure. Time-fixed effects take into account global shocks, structural breaks, and common international trends, such as changes in capital flows, global interest rates, or regulatory shifts, that could simultaneously influence all countries in a given year. This two-way fixed effects design allows us to isolate within-country variation over time while controlling for unobserved heterogeneity across countries and time.

In addition, we estimate our model without time-fixed effects. We do so for several reasons. First, stock market concentration tends to evolve slowly, with limited year-to-year volatility. Including time-fixed effects may therefore absorb much of its variation, attenuating the estimated coefficients. Second, there is a risk of overcontrolling, where time effects capture some of the very mechanisms we seek to study, thereby biasing results downward or masking meaningful dynamics. Lastly, our panel includes a relatively small number of time periods, therefore including a full set of year-fixed effects may reduce degrees of freedom and inflate standard errors. Removing time effects in this context serves as a robustness test that complements our main specification, by testing whether our results would hold even without common-time controls.

Our benchmark panel regression model is as follows:

$$
\begin{aligned}
\text{Inequality}_{c,t} = {} & \beta_0 + \beta_1\,\text{SMC}_{c,t-1} + \beta_2\,\text{SMCap}_{c,t-1} + \beta_3\,\text{SMT}_{c,t-1} \\
& + \beta_4\,\text{FD}_{c,t-1} + \beta_5\,\text{BC}_{c,t-1} \\
& + \beta_6\,(\text{SMC} \times \text{SMCap})_{c,t-1} + \beta_7\,(\text{SMC} \times \text{BC})_{c,t-1} \\
& + \sum_i \gamma_i\,\text{Controls}_{c,i,t} + \sum_j \phi_j\,\text{CountryDummy}_j + \sum_k \psi_k\,\text{YearDummy}_k + \varepsilon_{c,t}
\end{aligned}
\tag{3}
$$

In line with relevant literature, we add the following macroeconomic control variables to the regressions: *Savings*, which is Gross Savings divided by GDP; *Inflation*, which is inflation rate based on GDP deflator; *Trade*, which is the sum of exports and imports as a share of GDP; and *GDP Growth*, which is the per capita GDP growth rate. We cluster standard errors by country. Stock market concentration and the other financial market characteristics are lagged by one subperiod.

We include interaction terms between stock market concentration and two key financial structure variables—bank concentration and stock market capitalization—to assess whether the inequality effects of concentration are conditional on the size and composition of the financial system. The SMC $\times$ SMCap interaction captures whether the effect of concentration differs in larger versus smaller equity markets. In deep markets, high concentration might reflect successful scaling and efficient capital allocation, whereas in shallow markets, it may reflect limited firm access and low competition. A significant interaction would suggest that the size of the market moderates the link between concentration and inequality. The SMC $\times$ BC interaction tests whether the structure of the banking sector alters the concentration-inequality relationship. In countries with highly concentrated banking sectors, the combination of equity and banking concentration might reinforce the dominance of incumbents. Alternatively, if banks serve as an offsetting source of capital access, high bank concentration might mitigate the exclusionary effects of stock market concentration.

4 Results

We begin with plots and regressions for a broad look at the correlation between stock market concentration and income inequality. Figure 1 shows that the average level of stock market concentration across countries has decreased modestly over the past two decades, indicating a slight decrease in the dominance of the largest firms. However, the empirical analysis that follows reveals that periods of higher stock market concentration within individual countries are associated with subsequent increases in income inequality, even after accounting for country- and time-fixed effects. This suggests that even short-term or relative increases in stock market concentration within countries can have lasting distributive consequences, particularly in institutional contexts with weak constraints on market power.

[INSERT Figure 1]

Figure 2 plots the residuals of Gini coefficients and Stock market concentration of the top 10 firms, generated by regressing them on the control variables and country fixed effects. We find an upward slope, which indicates that, even after accounting for structural factors and time-invariant country characteristics, residual stock market concentration of the top 10 firms is systematically associated with residual income inequality.

[INSERT Figure 2]

Next, through Tables 4-8, we present the regressions for a more formal analysis. In all tables, Columns (a) to (d) include both time- and country-fixed effects, while Columns (e) to (h) include only country-fixed effects. We control for macroeconomic factors in all specifications. To explore whether the effect of stock market concentration depends on other structural characteristics, we include interaction terms. Specifically, columns (b) and (f) include interactions of stock market concentration with stock market capitalization; columns (c) and (g) include interactions of stock market concentration with bank concentration; columns (d) and (h) include both types of interaction terms.

Table 4 presents regression estimates for the Gini index. The key result is that stock market concentration (SMC) is positively associated with the Gini index. Across all specifications, the coefficient on SMC is positive and statistically significant either at the 10% or the 5% level, even after controlling for other macro-financial variables and fixed effects. In terms of financial development (FD), across all specifications, we observe a strong, negative, and highly significant effect on the Gini coefficient. This relationship holds even after accounting for stock market dynamics, bank concentration, macroeconomic variables, and fixed effects, pointing to the independent role of institutional financial infrastructure in mitigating inequality.

In terms of the interaction terms, although we find no significance in any of our specifications in Table 4, the negative sign of some of the interaction terms suggests an interesting hypothesis: high stock market concentration may be less harmful in large liquid markets where smaller firms still have funding access (negative SMC×SMCap). On the other hand, bank concentration does not have a clear inequality-worsening effect, as implied by the ambiguity of the sign of SMC×BC term.

[INSERT Table 4]

In Table 5, the dependent variable is the income share of the top 1% (P99). The findings are statistically significant and remarkably consistent across all specifications. The coefficient on stock market concentration (SMC) is small but positive and significant at the 5% level, suggesting that increases in the concentration of equity markets are directly related to rising income shares at the very top of the distribution. Our results imply that highly concentrated stock markets disproportionately benefit the wealthiest, most likely because they own a bigger share of financial assets and are able to profit from large-capitalization gains.

In contrast, financial development (FD), which had a strong and significant negative effect on Gini, is not statistically significant for the top 1%. This suggests that while financial advancements can reduce broader income inequality, they may not be sufficient to counteract the disproportionate gains enjoyed by the top 1% in highly concentrated markets. Finally, in terms of the interaction terms, they continue to be statistically insignificant in this model, even though the results seem to be less conclusive in this case.

[INSERT Table 5]

Table 6 examines the relationship between stock market concentration (SMC) and the top 10% income share (P90). These findings also indicate that stock market concentration is positively and significantly associated with top-end income shares. Across nearly all specifications, the SMC coefficient is positive and statistically significant (mostly at the 5% level). What is striking is the the consistency in the effect size and statistical significance of stock market concentration across P90 and P99, despite some differences in magnitude. This implies that stock market concentration increases inequality not only through extreme elite capture (top 1%), but also through broader upper-class wealthy (top 10%).

It should be noted that the effect of financial development (FD) remains statistically insignificant, similarly for the case of the top 1%. On the other hand, stock market capitalization (SMCap) and stock market turnover (SMT) show small but statistically significant positive associations with the top 10% income share, implying that broader and more active capital markets can also reinforce income concentration when structural conditions favor the wealthy. Finally, interaction terms involving SMC and SMCap or BC remain statistically insignificant.

[INSERT Table 6]

Table 7 complements our earlier findings by showing the downward pressure that stock market concentration places on the bottom 50% income share. Across all specifications, the coefficient on stock market concentration (SMC) is negative and statistically significant, either at the 5% or the 10% level. The results imply that as market concentration rises, income shifts away from the bottom 50% toward the top deciles. This aligns with literature on rent extraction, capital-biased technological change, and the decline in labor's bargaining power.

Financial development (FD) is again insignificant in explaining variation in the bottom 50%

income share. This suggests that while financial advancements may help reduce overall inequality, as was observed in the Gini regressions, it may not directly improve the economic position of the bottom half of the population.

[INSERT Table 7]

Table 8 extends findings of Table 4 by allowing for a nonlinear relationship between financial development and income inequality, through the inclusion of a quadratic term for Financial Development ($\mathbf{FD^2}$). The results reinforce earlier evidence that stock market concentration (SMC) is positively and significantly associated with higher income inequality (as measured by the Gini coefficient). In all specifications, the SMC coefficient is statistically significant.

However, in contrary to the inverted-U relationship of inequality and financial development shown in literature (Greenwood & Jovanovic, 1990; Haan & Sturm, 2017), our results suggest a U-shaped relationship between financial development and inequality. While early financial development is associated with reductions in inequality, possibly through expanded credit and financial inclusion, more advanced financial systems tend to reinforce inequality. This may reflect the global shift toward financialization during the post-1990 era, where gains from financial innovation and market expansion accrue disproportionately to higher-income groups.

In terms of the interactions terms, the positive and weakly significant interaction between SMC and bank concentration (column f) suggests that stock market concentration might be more inequality-enhancing in countries where the banking sector is also highly concentrated.

[INSERT Table 8]

5 Conclusions

This paper investigates the relationship between stock market concentration and income inequality using a panel of 46 countries from 1989 to 2016. According to our findings, stock market concentration, as measured by the market capitalization share the top 10 firms, is positively associated with rising income inequality. This relationship holds even after controlling for macroeconomic conditions, financial development, and both country and time fixed effects. Furthermore, our results are consistent and robust across different specifications for income inequality measures, including the Gini coefficient and the rising income shares of the top 1%, top 10%, as well as the declining income share of the bottom 50% of the population.

Our results suggest that equity market structures matter for distributional outcomes. Concentrated stock markets appear to disproportionately benefit top-income groups, likely due to the concentrated ownership of financial assets and the disproportionate gains captured by shareholders of dominant firms. In contrast, as stock market concentration increases, the income share of the bottom half of the population declines, pointing to a pattern of redistribution from the bottom to the top.

In terms of the role of financial development, we find that, while financial financial advancements may help decrease income inequality at lower levels of development, their effect is not uniformly progressive. In fact, when we take into account a non-linear relationship between financial development and inequality, it appears to be U-shaped: early-stage development reduces inequality, but more advanced systems tend to reinforce it. This result contradicts earlier findings in the literature and may reflect post-1990s patterns of financialization, where innovation, deregulation, and capital market expansion have disproportionately favored high-income groups.

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Data Availability

The data can be provided upon request.

Appendix

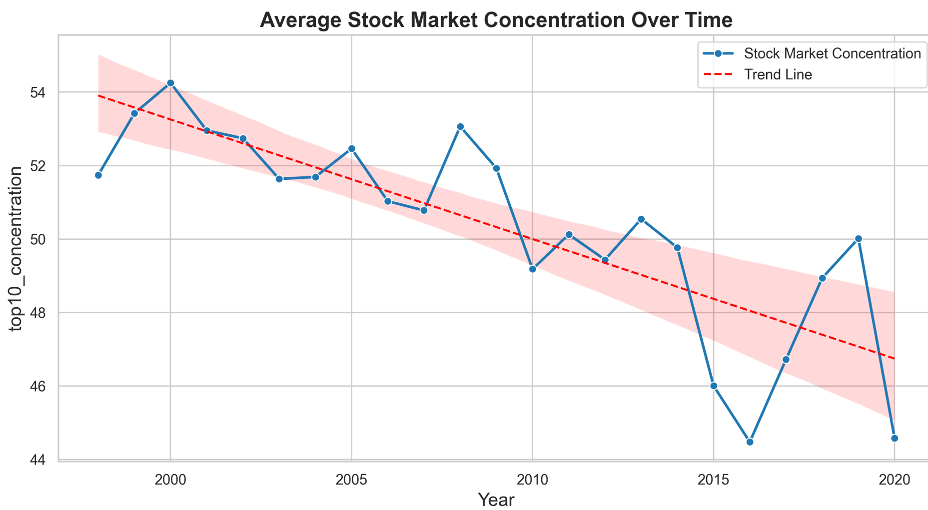

Figure 1: Average Stock Market Concentration over time.

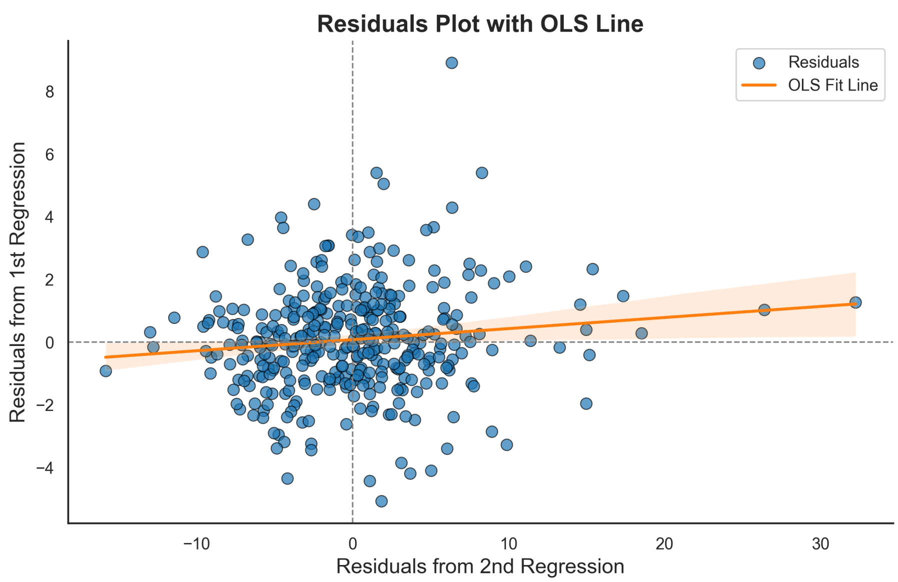

Figure 2: Residuals plot.

Table 1: Variable Definitions and Data Sources

Variable	Description	Data Source
Gini	Gini index of income inequality	WDI, World Bank
P99	Income share of the top 1% population	World Inequality Database (WID)
P90	Income share of the top 10% population	World Inequality Database (WID)
P50	Income share of the bottom 50% population	World Inequality Database (WID)
SMC	Stock Market Concentration (Top 10 firms, %)	World Federation of Exchanges
SMCap	Stock Market Capitalization (% of GDP)	World Federation of Exchanges
BC	Asset share of the three largest banks (%)	WDI, World Bank
SMT	Stock Market Turnover Ratio (%)	World Federation of Exchanges
FD	IMF Financial Development Index	IMF/IFS Statistics
Savings	Gross Domestic Savings (% of GDP)	WDI, World Bank
Inflation	Inflation rate (GDP deflator, annual %)	WDI, World Bank
Trade	Trade Openness (Trade as % of GDP)	WDI, World Bank
GDP Growth	GDP per capita growth (annual %)	WDI, World Bank

Note: This table lists the key variables used in the empirical analysis, along with their corresponding descriptions and data sources.

Table 2: Aggregate Summary Statistics

Variable	Mean	Std Dev.	Min	Max	Obs
Gini	36.38	8.18	22.9	64.8	824
P99	0.142	0.0486	0.0361	0.3415	1551
P90	0.414	0.0979	0.2061	0.6695	1551
P50	0.1707	0.0512	0.0525	0.3245	1551
SMC	49.42	17.61	3.23	91.03	686
SMCap	82.15	136.08	0.023	1777.54	1174
BC	65.20	18.72	21.45	100.00	976
SMT	206.04	4860.33	1.13	165149.1	1154
FD	0.526	0.225	0.098	1.00	1551
Savings	24.51	8.83	4.31	64.73	1504
Inflation	22.54	227.79	-6.01	6261.24	1514
Trade	78.20	67.63	13.75	442.62	1504
GDP Growth	2.11	3.49	-14.49	23.44	1514

Note: This table reports summary statistics of the main variables used in the analysis for 46 countries between 1989 and 2016.

Table 3: Summary Statistics and Correlations of main variables

Panel A: Average Values by Country

Country	Gini	P99	P90	P50	SMC	SMCap	BC	SMT	FD	Savings	Inflation	Trade	GDPgrowth
Argentina	46.08	0.133	0.465	0.115	26.72	14.12	42.59	33.02	0.307	19.34	176.55	28.17	1.12
Australia	33.84	0.111	0.343	0.218	56.97	92.67	71.30	60.93	0.837	25.17	2.80	39.95	1.58
Austria	30.18	0.092	0.325	0.180	37.43	23.41	63.15	63.84	0.576	27.07	1.89	89.82	1.37
Bangladesh	31.93	0.159	0.432	0.166	55.68	17.14	50.18	18.82	0.198	20.11	6.29	31.66	4.10
Belgium	28.04	0.083	0.323	0.207	–	59.59	77.75	29.79	0.593	25.46	1.96	141.83	1.34
Brazil	55.81	0.225	0.589	0.096	49.90	50.10	58.68	63.00	0.488	18.87	302.01	23.60	0.98
Canada	32.93	0.114	0.352	0.176	71.96	119.08	68.71	53.32	0.768	22.86	2.18	65.69	1.02
China	38.88	0.105	0.310	0.237	76.42	55.52	56.69	194.79	0.464	43.51	4.79	41.53	8.13
Colombia	53.68	0.125	0.388	0.162	28.08	45.43	71.01	14.24	0.277	17.78	11.82	36.11	1.84
Denmark	26.69	0.226	0.621	0.071	–	42.94	82.70	49.17	0.647	26.74	1.90	88.07	1.37
Egypt, Arab Rep.	30.95	0.114	0.340	0.207	51.51	33.92	60.10	42.63	0.289	12.44	10.59	47.36	2.19
Finland	27.10	0.105	0.303	0.237	–	24.78	94.37	296.78	0.542	26.41	1.95	69.94	1.37
France	31.99	0.189	0.495	0.156	–	64.20	62.74	78.59	0.684	22.17	1.45	55.14	1.14
Germany	30.24	0.116	0.348	0.202	55.25	41.32	74.54	112.65	0.697	25.33	1.67	63.18	1.44
Greece	34.45	0.097	0.315	0.226	40.75	36.66	80.78	42.63	0.492	12.88	4.76	53.59	0.82
Hong Kong SAR, China	–	0.106	0.331	0.207	54.01	672.56	67.07	50.96	0.703	29.16	2.42	317.32	2.46
Hungary	29.83	0.120	0.358	0.191	6.20	20.19	68.46	62.33	0.418	25.20	10.23	129.76	1.86
India	34.19	0.105	0.350	0.186	68.89	78.12	33.73	80.21	0.426	28.09	6.63	35.10	4.26
Indonesia	33.78	0.178	0.466	0.145	49.50	35.75	45.64	34.31	0.318	30.36	10.96	52.94	3.36
Ireland	32.66	0.097	0.305	0.251	15.68	51.76	73.74	20.16	0.684	39.34	2.41	168.89	4.88
Israel	39.91	0.166	0.439	0.149	50.96	63.67	75.83	34.70	0.519	23.33	4.96	63.77	1.97
Italy	34.54	0.111	0.342	0.206	43.24	29.15	60.11	6460.76	0.661	21.76	2.69	48.76	0.67
Japan	33.27	0.187	0.507	0.127	75.18	81.29	41.77	85.37	0.757	28.23	-0.05	25.74	0.98
Kenya	43.87	0.179	0.475	0.163	–	24.19	46.37	4.82	0.145	11.30	10.55	51.14	0.83
Malaysia	44.70	0.121	0.416	0.182	63.75	149.78	67.69	28.10	0.579	38.43	3.39	167.31	3.22
Mexico	50.03	0.181	0.516	0.122	39.40	29.36	53.84	29.91	0.339	20.55	11.50	54.68	0.79
Morocco	39.88	0.114	0.329	0.226	27.24	55.53	67.52	6.28	0.268	26.03	2.01	61.62	2.21
Netherlands	28.52	0.193	0.479	0.143	–	86.98	83.99	79.88	0.751	29.52	1.92	127.94	1.66
New Zealand	–	0.134	0.482	0.144	46.00	39.66	69.42	20.19	0.548	23.72	2.32	57.03	1.35
Norway	27.17	0.185	0.594	0.060	30.32	45.41	94.03	67.36	0.599	34.47	3.69	69.66	1.44
Pakistan	30.38	0.176	0.443	0.151	–	21.42	59.36	189.65	0.234	11.40	10.20	30.79	1.68
Peru	47.40	0.064	0.283	0.237	38.13	37.99	75.48	8.66	0.262	21.51	286.83	41.32	2.16
Philippines	45.24	0.104	0.302	0.251	48.47	57.93	54.28	19.96	0.333	17.16	5.36	65.98	2.25
Poland	32.41	0.134	0.363	0.192	39.86	25.43	53.61	40.11	0.393	20.43	9.53	77.70	3.87
Portugal	35.93	0.234	0.577	0.077	–	36.53	80.12	64.11	0.640	17.03	3.71	69.01	1.44
Romania	35.96	0.190	0.492	0.125	–	9.14	64.42	12.28	0.213	19.02	43.01	65.62	2.89
Singapore	–	0.168	0.436	0.168	59.39	183.63	88.82	49.00	0.711	50.57	1.72	351.33	3.76
South Africa	61.88	0.118	0.337	0.216	65.60	187.64	80.36	22.57	0.443	18.43	8.26	48.72	0.64
Spain	34.65	0.102	0.370	0.186	50.79	62.29	68.65	100.74	0.756	22.73	2.89	53.77	1.31
Sri Lanka	37.44	0.127	0.378	0.181	57.53	20.27	54.16	13.92	0.221	20.41	9.10	66.85	3.78
Sweden	27.61	0.102	0.303	0.247	–	74.20	93.71	61.16	0.688	26.84	2.43	77.53	1.45
Switzerland	32.91	0.131	0.420	0.183	31.01	182.68	83.08	78.48	0.914	33.93	0.88	103.46	0.91
Thailand	39.78	0.215	0.542	0.108	57.39	67.43	46.06	73.13	0.555	33.00	3.12	111.38	3.26
Turkiye	43.42	0.210	0.538	0.133	51.07	25.15	54.99	159.80	0.390	23.45	37.18	47.77	3.22
United Kingdom	34.65	0.171	0.427	0.147	61.68	114.96	50.84	62.97	0.811	15.93	2.82	54.78	1.34
United States	40.32	0.164	0.574	0.094	73.16	119.32	33.90	138.14	0.847	18.48	2.13	24.86	1.57

Panel B: Pearson Correlations among Main Variables

	Gini	P99	P90	P50	SMC	SMCap	BC	SMT	FD	Savings	Inflation	Trade	GDP Growth
Gini	1.00												
P99	0.1038*	1.00											
P90	0.1924*	0.9028*	1.00										
P50	-0.2016*	-0.8052*	-0.9423*	1.00									
SMC	0.0505	0.0708	0.0697	-0.0434	1.00								
SMCap	0.0046	-0.1082*	-0.1226*	0.1274*	0.2155*	1.00							
BC	-0.3085*	-0.1093*	-0.1557*	0.1640*	-0.3164*	0.054	1.00						
SMT	-0.0025	-0.0151	-0.0202	0.0254	-0.0084	-0.0181	0.0323	1.00					
FD	-0.4103*	0.0516*	0.0943*	-0.0871*	0.2585*	0.3329*	0.2379*	0.0123	1.00				
Savings	-0.2433*	-0.0491	-0.0366	0.0725*	0.0796*	0.1660*	0.2123*	-0.0048	0.3436*	1.00			
Inflation	0.2038*	0.0061	0.0264	-0.0302	0.0850*	-0.0355	-0.1518*	-0.0024	-0.1154*	-0.0356	1.00		
Trade	-0.4135*	-0.0594*	-0.1117*	0.1281*	-0.0411	0.6016*	0.2962*	-0.0165	0.3108*	0.5588*	-0.0680*	1.00	
GDP Growth	0.0418	-0.0197	-0.0615*	0.0844*	0.0733	-0.0043	-0.0916*	-0.0019	-0.1054*	0.2767*	-0.1433*	0.0982*	1.00

Note: This table reports the summary statistics and correlations of the main variables for all country-year observations from a 46-country sample (1989–2021). Variables include income inequality measures (Gini, P99, P90, P50), stock market concentration of top 10 firms (SMC), market capitalization (SMCap), bank concentration (BC), stock market turnover ratio (SMT), financial development (FD), gross savings (% GDP), inflation, trade openness, and per capita GDP growth. Panel A reports country averages. Panel B shows Pearson correlations. * indicates significance at or below the 5% level.

Table 4: Panel Regressions of Gini on Stock Market Concentration

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
SMC	0.046*	0.045**	0.041	0.040*	0.0551**	0.0574**	0.0483*	0.0502*
	(0.023)	(0.021)	(0.025)	(0.023)	(0.0254)	(0.0253)	(0.0276)	(0.0277)
SMCap	0.005	0.005	0.008	0.008	0.0139*	0.0138*	0.0187***	0.0186***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.0070)	(0.0070)	(0.0067)	(0.0068)
BC	-0.014	-0.014	-0.016	-0.015	-0.0102	-0.0135	-0.0119	-0.0145
	(0.096)	(0.014)	(0.010)	(0.014)	(0.0123)	(0.0155)	(0.0125)	(0.0157)
SMT	0.000	0.000	0.001	0.001	0.0044	0.0045	0.0050	0.0051
	(-0.003)	(0.003)	(0.004)	(0.004)	(0.0040)	(0.0040)	(0.0039)	(0.0039)
FD	-18.191***	-18.197***	-18.077***	-18.086***	-21.134***	-21.039***	-21.052***	-20.979***
	(4.091)	(4.080)	(4.107)	(4.098)	(5.210)	(5.324)	(5.318)	(5.427)
Savings	0.120	0.121	0.124	0.124	0.1213	0.1199	0.1259	0.1248
	(0.141)	(0.140)	(0.141)	(0.140)	(0.1220)	(0.1207)	(0.1221)	(0.1211)
Inflation	-0.157***	-0.157***	-0.156***	-0.156***	-0.1468***	-0.1464***	-0.1456***	-0.1453***
	(-0.044)	(0.044)	(0.044)	(0.044)	(0.0396)	(0.0395)	(0.0395)	(0.0395)
Trade	-0.027	-0.027	-0.027	-0.027	-0.0325	-0.0323	-0.0335	-0.0334
	(-0.031)	(0.031)	(0.031)	(0.031)	(0.0217)	(0.0216)	(0.0220)	(0.0220)
GDP Growth	-0.062	-0.063	-0.058	-0.059	-0.0302	-0.0285	0.1259	-0.0258
	(-0.083)	(0.083)	(0.084)	(0.084)	(0.0577)	(0.0569)	(0.1221)	(0.0569)
SMCxSMCap			-0.009	-0.009			-0.0123	-0.0122
			(0.009)	(0.008)			(0.0085)	(0.0085)
SMCxBC		-0.001		-0.001		0.0031		0.0024
		(0.009)		(0.009)		(0.0079)		(0.0078)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	No	No	No	No
Countries	32	32	32	32	32	32	32	32
Observations	385	385	385	385	385	385	385	385
R-squared	0.38	0.38	0.38	0.38	0.3151	0.3155	0.3207	0.3209

Note: This table presents the results of panel regressions in which Gini is regressed on stock market concentration (top 10 firms). The sample includes country-year observations for 46 countries during the period 1989-2016. All of the variables are defined in Table 1. The t-statistics in parentheses are based on robust standard errors clustered by country. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Panel Regressions of Top 1% Income Share on Stock Market Concentration

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
SMC	0.0004071**	0.000422**	0.0004195**	0.00044**	0.00036**	0.000385**	0.000386**	0.0004149**
	(0.0001862)	(0.000194)	(0.0002036)	(0.00021)	(0.00018)	(0.000180)	(0.000193)	(0.0001952)
SMCap	0.0000168	0.000017	0.0000164	0.00002	0.00002*	0.000020*	0.000019*	0.0000189*
	(0.0000120)	(0.000012)	(0.0000113)	(0.00001)	(0.00001)	(0.000011)	(0.000010)	(0.0000104)
BC	0.0000630	0.000041	0.0000649	0.00004	0.00010	0.000055	0.000099	0.0000556
	(0.0000942)	(0.000109)	(0.0000982)	(0.00011)	(0.00008)	(0.000111)	(0.000086)	(0.0001123)
SMT	0.0000123	0.000013	0.0000123	0.00001	0.00000	0.000003	0.000003	3.51E-06
	(0.0000259)	(0.000026)	(0.0000260)	(0.00003)	(0.00003)	(0.000028)	(0.000028)	(0.0000283)
FD	-0.0351681	-0.034729	-0.0363254	-0.03595	-0.01421	-0.012876	-0.016906	-0.0156555
	(0.0329126)	(0.033094)	(0.0321371)	(0.03231)	(0.04320)	(0.043079)	(0.042942)	(0.0428739)
Savings	0.0000642	0.000050	0.0000504	0.00003	0.00022	0.000193	0.000182	0.0001514
	(0.0003502)	(0.000354)	(0.0003303)	(0.00033)	(0.00031)	(0.000315)	(0.000290)	(0.000292)
Inflation	0.0002759	0.000279	0.0002726	0.00028	0.00028	0.000289	0.000276	0.0002792
	(0.0003576)	(0.000359)	(0.0003580)	(0.00036)	(0.00026)	(0.000260)	(0.000263)	(0.0002612)
Trade	-0.0000910	-0.000090	-0.0000888	-0.00009	-0.00006	-0.000062	-0.000059	-0.0000569
	(0.0000725)	(0.000073)	(0.0000685)	(0.00007)	(0.00007)	(0.000071)	(0.000067)	(0.0000665)
GDP Growth	-0.0000876	-0.000075	-0.0000965	-0.00008	0.00026	0.000277	0.000247	0.0002623
	(0.0003248)	(0.000319)	(0.0003338)	(0.00033)	(0.00022)	(0.000217)	(0.000226)	(0.0002238)
SMCxSMCap			0.0000163	0.00002			0.000036	0.0000386
			(0.0000506)	(0.00005)			(0.000046)	(0.0000449)
SMCxBC		0.000021		0.00002		0.000038		0.0000406
		(0.000058)		(0.00006)		(0.000065)		(0.0000648)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	No	No	No	No
Countries	36	36	36	36	36	36	36	36
Observations	585	585	585	585	585	585	585	585
R-squared	0.09	0.1	0.1	0.1	0.041	0.041	0.042	0.0425

*Note:*This table presents the results of panel regressions in which the top 1% income share of the population is regressed on stock market concentration. The sample includes country-year observations for 46 countries during the period 1989-2016. All of the variables are defined in Table 1. The t-statistics in parentheses are based on robust standard errors clustered by country. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Panel Regressions of Top 10% Income Share on Stock Market Concentration

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
SMC	0.0003422**	0.000396**	0.0003314**	0.00039**	0.00030*	0.000357*	0.000303	0.0003668**
	(0.0001548)	(0.000161)	(0.0001708)	(0.00018)	(0.00018)	(0.000193)	(0.000194)	(0.000208)
SMCap	0.0000208	0.000022	0.0000212	0.00002	0.00002*	0.000024*	0.000023*	0.000024*
	(0.0000148)	(0.000015)	(0.0000142)	(0.00001)	(0.00001)	(0.000014)	(0.000014)	(0.0000137)
BC	0.0001718	0.000092	0.0001701	0.00009	0.00019*	0.000094	0.000193*	0.0000943
	(0.0001199)	(0.000166)	(0.0001226)	(0.00017)	(0.00011)	(0.000167)	(0.000112)	(0.0001677)
SMT	0.0000690**	0.000071**	0.0000691**	0.00007**	0.00004*	0.000045*	0.000044*	4.46E-05*
	(0.0000297)	(0.000029)	(0.0000294)	(0.00003)	(0.00003)	(0.000025)	(0.000026)	(0.0000255)
FD	-0.0331158	-0.031505	-0.0321100	-0.03083	-0.02023	-0.017089	-0.020773	-0.0179701
	(0.0408495)	(0.041424)	(0.0396232)	(0.04014)	(0.03972)	(0.039603)	(0.039073)	(0.038955)
Savings	0.0003789	0.000326	0.0003909	0.00033	0.00046	0.000399	0.000454	0.0003863
	(0.0005361)	(0.000541)	(0.0005204)	(0.00052)	(0.00047)	(0.000469)	(0.000457)	(0.0004542)
Inflation	0.0000846	0.000097	0.0000875	0.00010	0.00017	0.000176	0.000165	0.0001732
	(0.0005491)	(0.000551)	(0.0005505)	(0.00055)	(0.00043)	(0.000427)	(0.000432)	(0.000428)
Trade	-0.0000968	-0.000095	-0.0000987	-0.00010	-0.00008	-0.000079	-0.000081	-0.0000777
	(0.0000955)	(0.000096)	(0.0000931)	(0.00009)	(0.00009)	(0.000092)	(0.000090)	(0.0000893)
GDP Growth	-0.0004870	-0.000439	-0.0004793	-0.00043	0.00006	0.000092	0.000053	0.0000871
	(0.0005174)	(0.000528)	(0.0005282)	(0.00054)	(0.00032)	(0.000318)	(0.000326)	(0.0003247)
SMCxSMCap			-0.0000142	-0.00001			0.000007	0.0000122
			(0.0000632)	(0.00006)			(0.000057)	(0.0000557)
SMCxBC		0.000075		0.00007		0.000090		0.0000909
		(0.000073)		(0.00007)		(0.000081)		(0.0000811)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	No	No	No	No
Countries	36	36	36	36	36	36	36	36
Observations	585	585	585	585	585	585	585	585
R-squared	0.09	0.096	0.09	0.096	0.052	0.056	0.052	0.056

*Note:*This table presents the results of panel regressions in which the top 10% income share of the population is regressed on stock market concentration. The sample includes country-year observations for 46 countries during the period 1989-2016. All of the variables are defined in Table 1. The t-statistics in parentheses are based on robust standard errors clustered by country. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Panel Regressions of Bottom 50% Income Share on Stock Market Concentration

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
SMC	-0.0001701**	-0.000210**	-0.0001534*	-0.00019**	-0.00017*	-0.000215**	-0.000165*	-0.0002088*
	(0.0000834)	(0.000091)	(0.0000921)	(0.00010)	(0.00009)	(0.000105)	(0.000099)	(0.0001107)
SMCap	-0.0000047	-0.000005	-0.0000053	-0.00001	-0.00001	-0.000007	-0.000007	-7.23E-06
	(0.0000075)	(0.000007)	(0.0000073)	(0.00001)	(0.00001)	(0.000007)	(0.000007)	(7.27E-06)
BC	-0.0000576	0.000001	-0.0000551	0.00001	-0.00006	0.000005	-0.000062	5.48E-06
	(0.0000700)	(0.000093)	(0.0000714)	(0.00001)	(0.00006)	(0.000087)	(0.000060)	(0.0000872)
SMT	-0.0000516***	-0.000053***	-0.0000517***	-0.00005***	-0.00004***	-0.000037***	-0.000036***	-3.64E-05***
	(0.0000150)	(0.000014)	(0.0000144)	(0.00001)	(0.00001)	(0.000012)	(0.000012)	(0.0000115)
FD	0.0156805	0.014484	0.0141297	0.01319	0.01746	0.015278	0.016618	0.0147052
	(0.0188817)	(0.019158)	(0.0185018)	(0.01871)	(0.01692)	(0.016863)	(0.016766)	(0.016619)
Savings	-0.0004692	-0.000430	-0.0004876	-0.00045	-0.00041	-0.000367	-0.000421	-0.0003749
	(0.0003142)	(0.000316)	(0.0003107)	(0.00031)	(0.00028)	(0.000275)	(0.000275)	(0.0002713)
Inflation	0.0002085	0.000200	0.0002040	0.00020	0.00013	0.000119	0.000122	0.0001169
	(0.0003358)	(0.000336)	(0.0003372)	(0.00034)	(0.00030)	(0.000300)	(0.000305)	(0.0003016)
Trade	-0.0000143	-0.000016	-0.0000114	-0.00001	-0.00001	-0.000011	-0.000008	-0.0000101
	(0.0000461)	(0.000046)	(0.0000457)	(0.00005)	(0.00004)	(0.000045)	(0.000045)	(0.0000445)
GDP Growth	0.0005316	0.000496	0.0005197	0.00049	0.00020	0.000175	0.000195	0.0001717
	(0.0003413)	(0.000346)	(0.0003473)	(0.00035)	(0.00022)	(0.000214)	(0.000220)	(0.0002173)
SMCxSMCap			0.0000218	0.00002			0.000011	7.94E-06
			(0.0000424)	(0.00004)			(0.000038)	(0.0000381)
SMCxBC		-0.000056	-0.0000545	-0.00005		-0.000063		-0.0000621
		(0.000041)		(0.00004)		(0.000042)		(0.0000423)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	No	No	No	No
Countries	36	36	36	36	36	36	36	36
Observations	585	585	585	585	585	585	585	585
R-squared	0.099	0.1	0.1	0.105	0.07	0.07	0.066	0.073

Note: This table presents the results of panel regressions in which the bottom 50% income share of the population is regressed on stock market concentration. The sample includes country-year observations for 46 countries during the period 1989-2016. All of the variables are defined in Table 1. The t-statistics in parentheses are based on robust standard errors clustered by country. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Panel Regressions of Gini on Stock Market Concentration (Quadratic Fin Dev)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
SMC	0.0473**	0.0516***	0.0421*	0.0461**	0.0540**	0.0609**	0.0469*	0.0535*
	(0.0220)	(0.0182)	(0.0245)	(0.0206)	(0.0252)	(0.0246)	(0.0278)	(0.0273)
SMCap	0.0111	0.0111	0.0149**	0.0148**	0.0167**	0.0166**	0.0218***	0.0215***
	(0.0077)	(0.0077)	(0.0060)	(0.0061)	(0.0064)	(0.0064)	(0.0049)	(0.0049)
BC	-0.0151	-0.0206	-0.0168	-0.0219	0.0121	-0.0219	-0.0140	-0.0230
	(0.0104)	(0.0136)	(0.0105)	(0.0139)	(0.0123)	(0.0142)	(0.0125)	(0.0142)
SMT	-0.0005	-0.0003	0.0002	0.0004	0.0035	0.0037	0.0042	0.0043
	(0.0031)	(0.0030)	(0.0032)	(0.0032)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
FD	-51.03***	-51.72***	-51.18***	-51.81***	-58.61***	-59.33***	-58.68***	-59.35***
	(12.41)	(12.38)	(12.63)	(12.59)	(14.64)	(14.70)	(14.85)	(14.89)
FD^2	26.86***	27.46***	27.08***	27.63***	31.67***	32.52***	31.80***	32.59***
	(9.85)	(9.76)	(9.91)	(9.82)	(10.51)	(10.57)	(10.58)	(10.62)
Savings	0.1367	0.1351	0.1407	0.1392	0.1383	0.1347	0.1432	0.1398
	(0.1431)	(0.1416)	(0.1436)	(0.1422)	(0.1258)	(0.1243)	(0.1259)	(0.1247)
Inflation	-0.1636***	-0.1628***	-0.1624***	-0.1617***	-0.1557***	-0.1549***	-0.1545***	-0.1538***
	(0.0440)	(0.0436)	(0.0437)	(0.0434)	(0.0376)	(0.0370)	(0.0374)	(0.0369)
Trade	-0.0230	-0.0231	-0.0238	-0.0239	-0.0269	-0.0262	-0.0279	-0.0273
	(0.0327)	(0.0327)	(0.0327)	(0.0327)	(0.0235)	(0.0233)	(0.0237)	(0.0236)
GDP Growth	-0.0800	-0.0766	-0.0753	-0.0722	-0.0485	-0.0439	-0.0454	-0.0412
	(0.0795)	(0.0799)	(0.0796)	(0.0802)	(0.0558)	(0.0557)	(0.0558)	(0.0558)
SMCxSMCap			-0.0102	-0.0100			-0.0129	-0.0125
			(0.0083)	(0.0081)			(0.0081)	(0.0080)
SMCxBC		0.0054		0.0049		0.0092*		0.0085
		(0.0079)		(0.0076)		(0.0056)		(0.0054)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	No	No	No	No
Countries	32	32	32	32	32	32	32	32
Observations	385	385	385	385	385	385	385	385
R-squared	0.43	0.43	0.43	0.43	0.38	0.39	0.39	0.39

*Note:*This table presents the results of panel regressions in which Gini is regressed on stock market concentration. Financial Development is included with a quadratic term in the specification. The sample includes country-year observations for 46 countries during the period 1989-2016. All of the variables are defined in Table 1. The t-statistics in parentheses are based on robust standard errors clustered by country. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.