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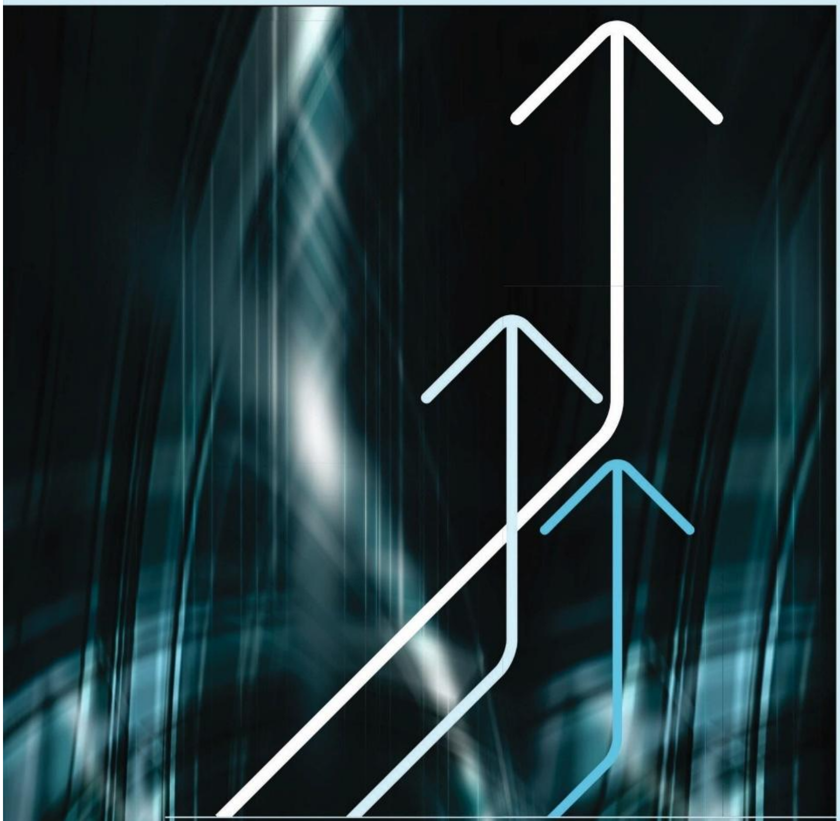

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Contents

CREDIT MANAGEMENT PRACTICES, FIRM SIZE AND FINANCIAL SUSTAINABILITY OF DEPOSIT-TAKING SAVINGS AND CREDIT COOPERATIVE SOCIETIES IN KENYA

John Ndung'u GACHENGA, PhD Candidate*
Dennis Kamau MUTHONI, PhD**
Wilson Kipkemboi METTO, PhD***

Abstract

The study examined the moderating effect of firm size on the relationship between credit management practices and the financial sustainability of DT-SACCOs in Kenya. The study was grounded in information asymmetry theory, utilising a positivist paradigm and an exploratory research design. The target population consisted of 176 finance managers from 176 DT-SACCOs, providing a robust framework for analysis. The sample size was obtained using Yamane's formula, which resulted in 122 respondents, with a high response rate of 98 per cent for the structured questionnaires administered. Data was analysed using descriptive and inferential statistics. The inferential statistics revealed a strong positive association between credit management practices and financial sustainability, with p-values of 0.013. Notably, the Nagelkerke R-squared change demonstrated that firm size moderates the connection between credit management practices and financial sustainability. The study recommends enhancing financial sustainability through credit information sharing and establishing a deposit guarantee fund to protect members' funds in the event of license revocation or closure.

* *School of Co-operatives and Community Development, The Co-operative University of Kenya, Nairobi, Kenya. Corresponding author, e-mail: johngachenga@gmail.com*
** *Lecturer, School of Business and Economics, The Co-operative University of Kenya, Nairobi, Kenya*
*** *Lecturer, School of Co-operative and Community Development, The Co-operative University of Kenya, Nairobi, Kenya*

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JEL Classification: G21, P13, L25

1. Introduction

Deposit Taking Savings and Credit Cooperative Societies (DT-SACCOs) are critical pillars of financial inclusion globally, offering accessible savings and credit services to populations underserved by traditional financial institutions (Sing'ombe, 2022). Globally, SACCOs have mobilised over $3.1 trillion in savings, with approximately 84% of these funds directed toward lending, underscoring their pivotal role in fostering socio-economic development (WOCCU, 2024). However, the sector's rapid growth has not been without challenges. Notably, 15.1% SACCOs are currently facing sustainability threats due to ineffective credit management practices, high default rates and inadequate internal controls (WOCCU, 2024; WOCCU, 2022). These challenges are particularly pronounced among small and medium-sized SACCOs, where institutional capacity is often limited.

Across the African continent, SACCOs play a vital role in addressing credit access gaps, especially in rural and informal economies (AFDB, 2021). Yet, poor credit assessment procedures, lack of proper risk mitigation frameworks and weak enforcement of loan repayment policies have undermined the sector's stability. The World Council of Credit Unions (WOCCU, 2024) reports a sharp decline in the number of active SACCOs across Africa, with 37.4% of institutions being declared financially unsound. These systemic issues have not only strained liquidity positions but also eroded member trust, resulting in declining savings and loan uptake (Ali & Ndede, 2024). The situation is further aggravated by information asymmetry, where borrowers possess more knowledge about their financial capacities than lenders, often resulting in unmanageable credit exposure and non-performing loans (Apwoka et al., 2021).

In Kenya, DT-SACCOs are key players in the financial sector, managing substantial savings and credit portfolios and supporting the livelihoods of diverse socio-economic groups. Nevertheless, their sustainability is under growing pressure due to persistent weaknesses in credit management. According to the Sacco Societies Regulatory Authority (SASRA, 2023), over 62 percent of DT-SACCOs failed to meet the non-performing asset threshold of 5 percent and many exceeded the ideal lending-to-deposit ratio of 100 percent, reaching levels as high as 113.4 percent (SASRA, 2023). This over-extension indicates a growing reliance on borrowed funds, exposing SACCOs to liquidity shocks and financial distress. Furthermore, loan repayment challenges remain acute, with Kshs 2.59 billion in non-remitted loan deductions recorded in 2023, affecting 82 DT-SACCOs and over 57,000 members (SASRA, 2023).

An emerging issue within this context is the role of firm size in shaping SACCO sustainability. While larger SACCOs may enjoy benefits such as economies of scale, diversified loan portfolios, and stronger governance structures, smaller SACCOs often grapple with limited resources, weak credit appraisal systems, and poor loan recovery mechanisms (Onsongo et al., 2025). These disparities raise critical questions about how organisational size moderates the relationship between credit management practices and financial sustainability. Despite ongoing regulatory reforms and enhanced supervision, 36% of DT-SACCOs were declared financially unsound in 2023, with several institutions experiencing license revocations due to insolvency and governance lapses (SASRA, 2023).

Given these concerns, this study investigates the relationship between credit management practices and the financial sustainability of DT-SACCOs in Kenya, with a particular focus on the moderating role of firm size. By identifying key gaps and offering actionable insights, the research aims to inform policy formulation and support institutional reforms that enhance the resilience and long-term viability of SACCOs in Kenya.

2. Statement of the problem

Deposit-taking Savings and Credit Co-operative Societies are vital financial institutions in Kenya that contribute to financial inclusion, economic empowerment, and poverty reduction, particularly among underserved populations. Lending constitutes the core business of DT-SACCOs, accounting for approximately 84% of their asset portfolio. This dominant investment activity is expected to enhance their financial sustainability by generating interest income and supporting members' socio-economic growth through access to affordable credit. However, despite their critical role, 36 percent of DT-SACCOs face growing challenges related to poor credit management practices, threatening their financial viability and long-term sustainability. According to the

SASRA (2023), 62 percent of DT-SACCOs are currently at risk of being delisted due to unsustainable loan portfolios, with 82 DT-SACCOs owed KES 2.6 billion from unremitted loan repayments. As a result, an average of five SACCOs were delisted annually between 2014 and 2019 (Muriithi, 2023), a trend that persisted into 2023 when four SACCOs lost their licenses due to poor credit performance and mismanagement. This situation leads to massive revenue losses, increased provisions for bad debts and a diminished capacity to meet member demands and operational costs (Maina et al., 2020). Moreover, potential borrowers, especially low-income members, are denied access to credit as funds remain tied up in defaulted loans, exacerbating financial exclusion and stalling individual and community development initiatives. This challenge not only undermines the financial health of SACCOs but also jeopardises Kenya's broader socio-economic goals, including Vision 2030, which prioritises the development of a robust, inclusive financial sector. It equally poses a threat to the achievement of the Sustainable Development Goals (SDGs), especially SDG 1 (No Poverty), SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation and Infrastructure), all of which depend on accessible and well-managed financial systems (United Nations, 2022).

The extant literature on credit management practices and financial sustainability in SACCOs presents mixed and often inconclusive findings. For instance, Natufe and Evbayiro-Osagie (2023) identified a strong link between effective credit appraisal and financial sustainability in Nigerian microfinance institutions. In contrast, Ariyo (2023), studying cooperative societies in Uganda, found that strict credit policies enhanced loan recovery but had a minimal impact on long-term sustainability. In Rwanda, Nsengiyumva and Harelimana (2020) reported that credit risk controls improved financial sustainability when integrated with robust loan monitoring systems. Conversely, Gachini (2021) and Maina et al. (2020) highlighted that although many Kenyan SACCOs had credit policies in place, their effectiveness varied based on institutional size, governance quality, and enforcement capacity.

These divergent findings highlight a lack of consensus on the influence of credit management practices on financial sustainability, particularly in contexts with varied institutional capacities and regulatory environments. Moreover, the moderating role of firm size remains underexplored despite its potential to shape the effectiveness of credit governance mechanisms. In Kenya, where DT-SACCOs are a cornerstone of the financial ecosystem yet remain vulnerable to high levels of non-performing loans, a context-specific analysis is urgently needed.

This study, therefore, seeks to address this gap by examining the effect of credit management practices on the financial sustainability of DT-SACCOs in Kenya, with firm size introduced as a moderating variable. By generating insights specific to the SACCO sector's operational realities, the research aims to inform theory, guide policy and support the design of more sustainable credit management frameworks.

The rest of the paper is organized into five sections. The following Section (Section 3) presents a review of relevant theoretical and empirical literature on credit management practices, firm size and financial sustainability. Further, Section 4 outlines the research methodology, including the research design, sampling procedures, data collection instruments and analytical techniques. Section 5 provides the results and discussion, focusing on the relationship between credit management practices, firm size and financial sustainability among DT-SACCOs. The last Section offers a summary of the key findings, conclusions and policy implications.

3. Literature review

Information asymmetry theory was pioneered by Akerlof (1970), developed by Spence (1973) and extensively expounded by Rothschild and Stiglitz (1976). The theory postulates that there is an imbalance of information between parties, leading to different behaviours compared to a situation with symmetric information. It is assumed that one party involved in a transaction possesses more or superior information than the other party, creating a potential imbalance in their decision-making (Maina et al., 2020). Within the scope of the credit landscape of financial institutions, the interplay between lenders and borrowers is intricately shaped by the concepts of moral hazard and adverse selection, where lenders confront difficulties while gauging the creditworthiness of potential borrowers (Kariuki, 2018).

However, the recent developments in asymmetric theory have revealed that the risk within a firm varies based on its size (Maina et al., 2020). For instance, small-sized SACCOs with low capital tend to respond to moral hazard incentives by increasing the risk in their loan portfolios. This in turn, results in a higher number of non-performing loans when compared to large-sized SACCOs. On the other hand, large-sized SACCOs with more capital, gain a competitive advantage, allowing them to employ competent staff who make prudent decisions. This ultimately improves the sustainability of the SACCOs while reducing credit risk. It supports the assumption that the party with superior information has the incentive to exploit this advantage to maximise its own gains. However, the party with less information (borrower) may be aware of the existence of information asymmetry but may not be able to accurately gauge its extent (Rothschild and Stiglitz, 1976).

Despite the advancement, the theory faces critiques in its applicability due to its limited consideration of informal lending practices, which ultimately impact the quality of credit assessments and financial stability (FSD, 2021). This is in support of Kyombo et al. (2025), who revealed that information asymmetry in the informal sector is often addressed through social networks, local knowledge and community-based lending practices, which are not adequately captured by modern credit management practices. Selcuk (2024) further critiqued the theory, basing the argument on behavioural biases in credit decisions, depicting that information asymmetry often assumes rational behaviour in credit management, neglecting the impact of behavioural biases such as overconfidence and herd behaviour that may influence lending decisions, even when sufficient information is available. However, despite the critiques, the theory has played a major role in improving SACCOs liquidity.

SACCOs, being member-owned institutions, may be the only financial institutions that lend through a multiplier method and guarantorship model when advancing loans. This helps them leverage the information asymmetry to enhance credit management practices. Through recognising the existence of information imbalances, they have implemented strategies such as loan portfolio diversification, credit scoring and analysis, loan loss reserves, and SACCO solution insurance to mitigate lending risks (Sing'ombe, 2022). Equally, despite mitigating the moral hazard they also mitigate other challenges that may stem from adverse selection. This is done by improving communication channels to ensure members are well-informed about the borrowing process, implementing transparent credit scoring mechanisms and providing financial education to empower them in making informed financial decisions.

In the study, information asymmetry theory will explore the effect of credit management practice and financial sustainability of DT-SACCOs. The theory posits that information asymmetry stems from borrowers providing inaccurate financial information, creating a challenge in differentiating between reliable and unreliable prospective borrowers. The consequence of this misinformation is the escalating problem of non-performing loans over time resulting to contingent illiquidity, financial distress leading to conservatorship and SACCOs declared unsustainable.

An empirical review related to the study's objective was conducted. Siddique et al. (2021) did a study on the effect of credit risk management and bank-specific factors on the financial performance on the South Asian Commercial banks. Non-performing loan, capital adequacy ratio, cost efficiency, average lending rate and liquidity ratios were the study predictors where bank size, inflation and age were the controllable variables. The study employed panel data and analyzed with the help of ordinary least square regression. The analysis established factors related to nonperforming include inadequate supervision and monitoring of customers, market issues and customers' lack of knowledge about loans. The study concludes that banks should recruit experts to maintain strong liquidity, essential for survival in a competitive environment. It recommends that commercial banks strengthen their financial ecosystem to reduce non-performing loans.

Natufe and Evbayiro-Osagie (2023) conducted a study on credit risk management and the financial performance of deposit money banks: some new evidence. Credit risk management was measured through the capital adequacy ratio, liquidity ratio, loan-to-deposit ratio, risk asset ratio, non-performing ratio and size. The study adopted credit risk theory and financial distress theory. Longitudinal research design and census method were considered, with twelve years of data from 2010 to 2021. The model revealed that the loan-to-deposit ratio has an insignificant nexus on financial performance. However, capital adequacy ratio, liquidity ratio, risk asset ratio, non-performing ratio and size has a significant nexus on financial performance. The study recommended that the Central Bank strengthen its regulatory functions with regular reviews to compel improvements in the credit risk management systems of deposit money banks to mitigate the likelihood of failure in the credit life cycle of granted loans.

Ariyo (2023) employed credit terms, credit assessments and credit control to determine the effect of credit management and financial performance of Centenary Bank Uganda. A descriptive research design and simple random sampling were considered, where self-administered questionnaires helped to collect data from 40 respondents within the bank. Data collected was analysed using SPSS and Microsoft Excel. The analysis revealed a positive correlation between credit financing and the performance of Centenary Bank. The study conclusion and recommendations related to credit financing which is contrary to the study topic credit management and financial performance.

Nsengiyumva and Harelimana (2020) carried out a study with the aim of determining the contribution of loan management to the performance of savings and credit co-operatives in Rwanda. Loan management was measured through membership enrolment, client appraisal, credit risk control and collection policy whereas return on equity measured financial performance. Descriptive and inferential statistics were employed where the regression model revealed a positive nexus between membership enrolment, client appraisal, credit risk control and collection policy on financial performance of SACCOs. The study recommended SACCOs to employ competent employees to improve financial inclusion which may lead to increased membership and capital base. The study further recommended for education and training to SACCOs board of management to help them make prudent decisions.

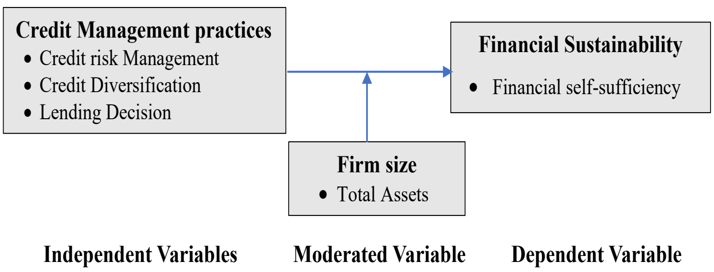
Gachini (2021) did a study on the evaluation of the role of credit risk management on the profitability of commercial banks in Kenya and revealed a positive relationship. Credit risk identification, credit risk analysis and credit risk management were study predictors whereas bank size moderated the nexus. The study was anchored on a positivist paradigm and a descriptive research design. The data collected was analysed with the help of inferential statistics and descriptive statistics. Descriptive statistics revealed that despite high ratings from CRBs and FICO, borrower screening remains the most important method of screening borrowers. The study revealed a positive nexus between capital adequacy ratio, loan-to-deposit ratio, non-performing loan ratio, management efficiency ratio and profitability of commercial banks in Kenya. Based on findings, the study recommended that banks employ credit risk identification practices to reduce non-performing loans, which have adversely affected banks' profitability as well as financial sustainability.

Maina et al. (2020) aimed to determine the effect of credit management practice, SACCO size and financial sustainability of deposit taking savings and credit co-operatives in Kenya. credit management was measured through credit risk mitigation, staff competence whereas SACCO size moderated the relationship. Descriptive cross-sectional survey design and cluster sampling to determine the sample size. Deceptive statistics revealed that when issuing loans, credit officers consider guarantors information more, followed by credit report and number of withdrawable deposits. However, borrowers' repayment habit seems not to play a big role when screening borrowers' credibility as this can lead to a misleading signal. The regression model revealed a significant relationship between credit management practice and financial sustainability of DT-SACCOs. The study recommended SACCOs to hire employees with the necessary skills and experience, which may lead to improved service delivery and operational efficiency.

The study utilized an explanatory research design.

Figure 1

Conceptual framework



Source: Authors' representation

4. Methods

The study adopted exploratory research design within a positivism philosophical paradigm. Positivist paradigm ensured that the study was value-free employing objective measures to examine social reality. Theories were empirically tested and statistical models employed to reinforce objectivity, unbiased observation and the understanding of a single external reality. Consequently, an exploratory research design was employed to investigate under-explored phenomena by formulating hypotheses based on theoretical frameworks, designing methodologies, collecting and analysing data and interpreting results to provide explanations. The sample size was determined using Yamane's formula resulting to 122 respondents. A two-stage sampling technique was employed, and data were collected using structured questionnaires. Out of the 122 respondents, 98 per cent (120) responded to the questionnaires. The reliability test affirmed the suitability of the data collection tools with a Cronbach's alpha value of 0.834.

A hierarchical binary logistic regression model was used where the following regression equations were applied to assess the potential moderating effect where equation 1 assessed the direct nexus between credit management practices and financial sustainability, equation 2 and 3 explored on the moderation and interaction effects.

$$Logit\ [p] = ln\frac{p}{1-p} = \beta_0 + \beta_1 CMP \quad (1)$$

$$Logit\ [p] = \beta_0 + \beta_1 CMP + \beta_2 FS \quad (2)$$

$$Logit\ [p] = \beta_0 + \beta_1 CMP + \beta_2 FS + \beta_3 CMP * FS \quad (3)$$

Where: $Logit\ [p]$ - the natural logarithm of the SACCOs will be financially sustainable; β_0= intercept; $\beta_1, \beta_2, \beta_3$= coefficients; CMP = credit management practices; FS = firm size (moderating variable); CMP*FS (credit management practices * firm size).

Nagelkerke R-squared change evaluated the strength of the moderating effect of firm size.

5. Results and discussions

Financial sustainability descriptive statistics

Financial self-sustainability (FSS) was employed to determine the DT-SACCOs' sustainability. The study expected that either the DT-SACCOs are financially sustainable, which was labelled as one, or otherwise labelled as 0. To determine the financial sustainability, the following formula was considered:

$$FSS = \frac{Adjusted\ Financial\ Revenue}{Adjusted\ Expense} \tag{4}$$

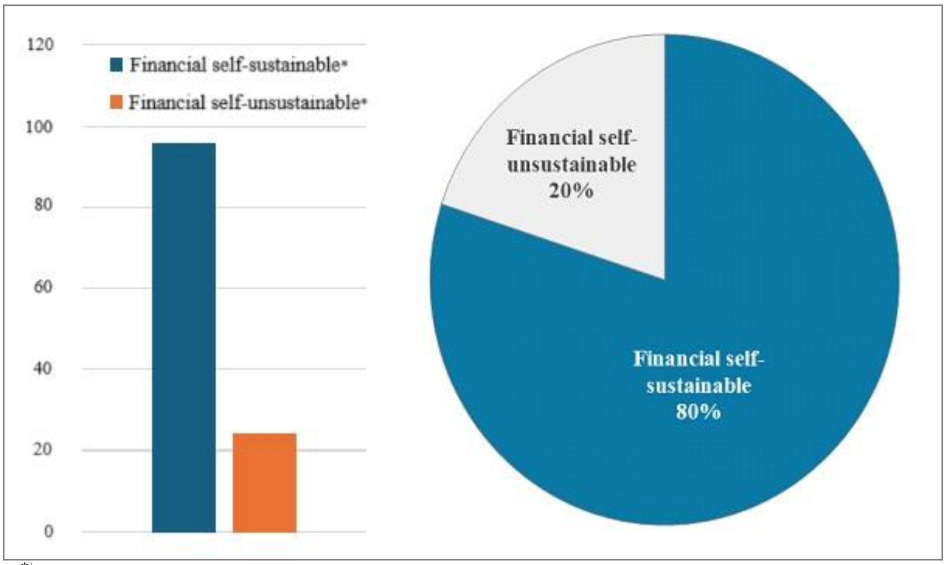
$$\begin{aligned} Adjusted\ Financial\ Revenue \\ &= Income\ from\ loans + Income\ from\ investments \\ &+ Other\ income - Grants/subsidies \end{aligned} \tag{5}$$

$$\begin{aligned} Adjusted\ Expenses \\ &= financial\ cost + operating\ cost \\ &+ loan\ loss\ provision \end{aligned} \tag{6}$$

The analysis established that 96 DT-SACCOs were financially self-sustainable, with 24 financially self-unsustainable (see Figure 2).

Figure 2

Financial Self-sufficiency



*) *as frequency*

Source: Authors' illustration

The 96 DT-SACCOs that are financially self-sustainable represent 80 percent of the total. In comparison, Mushonga (2018) found that 77 percent of financial co-operatives in South Africa were financially self-sustainable, although 82 percent faced difficulties in maintaining consistent profitability due to high operational expenses and inefficient management practices.

These findings align with those obtained by Anakpo et al. (2023), who emphasised that credit unions continue to face sustainability challenges, primarily stemming from capital limitations, elevated operational costs and heavy reliance on external funding.

Credit management practices, firm size and financial sustainability

Hierarchical regression models were used to assess the moderating effect of firm size on the relationship between credit management practices and the financial sustainability of deposit-taking SACCOs in Kenya. The analysis aimed to test whether firm size moderates the nexus. Nagelkerke R-squared change evaluated the strength of the moderating effect, as shown in Table 1.

Table 1

Hierarchical Regression Results

	Model 1			Model 2			Model 3		
Predictors	*Beta[a]*	*Wald*	*P*	*Beta[a]*	*Wald*	*P*	*Beta[a]*	*Wald*	*P*
(Constant)	-2.582	2.702	.100	-4.406	1.992	.158	2.779	.046	.830
CMP	.109	6.228	.013	.110	6.304	.012	-.102	.075	.785
FS				.196	.468	.494	-.614	.181	.671
CMP*FS							.024	.326	.568
Nagelkerke R^2	.084			.090			.094		

Source: Authors'

Based on the findings in Table 1, the hierarchical model 1 established a significant nexus between credit management practices and the financial sustainability of deposit-taking SACCOs, supported by a significant P-value of 0.013. The significance is further supported by Wald statistics (Wald = 6.228), which exceeds the critical Wald value of 1.96, indicating a significant relationship. The results align with previous studies by Ariyo (2023) and Maina et al. (2020), who found a positive link between credit management and financial performance and sustainability in DT-SACCOs. Moreover, the binary logistic regression model generated the following equation:

$$Logit\ [p] = \ln\left[\frac{p}{1-p}\right] = -2.582 + 0.109\ CMP$$

Model 2 investigated the moderating effect of firm size on the relationship between credit management practices and financial sustainability. The model revealed a significant nexus with a P-value of

0.012. this was in support of calculated Wald statistic of 6.304 which exceeded the critical Wald statistic value of 1.96. However, firm size on its own did not significantly predict financial sustainability, as indicated by a p-value of 0.494 and calculated Wald statistic of .468. The model generated the equation:

$$Logit\ [p] \ln\left[\frac{p}{1-p}\right] = -4.406 + 0.110\ CMP + 0.196\ FS$$

This indicates that a one-unit increase in credit management practices and firm size leads to a 0.110 and 0.196 increase in financial sustainability, respectively.

Model 3 explored the interaction effect of firm size on the relationship between credit management practices and financial sustainability. The inclusion of the interaction term resulted in an inverse relationship, with p-values of 0.785, 0.671 and 0.568 across the variables. These findings suggest that when firm size is considered as a moderating factor, the association between credit management practices and financial sustainability weakens, indicating a negative interaction effect. Consequently, the analysis generated the following equation:

$$Logit\ [p] = 2.779 - 0.102\ CMP - 0.614\ FS + 0.024\ CMP * FS$$

To determine the moderating effect of firm size on the relationship between credit management practices and financial sustainability, a hierarchical regression analysis was conducted across three models. Model 1 assessed the direct relationship between credit management practices and financial sustainability. The model established a Nagelkerke R-Squared value of 0.084, indicating that credit management practices explained 8.4% of the variance in the financial sustainability of DT-SACCOs. In Model 2, firm size was introduced as a moderating variable, resulting in an increase in the Nagelkerke R-Squared to 0.090. This change suggests that firm size has a positive moderating influence on the relationship. Model 3 incorporated the interaction term between credit management practices and firm size, which led to a further increase in the Nagelkerke R-Squared to 0.094. This additional improvement implies that the interaction between firm size and credit management practices enhances the model’s explanatory power, suggesting that the effect of credit management on financial sustainability is influenced by the size of the SACCO.

6. Conclusions

Considering the research findings, the study concludes that a significant association exists between credit management practices and the financial sustainability of DT-SACCOs in Kenya. Moreover, the study concludes that firm size strengthens the relationship between credit management practices and the financial sustainability of DT-SACCOs in Kenya. Grounded in the study's findings, tailored recommendations have been developed to assist SACCOs in enhancing their credit management systems, with the goal of promoting sustained financial stability.

The study recommends establishing a deposit insurance guarantee fund to protect members' savings and ensure reimbursement in the event of a SACCO's failure. This measure is crucial for maintaining trust, especially among tier-three SACCO members who may lack the capacity to monitor the financial health of their institutions. Implementing such a scheme helps stabilise the SACCO sector by reducing the likelihood of panic withdrawals during periods of financial distress.

The study further recommends that SACCOs embrace credit information sharing as a strategic approach to curb the growing problem of loan defaults. However, the effectiveness of this strategy depends on establishing a robust legal framework. Currently, participation in credit information sharing remains discretionary, which limits its impact. To address this, SASRA and policymakers should prioritise legal reforms to resolve existing inconsistencies and make credit information sharing mandatory for all SACCOs. This recommendation is supported by SASRA's observation that SACCOs rarely request credit reports from Credit Reference Bureaus (CRBs), despite frequently submitting member data to CRBs primarily for debt recovery purposes.

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THE BANKING SECTOR'S ASSETS IN ROMANIA. DEVELOPMENTS OVER THE PAST DECADE AND MID-RUN PROSPECTS

Andrei RĂDULESCU, PhD*

Abstract

The total assets of the banking sector in Romania increased significantly over the past decade, from RON 364.1 billion at the end of 2014 to RON 881.7 billion at the end of 2024, according to the statistics of the National Bank of Romania (NBR). This evolution was supported by several factors, including Romania's economic convergence towards the EU average. However, Romania continues to be a country with a very low banking assets-to-GDP ratio, below 50%. In this paper, we employ standard econometric tools and utilise quarterly data from NBR, Eurostat, and the Shillerdata platform to assess the evolution of the banking sector's assets in Romania over the past decade. The main result of our analysis shows that the increase in banking assets was more dependent on the financing needs of the Government than on the evolution of the nominal GDP in Romania. This, in turn, represents a risk factor for the evolution of economic activity, for the macroeconomic stability and for the monetary policy transmission at the moment of the outbreak of the following shocks.

Keywords: Banking sector, Romania, ordinary least squares

JEL Classification: C21, G21, O52

1. Introduction

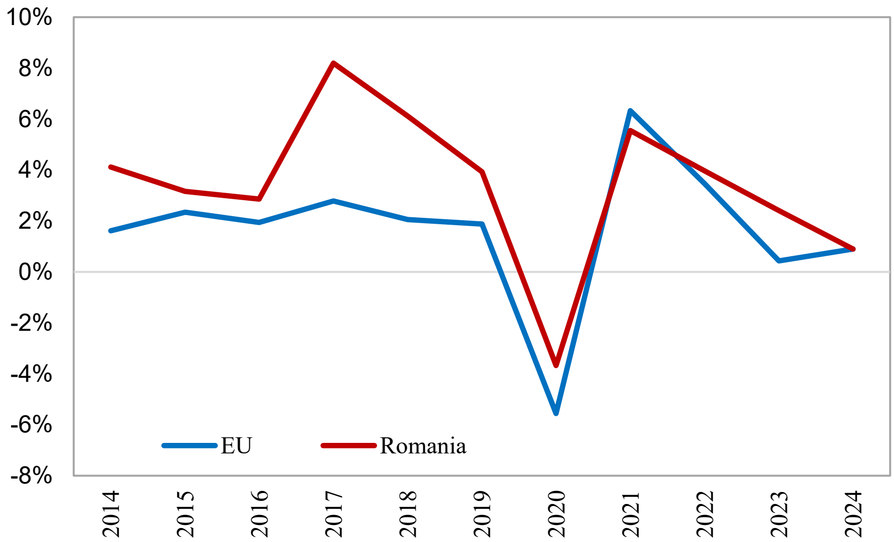
The total assets of the banking sector in Romania increased by more than 2.4 times between the end of 2014 and the end of 2024, reaching RON 881.7 billion, according to the NBR statistics (NBR, 2025). It can be noticed that there is an increase in the total assets in the Romanian banking sector after the outbreak of the coronavirus pandemic. This indicator climbed for the fourth year in a row in 2024 by a double-digit average annual pace, in acceleration to 12.3%.

* *Senior Researcher, Institute for World Economy, Romanian Academy, Bucharest, Romania. Corresponding author, e-mail: iemradulescu@gmail.com*

This evolution was supported by the several factors, including the EU economic convergence process of Romania – the national economy grew by an average annual pace of 3.3% during 2014-2024, more than double compared to the evolution of the economy of the European Union (1.6%), according to the statistics and estimates of Eurostat (2024, 2025), as can be noticed in Figure 1.

Figure 1

The annual rate of GDP - Romania vs. EU



Source: representation of the author based on Eurostat data (2024, 2025)

Furthermore, the deterioration of the public finances in Romania determined the increase in the financing needs of the Government. In this context, the exposure of the financial sector to the debt securities issued by the General government grew to a record high level of EUR 68.6bn at the end of 2024.

In this paper standard econometric tools are applied and the databases of the National Bank of Romania, Eurostat, and Shillerdata are used in order the assess the relation between the evolution of the annual rate of the assets of the banking sector in Romania and the developments of several macroeconomic and financial indicators during 2014-2024.

According to the results of the econometric estimates, the annual pace of the assets of the banking sector in Romania was more dependent on the evolution of the budget deficit-to-GDP ratio than on the annual dynamic of the nominal GDP in the past decade.

In this context, the annual growth pace of the total assets of the banking sector in Romania is expected to decelerate in the mid-run, given the prospects for the fiscal consolidation and for the slowing down of the annual pace of nominal GDP.

Therefore, Romania would continue to present a low level of the banking assets/GDP ratio in the coming years, after being in 98th place in the world in 2021, according to the statistics of the International Monetary Fund (IMF, 2024).

The remainder of the paper is structured as follows: Section 2 provides a brief review of the literature on the relationship between the banking sector's assets and macroeconomic indicators; the methodology is described in Section 3; the results of the econometric estimates are presented in Section 4; and the conclusions are drawn in Section 5.

2. Related literature

The relationship between the development of the banking sector and macroeconomic indicators has been intensively studied in recent decades, especially after the outbreak of the Great Financial Crisis in 2007-2008.

Berger et al. (2020) and Popov (2017) presented the main contributions to the literature on the relation between the banking sector and the real economy in recent decades.

On the one hand, the banking sector plays an important role in financing the real economic activity, especially in Europe and emerging and developing countries.

For instance, Hamdaoui and Cancelo (2024) evidenced a positive relation between the strength of the banking sector and the dynamics of the real economy in France, Spain, and Romania during 2000 – 2020.

Analysing the banking sector in Ukraine, Redkva (2018) found a direct correlation between the dynamics of the GDP and the evolution of the net banking assets.

However, Hasan et al. (2009) proved a weakening relation between financial development and economic growth across developed countries.

On the other hand, the banking sector is an important channel for the transmission of the monetary policy.

In this respect, Mermelas and Tagkalakis (2024) analysed the impact of the monetary policy shocks across the member countries of the Eurozone, showing a greater impact in the countries with a lower banking assets/GDP ratio.

Furthermore, Peek and Rosengren (2013) underlined the importance of bank lending in countries with lower access of banks and companies to the financial markets.

Last, but not least, the outbreak of the Great Financial Crisis and the recent exogenous shocks (coronavirus pandemic, and the geo-political tensions) brought to the forefront the issues related to financial stability.

In this respect, Cantu and Chui (2020) pointed out the vulnerabilities determined by the high weight of foreigners in the local currency bond markets, the development of non-bank financial corporations, and the exposure of the private sector to debt in foreign currency.

Furthermore, Dunz et al. (2024) emphasized that the upward trend of the exposure of the domestic banks to the government debt (up by over 35% on average in the emerging and developing countries from 2012 to 2023) may determine severe consequences in terms of macroeconomic, financial, and banking stability, for the countries with increasing vulnerabilities in public finance.

3. Methodology

In this paper, standard econometric tools are applied in order to assess the relation between the evolution of the banking sector's assets in Romania and several macro-financial indicators.

On the one hand, we considered domestic variables, including the evolution of nominal GDP and the dynamics of the budget deficit-to-GDP ratio.

On the other hand, we added a barometer of the international macro-financial climate, namely the dynamic of the S&P 500 index in USA, the largest economy in the world, with a nominal GDP close to

USD 30tn at the end of 2024, according to the estimates of the Bureau of Economic Analysis (BEA, 2025).

We estimated the following OLS (Ordinary Least Squares) regression using the econometric software E-Views:

$$ASSETS = C(1) + C(2) * GDP + C(3) * BugetDeficitGDP + C(4) * SP500 \quad (1)$$

Where:

$ASSETS =$ the annual pace of the total assets in the banking sector (in Romania);

$GDP =$ the annual pace of the nominal GDP (in Romania);

$BudgetDeficitGDP =$ budget deficit-to-GDP ratio (in Romania);

$SP500 =$ the annual pace for the S&P 500 (in the USA);

$C(1) =$ the intercept;

$C(2), C(3), C(4) =$ the estimated coefficients for the independent variables.

We worked with quarterly observations for the period from 4Q 2014 to 3Q 2024, as the data for the evolution of the budget deficit-to-GDP ratio in 4Q 2024 had not yet been released by Eurostat.

The statistics on the evolution of the annual pace of total assets in the Romanian banking sector were obtained from the NBR's database (2025).

On the other hand, Eurostat (2025) was the database used for the annual pace of the nominal GDP and the budget deficit-to-GDP ratio in Romania.

Lastly, but not least, the annual pace for the S&P 500 index was calculated using the statistics available on Shillerdata (2025).

4. Interpretation of the results

The results of the OLS estimated regression are presented in Table 1.

First, all the estimated coefficients are statistically significant at the 10% level, as shown in Table 1.

Furthermore, the measure of the strength of the relation between the annual pace of the banking assets and the independent variables (R-squared) is good, with a level close to 60%.

Table 1

The results of the OLS estimated regression (1)

Dependent Variable: ASSETS
Method: Least Squares
Date: 03/05/25 Time: 11:11
Sample(adjusted): 2014:4 2024:3
Included observations: 40 after adjusting endpoints
ASSETS = C(1)+C(2)*NOMINALGDP+C(3)*BUDGETDEFGDP+C(4)
*SP500

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2.144811	1.151775	1.862178	0.0708
C(2)	0.205237	0.078652	2.609440	0.0131
C(3)	0.870807	0.139742	6.231532	0.0000
C(4)	0.058913	0.033570	1.754936	0.0878

R-squared	0.589517	Mean dependent var	8.900277
Adjusted R-squared	0.555310	S.D. dependent var	4.214010
S.E. of regression	2.810117	Akaike info criterion	4.998969
Sum squared resid	284.2833	Schwarz criterion	5.167857
Log likelihood	-95.97938	Durbin-Watson stat	1.312666

Source: econometric estimates in E-Views, 2025

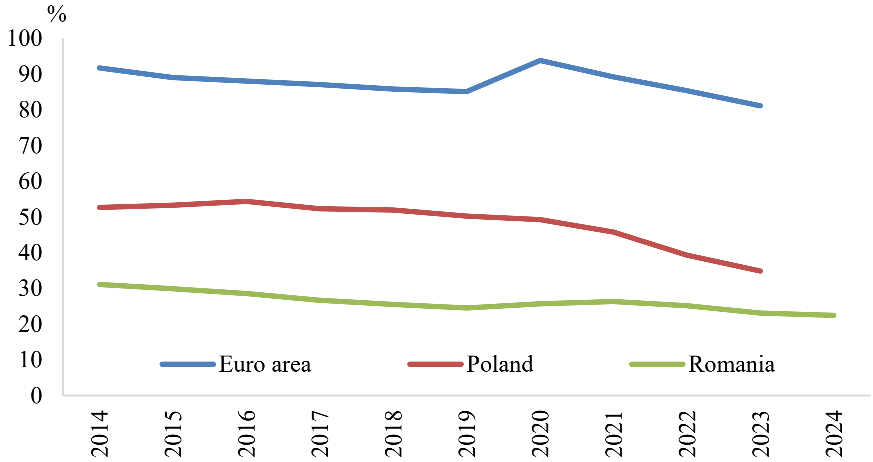
On the one hand, a positive relationship can be observed between the annual pace of total assets in the domestic banking sector and the annual dynamics of nominal GDP in Romania from 2014 to 2024, with an estimated coefficient of 0.21. In other words, an increase of the nominal GDP by 1pp determined the advance of the assets in the banking sector by 0.21pp in Romania in the past decade.

The low level of this coefficient is explained by the downward trend for the non-government loans/GDP ratio since the outbreak of the Great Financial Crisis, as reflected in Figure 2. According to the World Bank (2025) database and to our estimates, the non-government loans/GDP ratio in Romania declined to below 23% in 2024, the lowest level since 2005.

This, in turn, was determined by the fact that the nominal GDP generally increased at a stronger pace than the non-government loans starting in 2010, given the consequences of the financial crisis.

Figure 2

The non-government loans-to-GDP ratio



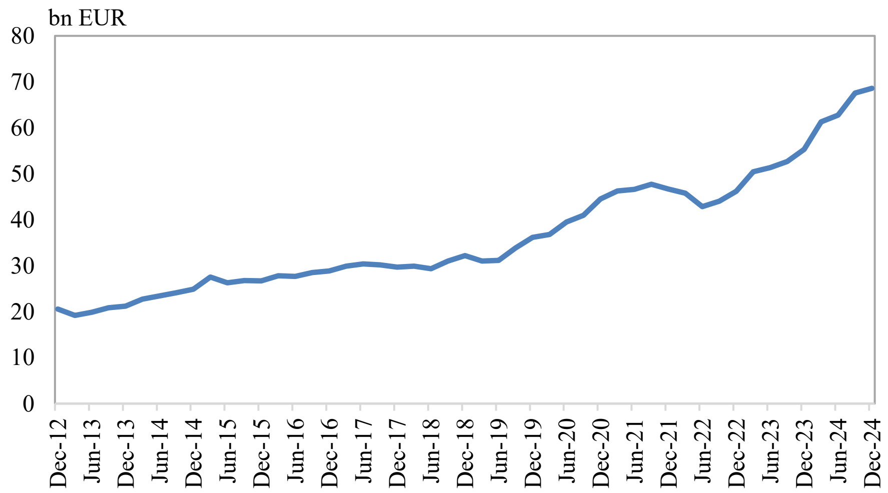
Source: representation of the author based on World Bank (2025) database for the period 2014-2023 and on the author's estimate for 2024

Furthermore, there is a positive relation between the annual pace of the total assets in the domestic banking sector and the dynamics of the budget deficit-to-GDP ratio, the estimated coefficient for the period 2014-2024 being 0.87. Therefore, a one percentage point (pp) widening of the budget deficit-to-GDP ratio determined a 0.87 percentage point (pp) increase in banking assets during the analysed period.

The holdings by financial corporations of debt securities issued by the general government rose 2.76 times, from EUR 24.9bn in December 2014 to EUR 68.6bn in December 2024 (a record high level), according to the NBR statistics.

Figure 3

Holdings by financial corporations of the government debt



Source: representation of the author based on NBR database (2025)

In other words, the widening trend for the budget deficit-to-GDP ratio, following several years of fiscal consolidation (after the outbreak of the Great Financial Crisis), had a bigger impact for the increase of the assets in the Romanian banking sector than the evolution of the nominal GDP.

This is the main contribution of our article to the existing literature on the relations between the banking sector and the macroeconomic indicators. The results are very important and represent a strong signal for the policymakers in Romania to implement measures in order to avoid the building up of tensions and risks that may lead to a banking crisis determined by the deterioration of public finances. Furthermore, the results are also relevant for the banks in Romania, which should focus more on developing services in order to finance more economic activity, especially the investment plans of companies.

Last, but not least, there is a positive relation between the annual pace of the banking sector's assets and the climate on the US stock market, the estimated coefficient being 0.06. Therefore, a positive climate in the global financial market contributed to the increase in assets in the Romanian banking sector. The advance of the

S&P 500 by 1pp determined the increase of the assets in the Romanian banking sector by 0.06pps during 2014-2024.

We point out that if we exclude the intercept, the estimated coefficients are 0.31 for the annual pace of the nominal GDP, 1.02 for the budget deficit-to-GDP ratio and 0.08 for the annual pace of S&P 500 index. Furthermore, in this alternative, the estimated coefficients are statistically significant at 3%. On the flipside, the R-squared is slightly lower than in the regression with an intercept, at 55%.

The results of the econometric estimates corroborated with the prospects for the slowing down of the annual growth pace of the nominal GDP and for the fiscal consolidation (needed more than ever since the Great Financial Crisis in order to avoid the sovereign rating cut) and the challenges for the international financial markets during Trump 2.0 Administration are factors that express perspectives for the slowing down of the annual pace of the total assets of the banking sector in Romania in the coming years.

Furthermore, we point out that, in the adverse macroeconomic scenario (in this case Romania would be downgraded to "junk" by the international rating agencies), the value of the holdings of Government bonds may significantly decline for a while, with negative impact for the evolution of the total assets, but also for the macroeconomic and financial stability in Romania.

5. Conclusions

This paper assessed the evolution of the banking sector's assets in Romania during the interval 2014-2024 by implementing standard econometric tools and using the databases of the National Bank of Romania, Eurostat, and Shillerdata platform.

The results of the econometric estimates emphasised the positive relation between the annual pace of the total assets in the Romanian banking sector and the annual pace of nominal GDP, the budget deficit-to-GDP ratio and the annual pace of S&P 500 index in the past decade.

On the other hand, according to these results, the increase of the banking sector's assets was more dependent on the widening trend for the budget deficit-to-GDP ratio than on the evolution of the nominal GDP in Romania in the past decade. This represents a vulnerability for the future evolution of the real economy, and also a structural risk factor for the financial and macroeconomic stability and for the monetary policy transmission at the moment of the outbreak of the next world/European/regional shocks (endogenous and/or exogenous).

In other words, the significant increase of the banking sector's assets in the recent years is not sustainable. In this context, structural reforms are needed in the banking sector in Romania, including the change of the business models, turning the focus on the corporate/investment banking, increasing the financial inclusion through ambitious campaigns, and hedging the risk of the high-level exposure to the public debt.

Last, but not least, Romania should accelerate the structural reforms, in order to improve the annual pace of the potential growth and to consolidate the public finance, very important aspects in order to diminish the risks related to the sustainability of the public finance and to the middle-income trap.

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FORECASTING STOCK MARKET LIQUIDITY WITH MACHINE LEARNING: AN EMPIRICAL EVALUATION IN THE GERMAN MARKET

Bogdan Ionut ANGHEL, PhD Candidate*

Abstract

The study benchmarks four machine-learning algorithms—Random Forest, XGBoost, CatBoost and Long Short-Term Memory (LSTM) networks—for forecasting stock market liquidity in Germany's DAX equity market. Using data from January 2006 to May 2025, a Liquidity Score is constructed as a turnover-to-volatility ratio, designed to penalize wide intraday price swings while rewarding active trading behavior. This metric captures key microstructural aspects of liquidity and serves as the dependent variable throughout the analysis. It is paired with 41 independent variables that capture volatility, price ranges, return dynamics, technical indicators and cross-asset linkages. Empirical testing shows that the two gradient-boosting ensembles consistently outperform both Random Forest and the LSTM model, tracking sudden liquidity swings more accurately and delivering the tightest forecast errors. The evidence highlights (i) the practical superiority of tree-based boosting for high-frequency liquidity prediction, (ii) the value of rich, carefully engineered feature sets in modelling non-linear market micro-structure effects and (iii) the limitations of standard LSTM architectures when financial sequences are short and noisy. The findings offer actionable insights for traders, treasurers and regulators seeking real-time early-warning indicators of liquidity stress in European blue-chip equities.

Keywords: stock market, German equity market, liquidity, machine learning, time series forecasting

JEL Classification: G12, G15, C5, C8, C45, C53

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* *Faculty of International Business and Economics, Bucharest University of Economic Studies, Bucharest, Romania. Corresponding author, e-mail: bogdan.anghel@rei.ase.ro*

1. Introduction

Sharp contractions in market liquidity can intensify price volatility, raise transaction costs, and transmit financial stress across asset classes, making short-term liquidity forecasting essential for traders, treasurers, and regulators. However, such forecasting remains inherently difficult due to the complex, non-linear, and regime-dependent interactions among order-flow variables, price dynamics, and cross-asset signals—features that traditional linear models are often ill-equipped to capture. Machine learning (ML) techniques offer a promising alternative by uncovering intricate patterns in high-dimensional, noisy datasets, yet their comparative effectiveness in forecasting liquidity in major European equity markets remains underexplored, with few studies employing standardized, real-time evaluation frameworks.

Against this backdrop the present study poses a single, guiding research question: Which of four widely used ML algorithms—Random Forest, XGBoost, CatBoost and Long Short-Term Memory network—provides the most accurate and robust day-ahead forecasts of DAX equity-market liquidity?

To answer this question the paper constructs a turnover-to-volatility Liquidity Score for the German blue-chip index and pairs it with forty-one predictors grouped into five conceptual blocks: volatility metrics, price-range measures, return dynamics, technical indicators and cross-asset signals. Each algorithm is tuned and assessed within an identical walk-forward framework that preserves the chronological order of observations and replicates the constraints of real-time deployment. The resulting head-to-head comparison allows the study to isolate the contribution of model architecture from that of feature engineering.

The article is structured as follows. Section 2 surveys the existing literature on liquidity forecasting and data-driven financial modelling, highlighting unresolved issues. Section 3 describes the data, defines the Liquidity Score and details the feature-engineering pipeline. Section 4 sets out the modelling framework, hyper-parameter tuning strategy and validation design. Section 5 reports empirical results, interprets comparative performance and discusses practical implications. Section 6 concludes, outlining limitations and suggesting directions for future research.

2. Literature review

The forecasting of liquidity in capital markets has become increasingly significant in the wake of heightened financial volatility and systemic risk. Over the past decade, the emergence of machine learning (ML) techniques has introduced sophisticated approaches capable of capturing the non-linear, dynamic patterns inherent in liquidity measures. This literature review synthesises findings from recent academic contributions on the application of ML to liquidity forecasting, highlighting trends, methodological advancements, and key challenges.

Traditional econometric models for liquidity forecasting have often relied on linear assumptions and limited feature sets. However, ML algorithms such as random forests, support vector machines, and deep learning architectures have demonstrated superior predictive capabilities, particularly in high-dimensional or noisy data environments (Guerra et al., 2022; Antony & Kumar, 2024).

Kirkby and Andrean (2024) applied supervised ML algorithms to forecast bid-ask spreads in foreign exchange markets, revealing that such models can effectively anticipate microstructural changes in market liquidity. Similarly, Cabrol et al. (2024) explored ML-based forecasting of bond illiquidity, noting that models incorporating non-linear interactions between fundamental variables outperformed benchmark methods.

From a regulatory standpoint, ML models offer promising tools for risk detection and early warning. Triepels et al. (2021) applied recurrent neural networks (RNNs) to monitor high-value payment flows in real time, identifying anomalous liquidity behaviours at the intraday level. Guerra et al. (2022) further argued that ML enables more nuanced supervisory modelling of liquidity risk, allowing regulators to identify stress scenarios not captured by conventional stress testing frameworks.

Furthermore, Pham et al. (2024) focused on exchange-traded funds (ETFs), demonstrating that ML can forecast ETF liquidity using trading activity, volatility, and underlying asset behaviour, offering practical insights for institutional investors.

Despite the growing success of ML in liquidity forecasting, several limitations persist. Issues such as model interpretability, overfitting in high-frequency datasets, and the limited availability of labelled liquidity events remain significant (Samitas et al., 2022; Yang et al., 2025). Additionally, data privacy concerns and the opacity of complex models, particularly deep learning, pose obstacles for regulatory adoption (Climent et al., 2019).

Nevertheless, ensemble models and explainable AI techniques are emerging as solutions to these challenges, offering balance between accuracy and transparency (Tavana et al., 2018; Zhu et al., 2020).

Overall, the literature confirms that machine learning offers substantial advantages over traditional methods in forecasting liquidity and managing liquidity risk. Through improved modelling of non-linearities, integration of textual data, and deployment in real-time supervisory systems, ML has emerged as a critical tool in modern financial analysis. Future research should focus on enhancing model explainability, integrating multi-modal data, and establishing standardised evaluation benchmarks for liquidity forecasting models.

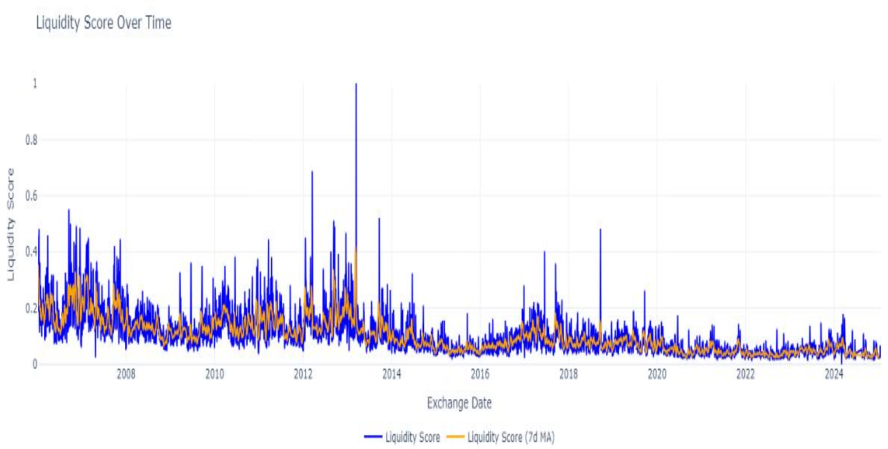
3.Methodology

The dataset comprises daily observations from 1 January 2006 to 1 May 2025 for four financial markets: the German equity index (DAX), the German volatility index (VDAX), spot gold, and the EUR/USD exchange rate. For each trading day, the data include open, high, low, and close quotations, trading volume (where available), and bid/ask prices. All data employed in this study were obtained from Refinitiv Datastream.

Liquidity was proxied by a Liquidity Score, defined as a turnover-to-volatility ratio designed to penalise wide intraday price ranges while rewarding active trading behaviour. This metric captures core microstructural elements of liquidity and aligns with longstanding empirical approaches in financial market research (notably Kyle, 1985; Amihud, 2002). The Liquidity Score served as the dependent variable throughout the analysis. Missing values were handled using a backward fill method. To enhance interpretability and visualize prediction accuracy, seven-day moving averages of both observed and predicted Liquidity Scores were plotted (see Figure 1).

Figure 1

Comparative Predictions on Liquidity Score (7-Day Rolling Mean)



Source: Author's contribution

The construction of predictor variables was organised according to five conceptual blocks, reflecting volatility, price ranges, returns, technical indicators, and cross-asset interactions. Rolling standard deviations of closing prices were computed to capture asset-specific volatility dynamics. For the DAX index, 5-day and 10-day windows were employed. For VDAX and gold, 5-day rolling windows were used. High–low price ranges for DAX, gold, and EUR/USD were calculated, and bid–ask spreads were included where available to account for microstructural noise.

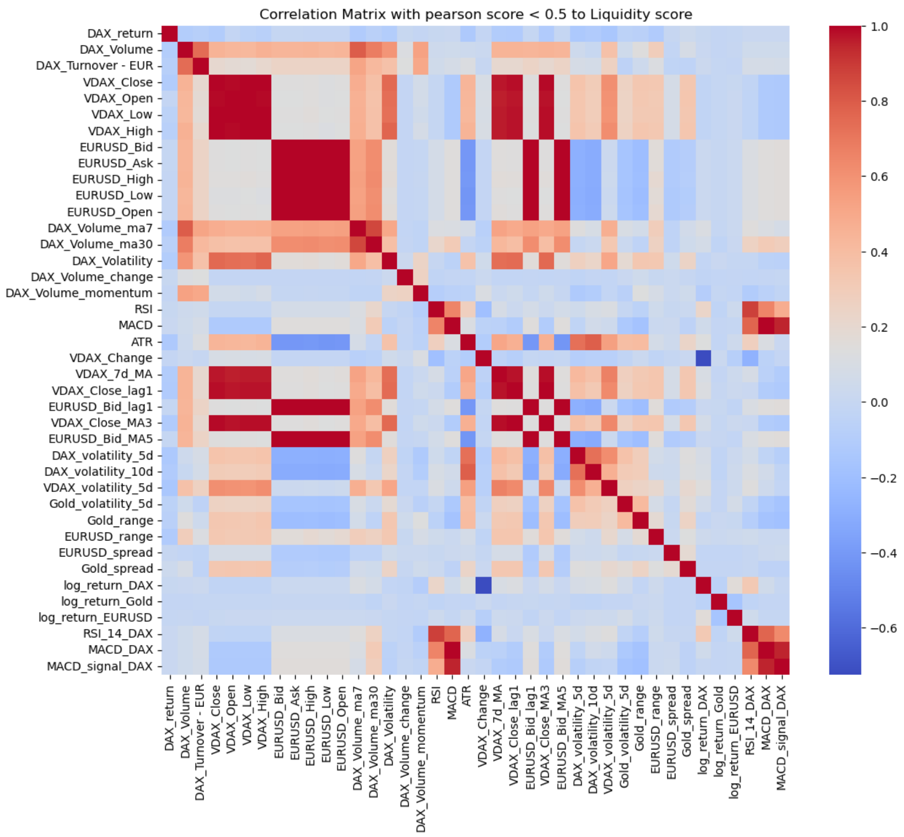
Logarithmic returns were computed as one-period, continuously compounded returns for DAX, gold, and EUR/USD, providing a standardised measure of price changes. Several technical indicators were incorporated to reflect momentum and trend-following dynamics. These included the 14-period Relative Strength Index (RSI), the Moving Average Convergence Divergence (MACD) along with its signal line, the 10-day and 50-day exponential moving averages (EMAs), the upper and lower bounds of Bollinger Bands, and the 14-day Average True Range (ATR). Additionally, one-day lags and short-term moving averages over 3-, 5-, and 7-day periods were included for

VDAX, gold, and EUR/USD to capture inter-asset linkages and short-run dynamics.

To mitigate the impact of multicollinearity while preserving explanatory strength, only predictors exhibiting an absolute Pearson correlation below 0.5 with the Liquidity Score were retained. This filtering procedure yielded a reduced yet robust subset of variables, forming the final feature matrix for model training. Figure 2 presents the matrix as a colour-graded heatmap, where warmer tones denote strong positive correlations, cooler tones indicate strong negative correlations, and the main diagonal reflects unit correlations by definition.

Figure 2

Correlation Matrix Heatmap



Source: Author's contribution

Figure 2 visualises the Pearson correlation matrix for the final set of retained predictors, all of which maintain an absolute correlation below the defined 0.5 threshold. The heatmap employs a diverging colour scale, with warm hues indicating positive correlations and cool tones representing negative relationships; the main diagonal, by construction, reflects unit correlation. The matrix reveals clusters of moderately interrelated features—such as lagged volatility measures and market microstructure indicators—which, although weakly correlated with the target individually, may contribute synergistically within non-linear modelling frameworks. This selective retention of weakly correlated variables reflects a modelling strategy that emphasises diversity, generalizability, and robustness over linear explanatory power, thereby reducing overfitting risks and enhancing model performance when employed in ensemble or deep learning architectures, as evaluated in Table 1 and depicted in Figure 3.

To account for the temporal autocorrelation structure characteristic of financial time series, the dataset was partitioned using a forward-chaining chronological split. The final 20% of the observations, corresponding to the most recent period in the time series, were reserved as an out-of-sample test set to ensure unbiased performance evaluation. The preceding 80% of the data was employed for model training and hyperparameter tuning under a time-consistent cross-validation scheme. An additive seasonal-trend decomposition using Loess (STL), parameterised with a 30-day trading seasonality window, was performed to isolate trend, seasonal, and residual components. The decomposition indicated the presence of weak but consistent cyclical behaviour in the liquidity time series. To assess the stochastic properties of the Liquidity Score, Augmented Dickey–Fuller (ADF) tests were conducted. The resulting p-values were consistently below the 0.05 threshold, leading to rejection of the null hypothesis of a unit root and supporting the stationarity assumption required for subsequent modelling.

Four supervised learning algorithms were selected for predictive modelling and comparative evaluation. These models were benchmarked using consistent performance metrics on the held-out test set to assess generalisation capability under realistic, temporally ordered conditions.

Random Forest (RF), introduced by Breiman (2001), aggregates an ensemble of decorrelated decision trees to reduce variance while preserving low bias. In a financial context, Liaw and

Wiener (2002) demonstrated RF's versatility for regression problems involving noisy, high-dimensional inputs. The method's robustness to multicollinearity and its built-in measure of variable importance make it an attractive baseline for liquidity forecasting. It was implemented with hyperparameters including the number of trees (ranging from 100 to 500), maximum tree depth (either unbounded or capped at 40), minimum samples per split (between 2 and 10), minimum samples per leaf (between 1 and 4), and feature selection strategy (auto, square root, or logarithm base 2). These parameters were optimised using a 50-draw randomised search combined with three-fold expanding-window cross-validation.

Chen and Guestrin (2016) proposed XGBoost as a highly efficient implementation of gradient-boosted decision trees, integrating regularisation, sparse-aware splitting and parallel computation. Its effectiveness in structured financial data has been showcased by Bentejac et al. (2021), who reported top-tier accuracy across a suite of time-series prediction tasks. The model was configured with similar optimisation procedures. The hyperparameter space included between 100 and 500 boosted trees, tree depths from 3 to 11, learning rates between 0.01 and 0.2, and subsample and column sample ratios ranging from 0.6 to 1.0.

The Long Short-Term Memory (LSTM) networks, originally formulated by Hochreiter and Schmidhuber (1997) to mitigate the vanishing-gradient problem, excel at capturing long-range temporal dependencies. Fischer and Krauss (2018) employed LSTMs to forecast stock returns and documented significant improvements over feed-forward networks and classical autoregressive models. Prior to training, Liquidity Score values were scaled to the [0,1] range and segmented into sequences of 30 days. The network architecture consisted of two LSTM layers: the first returned sequences, and the second produced a final state connected to a dense output layer. The model configuration involved a manual grid search across layer units, dropout rates, optimiser selection, number of epochs, and batch size. Early stopping with a patience threshold of five and a learning rate reduction on plateau were employed to prevent overfitting.

CatBoost, developed by Prokhorenkova et al. (2018), is a gradient boosting library that handles categorical features natively without the need for extensive preprocessing. By employing ordered boosting and a novel scheme for encoding categorical variables, CatBoost mitigates overfitting and achieves competitive performance on tabular datasets. In financial modeling, its efficiency in handling heterogeneous data types and robustness against overfitting make it particularly useful for tasks like credit scoring and market prediction, as evidenced in recent comparative studies (Hancock and Khoshgoftaar, 2020). Candidate settings involved 100 to 500 boosting iterations, depths from 3 to 11, learning rates between 0.01 and 0.2, L2-leaf regularisation values from 1 to 9, and border counts between 32 and 128. As with the other tree-based models, hyperparameter tuning was conducted via randomised search with cross-validation.

Predictive performance was evaluated on both training and test datasets using three standard metrics: mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2).

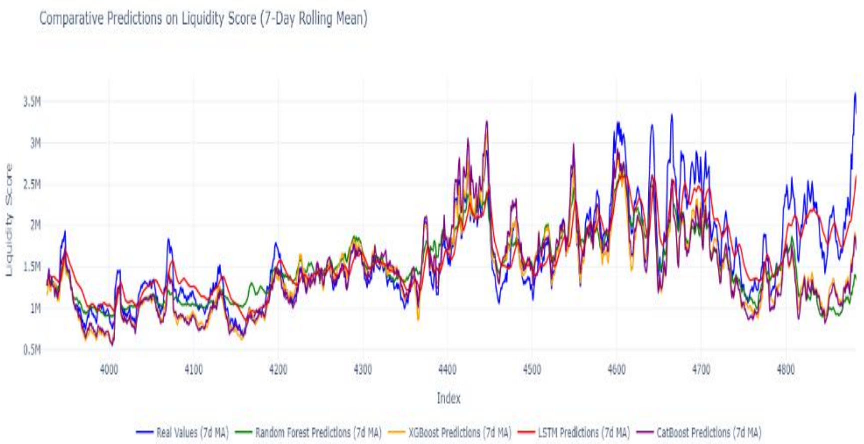
4. Results

Figure 3 presents a comparative time-series visualisation of the predicted and actual liquidity scores, smoothed using a 7-day rolling mean, for four distinct machine learning models: Random Forest, XGBoost, LSTM, and CatBoost. The application of the rolling mean serves to attenuate high-frequency fluctuations, thereby emphasising the underlying trends in liquidity dynamics.

This graphical representation substantiates the quantitative findings reported in Table 1, demonstrating that the gradient boosting models - CatBoost and XGBoost - exhibit superior performance in this forecasting task. Their effectiveness can be attributed to a favourable trade-off between bias and variance, as well as their capacity to model complex feature interactions, which enables more accurate and consistent liquidity predictions compared to both the Random Forest and LSTM models.

Figure 3

Predicted vs. Actual Liquidity Score (7-day rolling mean)



Source: Author's contribution

The real liquidity score is shown in blue, while the predicted values from the four models are shown in green (Random Forest), orange (XGBoost), red (LSTM), and purple (CatBoost). The visual comparison is directly contextualised by the predictive performance metrics summarised in Table 1, which reports the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 scores for both the training and test sets.

Table 1

Comparative Analysis of Models

Model	Set	MAE	RMSE	R^2
Random Forest	Train	97244.25	196117.72	0.9048
Random Forest	Test	377219.77	560692.67	0.514
XGBoost	Train	27862.92	35918.51	0.9968
XGBoost	Test	282033.17	418484.69	0.7293
LSTM	Train	301608.96	461820.94	0.474
LSTM	Test	476552.01	655444.26	0.3358
CatBoost	Train	40629.89	53966.24	0.9928
CatBoost	Test	281549.74	414466.17	0.7344

Source: Author's contribution

The XGBoost and CatBoost models clearly demonstrate superior generalisation capability, with test set R^2 values of 0.729 and 0.734 respectively, and the lowest RMSE and MAE scores among the models tested. Their forecast lines follow the actual liquidity values closely, capturing not only trend direction but also amplitude in periods of increased market turbulence — particularly around peak liquidity episodes.

In contrast, Random Forest exhibits significant performance degradation on the test set, dropping from an R^2 of 0.905 during training to just 0.514. This overfitting is also reflected visually: the green prediction line tends to lag behind actual liquidity changes and fails to replicate the higher-magnitude oscillations. The model is evidently not robust enough for forecasting extreme events.

The LSTM model, despite being a recurrent neural network capable of modelling sequential dependencies, underperforms both statistically and visually. With the lowest R^2 on the test set (0.336), it fails to capture the underlying signal effectively. The red curve appears smoothed and delayed, indicating that the model may have failed to learn the temporal structure inherent in the liquidity series, possibly due to insufficient tuning, model complexity, or lack of deeper layers.

5. Conclusion

The paper has examined the capacity of four leading machine-learning algorithms - Random Forest, XGBoost, CatBoost and Long Short-Term Memory network - to forecast daily liquidity in the German blue-chip equity market. Employing a Liquidity Score that balances turnover against intraday price dispersion and an extensive dataset, the study applied an identical walk-forward validation framework to ensure methodological comparability and to replicate real-time deployment conditions.

The empirical evidence indicates that gradient-boosting ensembles markedly surpass both Random Forests and the standard LSTM architecture. CatBoost, closely followed by XGBoost, consistently generated the lowest forecast errors and reproduced abrupt liquidity contractions more faithfully than its competitors. These results highlight the superior ability of boosting algorithms to capture complex, non-linear interactions among heterogeneous predictors while maintaining robustness against overfitting, and they underline the importance of a thoughtfully designed feature set that reflects the microstructural determinants of liquidity. By contrast, the LSTM's weaker performance suggests that recurrent networks may require longer or cleaner sequences—or more sophisticated tuning regimes—before they can rival tree-based methods in this context.

The study makes two substantive contributions to the literature. First, it introduces a parsimonious yet theoretically grounded liquidity metric that integrates both price impact and trading activity. Second, it proposes a systematic feature-engineering pipeline that balances informational breadth with parsimony by filtering for multicollinearity.

While the analysis focuses exclusively on the DAX index to ensure methodological depth and data consistency, this limits generalizability. Nonetheless, the modelling framework - especially the Liquidity Score and the structured feature set - is flexible and can be adapted to other developed equity markets. Future research could validate the findings by applying the same methodology to broader indices such as the EURO STOXX 50 or FTSE 100. Even a moderate cross-index comparison could strengthen external validity and reveal how model performance varies across market structures and liquidity regimes.

From a practical perspective, the study offers meaningful implications for multiple stakeholders. For traders and market-makers, the ability to anticipate short-term liquidity swings can inform order execution strategies, limit market impact, and optimise timing. Fund managers may integrate such forecasts into portfolio rebalancing processes or liquidity risk budgeting frameworks. Regulators and central banks can benefit from early-warning signals of liquidity stress, particularly in monitoring systemic risk in blue-chip segments of the market. The lightweight nature of the Liquidity Score and the real-time adaptability of boosting algorithms further enhance the feasibility of embedding such models into operational systems or supervisory dashboards.

Several limitations delimit the generalisability of the findings and motivate future research. The analysis is restricted to daily data for a single blue-chip index, leaving open the question of whether the observed performance hierarchy persists at intraday frequencies, in other asset classes or in less liquid markets. Furthermore, only four algorithms were evaluated, and issues of interpretability, computational efficiency and live implementation costs were beyond the present scope. Finally, the predictor set did not exploit textual sentiment, granular order-book information or alternative data sources that may refine short-horizon forecasts. Addressing these gaps, by extending the framework to higher-frequency horizons, incorporating richer feature spaces and deploying explainable, AI techniques represents a promising agenda for subsequent work.

Taken together, the results underscore the practical utility of gradient-boosting methods for short-horizon liquidity surveillance and provide a replicable methodological template for advancing research and practice in the forecasting of financial-market liquidity.

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DETERMINANTS OF HOUSEHOLD DEBT-TO-GDP FINANCIAL STABILITY, AND ECONOMIC RESILIENCE. A CROSS-COUNTRY PANEL ANALYSIS (2000–2023)

Chidera Favour EBELE, PhD Candidate*
Gideon IHUARULAM**

Abstract

This study investigates the determinants of household debt-to-GDP across ten economies, comprising both developed and developing countries, spanning the period from 2000 to 2023. Employing a panel econometric framework, including Fixed Effects, Random Effects, and Panel ARDL models, the analysis captures both short- and long-run dynamics of household indebtedness. The results reveal that GDP per capita has a negative correlation with household debt-to-GDP, consistent with the life-cycle hypothesis, while financial inclusion emerges as a significant long-term driver of credit expansion. Lending rates show a counterintuitive positive relationship with debt, suggesting financialization effects, and non-performing loan (NPL) ratios are positively associated with household debt levels, signalling financial sector fragility. The findings suggest that monetary policy alone may be insufficient to manage household debt sustainably, highlighting the need for macroprudential measures such as loan-to-income (LTI) and debt-to-income (DTI) caps. The study recommends aligning financial inclusion initiatives with robust consumer protection frameworks to mitigate the risks of over-indebtedness. These insights contribute to the evolving discourse on financial stability, debt sustainability, and economic resilience.

Keywords: credit market dynamics, financial access, dynamic panel analysis, household borrowing patterns, credit risk exposure

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* *Faculty of Social and Behavioural Sciences, Georgia State University, Atlanta, United States of America.*
** *(MFE) Master of Financial Economics, Faculty of Arts and Social Sciences, Nile University, Abuja, Nigeria. Corresponding author, e-mail: ihuarulamambrose@gmail.com*

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1. Introduction

Household debt has emerged as a defining feature of modern financial systems, playing a crucial role in shaping economic resilience and financial stability. Over the past two decades, economies worldwide have witnessed a steady rise in household indebtedness, driven by factors such as financial liberalisation, evolving credit markets, and changing consumption patterns. While access to credit fosters economic growth by enabling households to smooth consumption and invest in durable goods, excessive household debt accumulation poses risks to financial stability and macroeconomic performance (Joo & Mir, 2024). The 2008 Global Financial Crisis starkly highlighted the vulnerabilities associated with unsustainable debt levels, with household leverage amplifying financial distress and contributing to systemic banking crises.

The relationship between household debt and financial stability is multifaceted, as it encompasses both the benefits of credit access and the risks of over-indebtedness. While moderate levels of debt can support economic dynamism, excessive debt burdens can weaken household balance sheets, reduce consumption during downturns, and increase the probability of financial distress (Santoso & Sukada, 2009). The risks are particularly pronounced when debt service burdens rise in response to macroeconomic shocks, such as interest rate hikes, inflationary pressures, or unexpected income losses (Aldashev & Batkeyev, 2023). As such, understanding the factors that drive household debt accumulation, its implications for financial stability, and the role of financial inclusion in shaping debt sustainability has become an urgent research priority.

Over the past two decades, the rise in household debt has become a defining feature of both developed and developing economies. While access to credit is essential for financial inclusion and economic growth, excessive household debt poses significant risks to financial stability, especially in the face of macroeconomic shocks such as inflation, interest rate hikes, and rising unemployment. Despite growing scholarly interest, empirical evidence remains fragmented on how macroeconomic conditions, financial inclusion, and financial sector vulnerabilities interact to shape household debt dynamics across countries at various stages of development.

Moreover, limited cross-country research has systematically distinguished between short-term fluctuations and long-term debt sustainability, especially using integrated econometric frameworks. This gap in understanding constrains the design of informed and effective policy interventions aimed at balancing credit expansion with economic resilience. Therefore, this study seeks to address this void by conducting a robust panel analysis across ten economies from 2000 to 2023, offering nuanced insights into the drivers and risks of household debt accumulation.

The primary research objectives of the paper are to examine the macroeconomic determinants of household debt-to-GDP, investigate the role of financial inclusion in shaping household debt accumulation, and assess the contribution of financial sector stability. Also, we aim to provide policy-relevant insights on how macro-financial indicators interact with credit markets and influence the sustainability of household debt across diverse economic contexts.

2. Literature review

The theoretical foundation of household debt and financial stability is rooted in macroeconomic and financial stability theories. The financial accelerator model posited by Bernanke, Gertler, and Gilchrist (1999) suggests that debt amplifies economic fluctuations, as credit constraints tighten during downturns, exacerbating economic distress. Similarly, Minsky's (1986) financial instability hypothesis emphasises the cyclicality of credit markets, where prolonged periods of financial expansion lead to excessive risk-taking, ultimately culminating in instability. In contemporary financial systems, household debt interacts with macroeconomic variables such as GDP growth, employment levels, and inflation, influencing both short-term economic fluctuations and long-term financial stability (Oyadeyi et al., 2024).

Empirical evidence from emerging and advanced economies underscores the impact of household debt on financial fragility. Studies have shown that rising household debt-to-GDP ratios are often correlated with higher NPL ratios, reflecting increased financial distress among borrowers (Valderrama, 2023). This link is particularly significant in economies where financial regulation is weak, credit monitoring is inadequate, or household balance sheets are vulnerable to macroeconomic shocks. Given the interconnected nature of financial markets, household debt crises can spill over into banking systems, triggering broader systemic risks (IMF, 2025). The challenge for policymakers is to strike a balance between promoting financial inclusion and ensuring that debt remains sustainable over the long term.

Household debt accumulation is influenced by a complex interplay of macroeconomic variables, including GDP per capita, unemployment rates, lending rates, and inflation. Higher income levels generally encourage borrowing by improving creditworthiness and boosting household consumption, while periods of economic downturn often led to deleveraging due to declining disposable incomes and heightened uncertainty (IMF, 2024). In economies with low unemployment and stable growth, household debt expansion is often perceived as sustainable. However, high unemployment levels can lead to debt distress, particularly in economies where debt service ratios are high relative to disposable income (Santoso & Sukada, 2009).

Interest rates also play a critical role in shaping household borrowing patterns. Low lending rates tend to encourage higher levels of borrowing by reducing the cost of credit, but they can also create vulnerabilities when rates eventually rise, increasing the burden of debt servicing (ECB, 2018). Inflation dynamics further complicate debt sustainability, as higher inflation erodes real household incomes, potentially exacerbating repayment difficulties. The interaction of these macroeconomic variables determines whether household debt contributes to economic resilience or financial instability. As such, understanding these relationships is essential for formulating effective policy interventions aimed at ensuring debt sustainability.

Financial inclusion is widely regarded as a key driver of economic development, expanding access to credit and promoting financial stability. However, its relationship with household debt sustainability remains contested. On one hand, increased access to financial services can enable households to manage liquidity constraints more effectively, facilitating productive investments and enhancing economic resilience (Yue et al., 2022). On the other hand, excessive credit expansion, particularly in the absence of strong regulatory frameworks, can lead to over-indebtedness and heightened financial fragility (Valderrama, 2023).

In many emerging economies, financial inclusion has been accompanied by rapid credit growth, raising concerns about the sustainability of household debt burdens (IMF, 2024). The expansion of digital financial services has further accelerated credit access, often without adequate risk assessment mechanisms. Consequently, the challenge lies in ensuring that financial inclusion initiatives are designed to promote responsible borrowing while mitigating the risks of excessive leverage (Cornelli et al., 2020). Empirical research suggests that financial inclusion can enhance debt sustainability when coupled with financial literacy programs and prudent lending practices (Joo & Mir, 2024). However, in cases where credit expansion outpaces regulatory oversight, financial inclusion may inadvertently contribute to rising debt distress.

Macroeconomic shocks, such as interest rate fluctuations, inflationary spikes, and rising unemployment, have profound implications for household debt sustainability. Interest rate hikes can significantly increase debt servicing costs, particularly in economies where variable-rate loans dominate household debt portfolios (ECB, 2018). Similarly, inflationary shocks can erode real incomes, reducing households' ability to meet debt obligations and increasing default risks (Oyadeyi et al., 2024). Rising unemployment further exacerbates these challenges, as job losses reduce disposable incomes and increase financial distress among indebted households (IMF, 2025).

The global financial landscape has witnessed several episodes of economic volatility that underscore the vulnerability of highly indebted households to macroeconomic shocks. The 2008 financial crisis, the European sovereign debt crisis, and the economic disruptions caused by the COVID-19 pandemic all highlight the risks associated with unsustainable household debt levels (IMF, 2024). These events demonstrate that macroeconomic shocks can trigger debt crises, with significant spillover effects on banking systems and broader economic stability. As such, developing effective risk mitigation strategies is essential for ensuring the resilience of household debt in the face of economic uncertainty.

This study contributes to the growing body of literature on household debt and financial stability by presenting a multi-country panel analysis that spans 2000 to 2023, a period marked by significant macro-financial shocks, including the global financial crisis, commodity price collapses, and post-pandemic inflationary pressures. Unlike prior studies that often focus on single-country settings or rely on static models, this paper applies fixed effects, random effects, and error correction frameworks to distinguish both short-run and long-run dynamics of household indebtedness. Notably, it identifies financial inclusion as a statistically and economically significant driver of household debt across diverse economic contexts, both in the short and long run, a relationship not consistently established in earlier empirical literature. The estimations also reveal how lending rates and non-performing loan (NPL) ratios influence borrowing behaviour, offering fresh insights into the transmission channels of monetary policy and systemic credit risk. These findings have important implications for the economies analysed: for emerging markets, they emphasise the dual-edged nature of expanding financial access without adequate debt management frameworks; for developed economies, the results highlight the moderating role of interest rate policy in curbing unsustainable debt accumulation.

Overall, the study advances empirical understanding by combining robust panel techniques with policy-relevant interpretation, equipping policymakers with actionable evidence to balance financial inclusion initiatives with debt sustainability strategies.

The subsequent sections of this study build upon the theoretical and empirical foundations outlined in this introduction. The methodological framework employs econometric modelling to analyse household debt dynamics across different economic contexts. The findings will inform policy recommendations aimed at promoting responsible borrowing, strengthening financial regulation, and enhancing economic resilience in the face of macroeconomic uncertainty. By integrating insights from a diverse set of economies, this research aims to provide a nuanced understanding of household debt dynamics, contributing to the ongoing discourse on financial stability and economic sustainability.

3. Methodology

This study employs a panel econometric approach to analyse the determinants of household debt-to-GDP, focusing on macroeconomic conditions, financial stability, and financial inclusion across ten economies. The countries are evenly divided between developed (Canada, United States, United Kingdom, Germany, and France) and developing (China, Brazil, India, South Africa, and Mexico) nations to reflect varying levels of financial infrastructure and credit market maturity. The selection was primarily driven by the availability and consistency of annual macro-financial data from 2000 to 2023 across all key variables of interest. Given the presence of long-run equilibrium relationships among the variables, the methodology is structured to capture both short-term dynamics and long-term trends while addressing potential econometric concerns such as endogeneity, heterogeneity, and serial correlation.

The dataset comprises panel data covering multiple countries over an extended time horizon (24 years), incorporating key macroeconomic and financial indicators relevant to household debt. The dependent variable is household debt-to-GDP (%). In contrast, the independent variables include household debt per capita (USD), debt service ratio (%), NPL ratio (%), GDP per capita (PPP, USD), unemployment rate (%), inflation rate (%), lending rate (%), and financial inclusion (commercial bank branches per 100,000 adults, first-differenced).

The dataset is sourced from the International Monetary Fund (IMF) reports - Global Financial Stability Report (IMF, 2024), and World Economic Outlook (IMF, 2025) -, and from the Bank for International Settlements (BIS) data portal (BIS, n.d.), ensuring a comprehensive and standardised collection of macroeconomic and financial stability indicators.

To account for both cross-country heterogeneity and dynamic relationships, a multi-stage econometric approach was adopted. The empirical strategy involves Fixed Effects (FE) and Random Effects (RE) models, followed by a Generalised Method of Moments (GMM) estimation to address endogeneity concerns.

The Fixed Effects (FE) model controls for unobserved heterogeneity by allowing each country to have its own intercept, thereby capturing time-invariant country-specific characteristics. The model is specified as:

$$Household\ Debt - to - GDP_{it} = \beta_0 + \beta_1 X_{it} + \epsilon_{it} \tag{1}$$

Where β_1 - country-specific fixed effects, X_{it} - the vector of independent variables, and ϵ_{it} - error term.

The Random Effects model (RE) assumes that country-specific effects are uncorrelated with the independent variables, expressed as:

$$Household\ Debt - to - GDP_{it} = \beta_0 + \beta_1 X_{it} + \mu_{it} + \epsilon_{it} \tag{2}$$

Where μ_{it} - country-specific random effects.

The Hausman test (1978) was applied to determine the appropriate specification, where a significant result favours the Fixed

Effects model, while an insignificant result supports Random Effects estimation (Aldashev & Batkeyev, 2023).

Given the confirmed presence of cointegration among variables, the study proceeds with a Panel Autoregressive Distributed Lag (Panel ARDL) model to distinguish between short-run fluctuations and long-run relationships. The Panel ARDL model accounts for heterogeneous lag structures across countries, allowing for a more flexible dynamic adjustment mechanism Bayar, Y. (2019).

The long-run equilibrium model takes the following form:

$$Household\ Debtto - GDP_{it} = \delta_0 + \sum_{j=i}^{p} Household\ Debt - to - GDP_{it_{-j}} + \sum_{k=0}^{q} {}_{yk}X_{it-k} + \epsilon_{it} \quad (3)$$

Where p and q represent optimal lag lengths, selected based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Model selection was performed using the Hausman test, with preference given to the Fixed Effects model where country-specific factors were correlated with regressors. In cases where the Random Effects model was selected, robust standard errors were used to address heteroskedasticity concerns.

This study also adopts the Panel Autoregressive Distributed Lag (ARDL) modeling framework to estimate both short-run and long-run relationships between household debt-to-GDP and its macro-financial determinants. The panel ARDL model is particularly suited for datasets characterized by a mix of I(0) and I(1) variables, as is the case here. Unlike static panel models such as Fixed Effects (FE) or Random Effects (RE), which only estimate contemporaneous relationships, the panel ARDL framework incorporates lagged dependent and independent variables, allowing for dynamic adjustment processes and error correction mechanisms across time. This structure enables a richer understanding of both immediate shocks and long-term equilibrium paths.

The decision to employ the Panel Autoregressive Distributed Lag (ARDL) model, rather than a full Error Correction Model (ECM), is based on both methodological flexibility and data structure suitability. Panel ARDL models, as outlined by Pesaran, Shin, and Smith (1999), are specifically designed to handle datasets with a mix of stationary and non-stationary variables (I(0) and I(1)), which aligns with the integration properties of the variables used in this study. Unlike traditional ECMs, the Panel ARDL framework can estimate heterogeneous short-run dynamics across countries while maintaining a pooled long-run relationship, making it well-suited for panels that include structurally diverse economies.

Given the moderate time dimension (T = 24 years) and the limited number of cross-sectional units (N = 10 countries), the panel ARDL model strikes a balance between robustness and computational feasibility. In contrast, alternative techniques such as the Pooled Mean Group (PMG) estimator require stronger assumptions about slope homogeneity and often assume a longer time horizon for reliable estimation. Likewise, System GMM estimators, while effective in addressing endogeneity, demand large panel dimensions and suffer from instrument proliferation in small samples (Roodman, 2009). The Panel ARDL approach avoids these issues, allowing for the estimation of both short-run fluctuations and long-run equilibrium relationships within a coherent, empirically grounded framework.

Variable selection is grounded in theoretical and empirical literature. GDP per capita, inflation, unemployment, and lending rates are standard macroeconomic indicators known to influence household debt through income capacity, price stability, and credit cost (Bernanke et al., 1999; Friedman, 1957; Modigliani & Brumberg, 1954). Financial sector stability is captured using the debt service ratio and NPL ratio, consistent with studies emphasising the risk channel of credit markets (Santoso & Sukada, 2009). Financial inclusion, measured as the number of commercial bank branches per 100,000 adults, is a key structural variable supported by Célerier and Matray (2019), who argue that access to formal credit can both empower households and increase their exposure to debt risk.

All variables were tested for multicollinearity using the Variance Inflation Factor (VIF), with results confirming that none of the predictors exhibit problematic correlation. Additionally, the inclusion of financial inclusion and financial vulnerability indicators provides a unique contribution to cross-country debt literature, particularly in capturing structural shifts in household access to credit (IMF, 2024; Joo & Mir, 2024). Together, these models, variables, and diagnostic justifications confirm the analytical robustness and theoretical relevance of the chosen methodology.

4. Data analysis and tests' results

Understanding the distribution and characteristics of the variables used in this study is crucial for assessing the relationship between household debt, financial stability, macroeconomic conditions, and financial inclusion. Table 1 in the Appendix presents the summary statistics of the key variables, capturing their central tendencies, dispersion, and range across the panel dataset covering multiple economies from 2000 to 2023. Given that the dataset has been transformed into first differences to ensure stationarity, the mean values for most variables approach zero. However, the standard deviations and extreme values provide insights into the dynamics of household debt and financial conditions across economies.

The household debt variables exhibit notable dispersion across the panel dataset. The Household Debt-to-GDP ratio, a key indicator of financial leverage, ranges from -10.71 to 3.63 percent, with a median value close to zero due to first differencing. The Household Debt per Capita (USD) follows a similar distribution, with extreme values indicating periods of rapid debt accumulation and deleveraging. The Debt Service Ratio (%), which captures the burden of debt repayments relative to income, displays a narrower range, suggesting that most economies experience moderate shifts in household debt repayment burdens over time.

The NPL ratio (%), a critical measure of banking sector stability, varies from -1.29 to 4.45 percent, with a negative median (-0.22), suggesting that, on average, countries have experienced marginal improvements in loan performance. However, the existence of positive extreme values highlights episodes of financial distress where loan defaults surged.

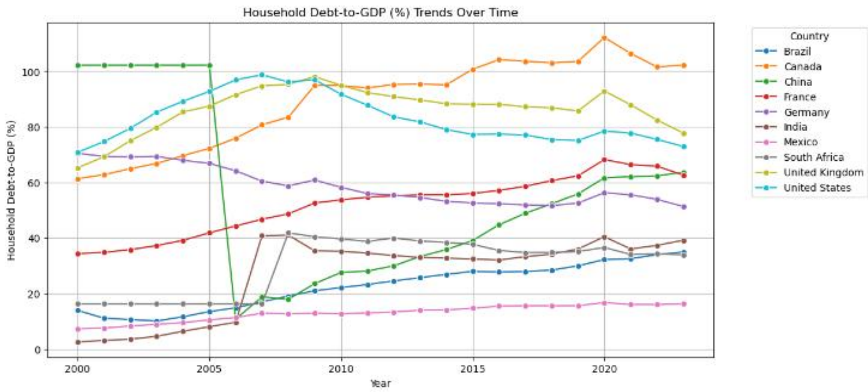
Macroeconomic indicators reflect significant heterogeneity across countries and periods. The GDP per Capita (PPP, USD) shows a broad range from -9.04 to 3.66, reflecting disparities in economic growth and national income distribution. The Unemployment Rate (%) varies between -0.94 and 4.12, indicating labour market fluctuations across economic cycles. The Inflation Rate (%) ranges from -1.68 to 4.40, capturing varying levels of price stability and monetary conditions. The Lending Rate (%), which influences the cost of borrowing, fluctuates between -0.77 and 4.55, showing the effects of different monetary policy regimes.

The Financial Inclusion Index, measured by the number of Commercial Banks per 100,000 Adults, presents a range from -1.86 to 2.39. The negative median (-0.13) suggests that financial inclusion has declined in some economies, possibly due to banking sector consolidation or digital financial services reducing the need for physical banking infrastructure. Nevertheless, the upper range highlights economies where financial inclusion efforts have expanded access to banking services.

Figure 1 presents a comparative analysis of household indebtedness across multiple economies from the early 2000s to the 2020s, highlighting variations in credit reliance, financial stability, and the impact of macroeconomic policies.

Figure 1

Household Debt-to-GDP



Author's Estimation 2025

Advanced economies such as Canada, the United Kingdom, and the United States exhibit persistently high household debt-to-GDP ratios, with a sustained upward trajectory driven by strong dependence on credit markets. Notably, Canada's debt levels peaked around 2020 before experiencing a slight decline, likely due to policy interventions, economic slowdowns, or shifts in borrowing behaviour.

China's rapid debt accumulation since the mid-2000s stands out, coinciding with its economic expansion, urbanisation, and financial liberalisation. While this trend underscores the growing role of consumer financing, it also raises concerns about financial stability and potential overleveraging in emerging markets.

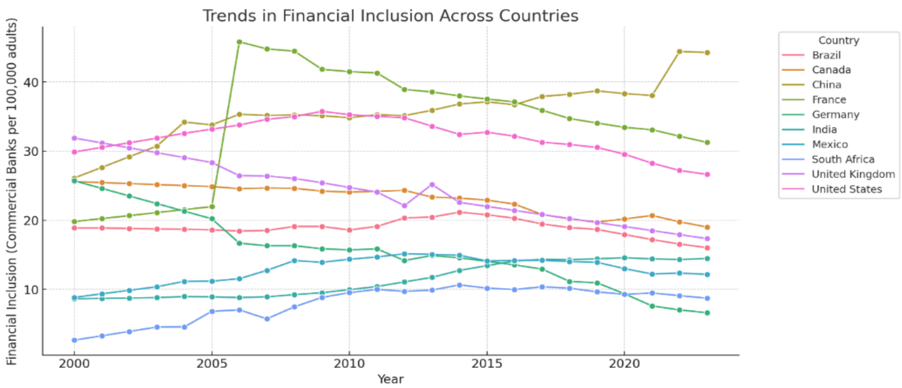
In contrast, Germany and France display stable and moderate debt-to-GDP ratios, reflecting a cautious credit culture and stringent financial regulations that mitigate excessive household borrowing.

Among emerging economies such as India, Brazil, South Africa, and Mexico, household debt levels remain significantly lower than those in developed economies. While debt-to-GDP ratios have gradually increased, limited financial inclusion and stricter lending policies continue to constrain widespread consumer credit access. However, India and Brazil have shown notable upward trends post-2010, reflecting greater financial penetration and evolving borrowing behaviours. An anomaly around 2005 indicates a sharp decline in one country's debt-to-GDP ratio, potentially due to regulatory reforms, debt forgiveness programs, or statistical reporting changes, requiring further investigation into the underlying economic context.

The visualisation in Figure 2 presents the evolution of financial inclusion, measured by the number of commercial bank branches per 100,000 adults, across ten selected economies from 2000 to 2023. This metric serves as a proxy for access to formal financial services, capturing structural shifts in banking infrastructure and financial accessibility over time.

Figure 2

Financial Inclusion Index Trends Over Time



Author's Estimation 2025

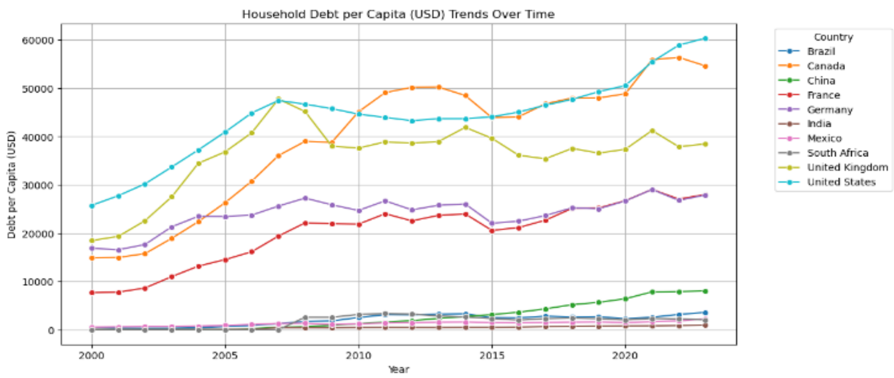
The trends reveal considerable variation across economies. China and France exhibit significant volatility, with China experiencing a sharp increase around 2005, followed by a gradual decline in recent years. In contrast, the United States and the United Kingdom display a consistent decline, reflecting a contraction in physical banking services, likely due to the rise of digital banking, FinTech alternatives, and the shift toward cashless transactions. This suggests a transition away from traditional banking models in favour of mobile banking and online financial platforms.

In contrast, emerging economies such as India, Mexico, and South Africa show steady increases in banking access, indicating the success of expansionary financial inclusion policies designed to integrate underserved populations into the formal financial sector. Meanwhile, Germany and Canada demonstrate relative stability, suggesting that their banking infrastructure has remained largely unchanged over the two-decade period.

Figure 3 provides insights into household indebtedness across economies from the early 2000s to the present. This metric reflects the financial burden on individual households and highlights differences in credit accessibility, borrowing behaviour, and broader economic conditions.

Figure 3

Household Debt per Capita



Author's Estimation 2025

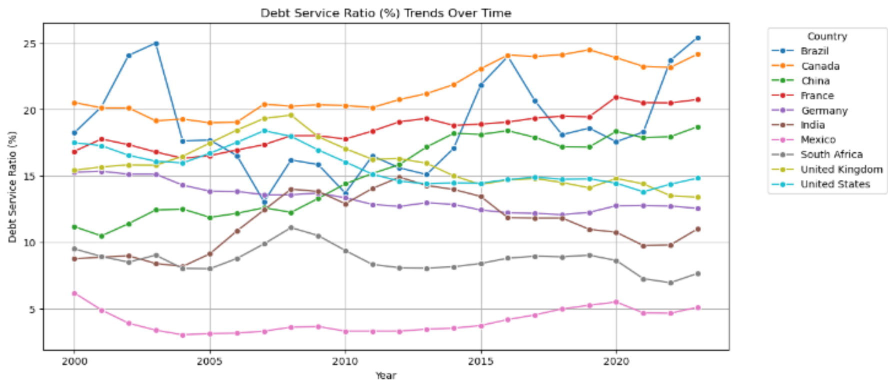
A clear divide exists between developed and emerging economies. The United States, Canada, and the United Kingdom report significantly higher household debt per capita, with the U.S. exceeding $60,000 in recent years, while Canada and the U.K. surpass $40,000. This heavy reliance on credit is driven by mortgage borrowing, consumer credit expansion, and favourable lending conditions. However, the 2008–2009 financial crisis led to a temporary decline, reflecting deleveraging efforts and tightened credit policies in its aftermath.

Among European economies, France and Germany maintain moderate household debt per capita levels, fluctuating between $20,000 and $30,000. In contrast, emerging economies such as China, Brazil, India, Mexico, and South Africa exhibit significantly lower debt per capita, remaining below $10,000 throughout the period. China stands out with a steady increase post-2010, reflecting the expansion of consumer credit, mortgage borrowing, and financial liberalisation. Similarly, Brazil and South Africa show gradual increases, but at levels far lower than their developed counterparts.

Figure 4 highlights the proportion of household income allocated to debt repayment across different economies. This metric serves as a key indicator of financial stress, debt affordability, and household borrowing sustainability.

Figure 4

Debt Service Ratio



Author's Estimation 2025

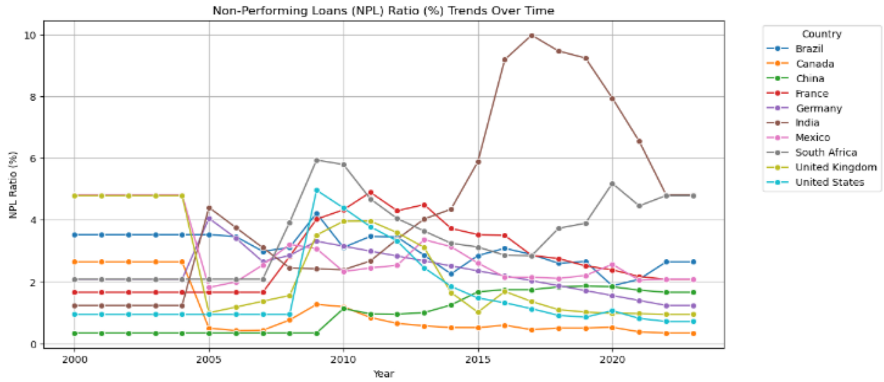
Advanced economies, particularly Canada, the United States, and France, consistently exhibit high DSRs, exceeding 15%, with Canada surpassing 25% in recent years. This suggests that a significant portion of household income is dedicated to debt servicing, reflecting a strong reliance on credit. While this supports consumption and investment, it also heightens financial vulnerability during economic downturns or periods of rising interest rates. The continuous increase in Canada's DSR raises concerns about debt sustainability, mortgage burdens, and financial system risks. The US economy shows fluctuations in its DSR, peaking before the 2008 financial crisis, followed by a post-crisis decline due to household deleveraging and stricter lending regulations. More recently, an upward trend in DSR suggests renewed credit expansion, particularly in the housing and consumer lending sectors. Meanwhile, France and Germany maintain relatively stable DSRs between 10% and 20%, indicating a more controlled debt burden compared to North America.

Among emerging economies, China, Brazil, and South Africa have experienced rising DSRs over time. China's sharp increase since 2010 coincides with financial sector liberalisation and increased consumer credit access, signalling financial deepening but also raising concerns about rising debt burdens and financial distress risks. Similarly, Brazil's DSR has fluctuated, occasionally exceeding 20%, reflecting periods of high household financial strain. By contrast, India and Mexico maintain significantly lower DSRs, consistently below 10%, indicating a lesser reliance on formal credit systems and relatively low household debt burdens. India's persistently low DSR reflects a conservative borrowing culture, lower financial penetration, and stricter lending regulations, limiting excessive household indebtedness.

Figure 5 provides insights into the quality of credit portfolios across different economies.

Figure 5

Non-Performing Loans Ratio



Author's Estimation 2025

The NPL ratio is a critical financial stability indicator, representing the percentage of loans that are in default or close to default. Higher NPL ratios signal greater financial distress and potential systemic risks, while lower ratios indicate healthier credit markets and robust borrower repayment capacity.

A key observation from the graph is the significant variation in NPL ratios among economies, reflecting differences in financial regulation, credit risk management, and economic conditions. South Africa and Mexico exhibit the most volatile trends, with South Africa peaking above 9% around 2015 before declining steadily. This suggests a period of economic distress, possibly due to macroeconomic downturns, currency depreciation, or sectoral crises affecting loan repayment capabilities. Mexico also shows high NPL ratios in the late 2000s, peaking around 6% before stabilizing.

In advanced economies such as Canada, the United States, the United Kingdom, and Germany, NPL ratios remain relatively low and stable, consistently below 3%. This stability reflects stronger financial institutions, robust risk assessment mechanisms, and higher levels of financial literacy among borrowers. However, a slight increase in NPLs is observed for the United States during the 2008 financial crisis, indicating temporary financial distress before regulatory interventions led to a decline.

Brazil and India show moderate fluctuations in NPL ratios, with occasional spikes followed by stabilization. Brazil's NPL ratio increased significantly post-2010, aligning with periods of economic uncertainty, inflationary pressures, and credit market adjustments. Similarly, India experienced a rise in NPL ratios post-2015, likely reflecting banking sector challenges and deteriorating asset quality in certain industries.

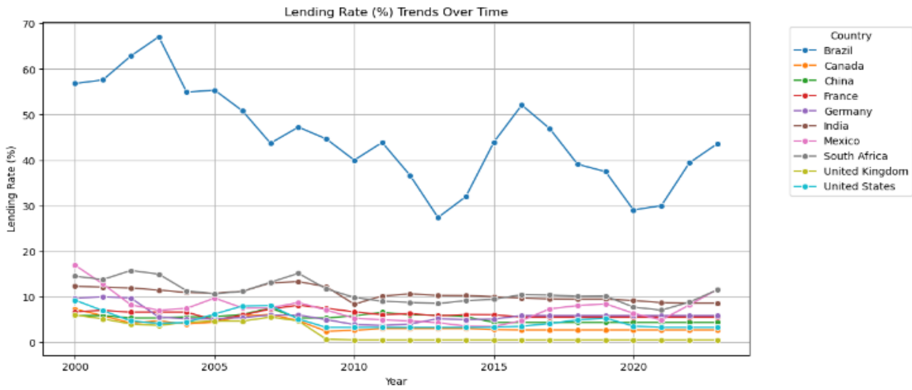
China's NPL ratio remains consistently low compared to other emerging markets, suggesting a relatively controlled credit environment. However, concerns exist regarding the accuracy of reported NPLs, given China's state-controlled banking system and government interventions in distressed assets. Despite the low official figures, potential risks in China's shadow banking sector and corporate debt markets may pose future financial vulnerabilities.

France and Germany display moderate NPL trends, remaining between 2% and 4% throughout the observed period. This suggests a relatively resilient banking system with effective credit risk management, though occasional increases in NPLs reflect economic downturns and adjustments in financial regulations.

Figure 6 provides insights into the cost of borrowing across different economies over the past two decades. Lending rates influence household and business credit demand, investment decisions, and overall economic growth. Variations in lending rates across countries reflect monetary policy stances, inflationary pressures, financial market structures, and credit risk assessments.

Figure 6

Lending Rate (%)



Author's Estimation 2025

A striking observation from the graph is the exceptionally high lending rates in Brazil, which consistently surpass those of other economies. Lending rates in Brazil reached as high as 65% in the early 2000s, followed by a gradual decline to around 30% by 2020, before rebounding slightly in recent years. Such extreme lending costs reflect structural inefficiencies in the Brazilian financial system, high inflation rates, and risk premiums associated with lending. While Brazil has taken steps to reduce lending costs, interest rates remain significantly higher than in most economies, potentially constraining credit expansion and economic growth.

South Africa and India also exhibit relatively high lending rates, though at more moderate levels. South Africa's lending rates fluctuated between 10% and 15%, reflecting economic volatility, inflationary pressures, and changes in monetary policy. Similarly, India maintained lending rates above 10% for much of the observed period, though a gradual downward trend is noticeable, consistent with economic liberalization and financial sector reforms.

In contrast, developed economies such as the United States, Canada, the United Kingdom, Germany, and France maintain significantly lower lending rates, typically below 10%. These economies benefit from stable inflation, efficient credit markets, and strong financial institutions, resulting in lower risk premiums on loans.

A notable trend in Canada, the United Kingdom, and the United States is the sharp decline in lending rates around the 2008 financial crisis, reflecting the response of central banks to the global economic downturn. Expansionary monetary policies, including interest rate cuts and quantitative easing, were implemented to stimulate borrowing, investment, and economic recovery.

China also maintains low and relatively stable lending rates, consistent with its state-controlled financial system, strong regulatory oversight, and managed interest rate policies. However, the artificially low lending rates raise concerns about credit misallocation and financial market distortions, particularly in China's highly leveraged corporate sector.

The correlation heatmap in Figure 7 (Appendix) provides an initial exploration of the relationships among household debt indicators, macroeconomic variables, and financial inclusion, as measured by the number of commercial bank branches per 100,000 adults. This analysis helps identify key patterns and potential linkages that will be further examined in the regression models.

Household debt-to-GDP exhibits a moderate positive correlation with GDP per capita (0.24), suggesting that higher economic output is generally associated with increased household borrowing. Similarly, household debt per capita (USD) shows a strong correlation with GDP per capita (0.92), indicating that wealthier economies tend to have higher absolute levels of household debt per capita. However, neither measure of household debt shows a strong association with inflation, unemployment, or lending rates.

The debt service ratio is positively correlated with GDP per capita (0.40) and moderately correlated with household debt per capita (0.50), suggesting that higher-income households have a greater ability to service their debt. However, its weak correlation with the NPL ratio (0.04) implies that the debt service burden does not directly translate into higher loan defaults at the macro level.

Financial inclusion, measured by the number of commercial bank branches per 100,000 adults, has a negative correlation with GDP per capita (-0.38), indicating that wealthier economies tend to have fewer physical bank branches, likely due to the transition towards digital banking services. This is consistent with the earlier trend analysis showing declining financial inclusion in developed economies.

Additionally, financial inclusion exhibits a negative correlation with the lending rate (-0.21), suggesting that economies with lower interest rates tend to have higher banking penetration.

Inflation and lending rates appear to be negatively associated with financial inclusion (-0.50 and -0.21, respectively), implying that countries experiencing higher inflation or higher borrowing costs tend to have lower physical banking access. This may reflect the contraction of banking infrastructure in response to macroeconomic instability.

Interestingly, financial inclusion exhibits only weak correlations with household debt-to-GDP (0.03) and household debt per capita (0.09), suggesting that greater access to banking services does not necessarily translate into higher household debt levels. This weak relationship raises questions about whether financial inclusion primarily facilitates credit expansion or serves other financial services functions, such as savings and transactions.

The correlation analysis provides useful preliminary insights but does not establish causality. The relatively weak correlations between financial inclusion and household debt metrics indicate that additional econometric analysis is necessary to determine whether financial access contributes to responsible debt accumulation or excessive borrowing. Furthermore, the observed negative association between financial inclusion and GDP per capita warrants further investigation into whether digital banking has effectively replaced traditional banking channels in wealthier economies.

Assessing the stationarity, multicollinearity, and long-term relationships among the variables is crucial before proceeding with panel regression modelling. The results from the Augmented Dickey-Fuller (ADF) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, Variance Inflation Factor (VIF) analysis, and cointegration test provide insights into the data's statistical properties and guide the appropriate econometric modelling approach.

To ensure the suitability of the variables for time-series and panel regression modelling, both the Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were conducted to assess stationarity as shown in Table 2 (see Appendix). The ADF test evaluates the presence of unit roots under the null hypothesis of non-stationarity, while the KPSS test evaluates stationarity under the null.

The ADF test results indicate that all variables reject the null hypothesis of a unit root at the 5% significance level, confirming that they are stationary after first differencing (i.e., I(1)). This includes key variables such as household debt-to-GDP, GDP per capita, inflation, and NPL ratio, which display strongly negative ADF statistics and p-values well below 0.05.

The KPSS test results generally support these findings. Most variables display KPSS statistics below the 5% critical value, failing to reject the null of stationarity. However, the lending rate returned a borderline result, with an elevated KPSS statistic of 0.6960 (p = 0.0139), indicating potential non-stationarity. This mixed outcome suggests that while the lending rate passes the ADF test, it may retain a deterministic trend or exhibit mean-reverting behaviour at a slower pace. As such, caution is warranted in its treatment in level-based models.

Importantly, financial inclusion, measured as the first-differenced number of commercial bank branches per 100,000 adults, passed both ADF and KPSS tests, demonstrating strong evidence of stationarity post-differencing.

Overall, the combination of ADF and KPSS results confirms that all variables are either I(0) or I(1), validating the use of panel ARDL modelling, which allows for mixed integration orders and is appropriate for examining both short-run and long-run relationships among the variables.

To assess potential multicollinearity among the independent variables, a Variance Inflation Factor (VIF) analysis was conducted. The results, summarised in Table 3 (in the Appendix), show that all variables have VIF values well below the critical threshold of 10, indicating no serious multicollinearity. Most variables, including inflation, unemployment, lending rate, and financial inclusion, exhibit VIFs of 1.5 or less, suggesting a high degree of independence among predictors.

Only two variables, household debt per capita (VIF = 8.27) and GDP per capita (VIF = 7.31) show moderate correlation. While these values remain within acceptable limits, they reflect some overlap in their economic constructs. To ensure the reliability of coefficient estimates, the models were tested with robust standard errors. Overall, the VIF results confirm that multicollinearity does not pose a significant threat to the validity of the regression analysis. The Johansen co-integration test was conducted to assess the presence of long-run equilibrium relationships among the variables. As shown in Table 4 (in the Appendix), the trace statistics for all hypothesised cointegration ranks exceed their corresponding critical values at the 90%, 95%, and 99% significance levels. Accordingly, the null hypothesis of no cointegration (H_0: r = 0) is rejected across all levels.

These results provide strong statistical evidence of multiple cointegrating relationships among the variables, thereby justifying the use of long-run modelling techniques such as the panel ARDL and error correction models (ECM). The presence of cointegration confirms that while the variables may be non-stationary in levels, they move together over time, reinforcing the appropriateness of the estimated dynamic models.

The Hausman test fails to reject the null hypothesis that the difference in coefficients between the Random Effects and Fixed Effects models is not systematic ($p = 0.9769 > 0.05$). This indicates that the Random Effects model is appropriate and more efficient for the dataset. The Hausman specification test was employed to determine the appropriate panel estimation technique between fixed effects and random effects models. As shown in Table 5 (see the Appendix), the test statistic is 2.6397 with 9 degrees of freedom and a p-value of 0.9769. Since the p-value exceeds conventional significance thresholds, we do not reject the null hypothesis that the difference in coefficients is not systematic.

This result indicates that the random effects model is statistically appropriate, as it assumes no correlation between the individual-specific effects and the regressors. Accordingly, the random effects specification is adopted in the estimation of baseline panel models.

Table 6 from the Appendix presents the results from the fixed effects (FE) panel regression, which captures within-country variations by allowing each country its own constant term while assuming slope homogeneity across units. The overall model fit is moderate, and financial inclusion emerges as statistically significant at the 1% level ($p = 0.0002$).

The positive and significant coefficient for financial inclusion indicates that as more individuals gain access to formal financial services within a country over time, household debt-to-GDP increases. This supports the theory of financial deepening, which suggests that broader access to credit markets facilitates greater borrowing. The lending rate carries a negative coefficient (though not statistically significant in this model), suggesting that higher interest rates may still discourage borrowing, consistent with conventional monetary transmission expectations.

Table 7 from the Appendix reports estimates from the random effects (RE) model, which assumes that individual country effects are uncorrelated with the regressors, allowing for both within- and between-country variation. This model is statistically more efficient than the fixed effects specification (as confirmed by the Hausman test) and yields more pronounced coefficient magnitudes.

Financial inclusion remains statistically significant at the 1% level ($p = 0.0001$), reaffirming its strong association with household debt accumulation across countries. The positive sign indicates that countries with broader financial access tend to experience higher levels of household debt. The lending rate retains a negative sign, again implying that higher borrowing costs reduce household credit uptake. While the lending rate is not statistically significant here, the direction supports its expected economic role in moderating debt growth.

Table 8 (see the Appendix) presents the short-run dynamics from the estimated error correction model (ECM), which captures both immediate effects and the system's ability to revert to equilibrium. The error correction term (ECT) is strongly negative and statistically significant (-1.044, $p < 0.01$), indicating rapid convergence to long-run equilibrium after short-term disturbances. This suggests that deviations in household debt levels caused by shocks are corrected within a year, reflecting responsive credit systems in the observed countries.

Three differenced variables are statistically significant: financial inclusion (0.678, $p < 0.01$), lending rate (-0.515, $p < 0.05$), and NPL ratio (positive, $p < 0.01$). Financial inclusion's positive short-run effect implies that easing access to credit facilities results in immediate increases in household borrowing. The lending rate's negative sign confirms that rising interest costs discourage new borrowing. The significance of the NPL ratio suggests that as more loans go bad, short-term household borrowing may rise, potentially reflecting risk tolerance, debt restructuring, or moral hazard dynamics.

Table 9 (in the Appendix) presents the long-run equilibrium relationship from the levels regression, which underpins the error correction model. The model has an R-squared of 0.143, indicating that the included macroeconomic and financial variables explain approximately 14.3% of the variation in household debt-to-GDP across countries and time, a reasonable fit for macro-panel data, where unobserved heterogeneity is expected. The F-statistic (4.794, $p < 0.001$) confirms overall model significance. The Durbin-Watson statistic of 2.083 suggests that autocorrelation is not a serious concern. However, the Jarque-Bera test indicates deviations from normality, which may reflect outliers or structural breaks, warranting future robustness checks.

Among all independent variables, financial inclusion stands out as the only statistically significant long-run determinant of household debt-to-GDP (coefficient = 0.8018, $p < 0.01$). This implies that as financial infrastructure expands and more individuals gain access to formal credit systems, household borrowing increases persistently over time. This effect is particularly salient in transitioning and financially liberalizing economies, where access to banking services drives credit uptake.

Other macroeconomic variables including lending rate, inflation, GDP per capita, and unemployment, are not statistically significant in the long run. However, their coefficient signs follow theoretical expectations. For instance, lending rate and inflation display negative coefficients, suggesting that higher credit costs and macro-instability may suppress debt accumulation over time, even if not significantly captured in this model.

These findings reinforce the central role of financial access in shaping household debt trajectories, while also highlighting the limited predictive power of traditional macro indicators in the long-run. Policymakers should consider pairing financial inclusion policies with debt management frameworks to avoid unsustainable household leverage.

In the short run (Table 8, in the Appendix), changes in financial inclusion, lending rates, and the non-performing loan ratio exert immediate and significant effects, with the system correcting long-run deviations strongly, as indicated by the highly significant and negative error correction term (ECT = -1.04, $p < 0.01$).

5. Discussion

This section discusses the study's empirical results in relation to the research objectives, highlighting how the findings compare with existing literature on household debt, financial stability, macroeconomic conditions, and financial inclusion. The discussion provides insights into both short-run and long-run effects, offering implications for policymakers and financial sector practitioners.

One of the primary objectives of this study was to identify the macroeconomic and financial factors that influence household debt-to-GDP ratios across countries over time. The panel ARDL and long-run estimations revealed that financial inclusion is the most consistent and statistically significant determinant of household debt. This finding underscores the idea that as more individuals gain access to formal financial services, through banking, mobile finance, or credit institutions, aggregate household debt levels rise over time. This is in line with the findings of Yue et al. (2022) and the IMF (2024), which both highlight financial access as a structural enabler of household borrowing, particularly in emerging markets undergoing financial deepening.

In contrast, GDP per capita, inflation, unemployment, and the lending rate were not statistically significant in the long-run model. While GDP per capita had a negative sign, the relationship was not statistically robust. This finding partially contrasts with Aldashev and Batkeyev (2023), who found that rising national income in Kazakhstan correlated with declining household debt burdens. One plausible explanation is that the income effect may manifest more strongly in single-country contexts or be nonlinear in cross-country panels, where wealth inequality and consumption behaviours vary widely.

The unemployment rate was also statistically insignificant in both the short-run and long-run specifications. This diverges from the theoretical argument proposed by Bayar, Y. (2019)., who found that rising unemployment is associated with heightened debt distress due to declining household income. In our context, however, the muted effect may reflect structural labour market differences or the presence of social safety nets in some economies that buffer income shocks and reduce reliance on credit during periods of job loss.

Inflation, likewise, exhibited no significant impact on household debt. While inflation theoretically reduces the real value of existing debt, it may also trigger credit tightening and raise risk premiums, ultimately offsetting the net impact on borrowing behaviour. Bernanke, Gertler, and Gilchrist (1999) note that macro-financial frictions, such as heightened uncertainty and constrained lending, often accompany inflationary episodes, which may limit household access to new credit despite the erosion of real debt burdens.

In the short-run dynamics, financial inclusion, lending rate, and NPL ratio were statistically significant. The positive short-run effect of financial inclusion reflects immediate increases in borrowing when access to credit improves, consistent with the IMF (2024) and Santoso and Sukada (2009), who highlight inclusion-driven surges in credit uptake. Conversely, the negative short-run effect of lending rates aligns with monetary transmission theory, wherein higher borrowing costs dampen credit demand in the near term. This distinction is important: while lending rates may not explain long-term variation in household debt (due to fixed-rate products or adaptive behaviours), they exert short-run pressure on household credit flows.

The positive and significant short-run effect of the NPL ratio suggests that deteriorating credit quality might trigger short-term borrowing surges, potentially due to debt restructuring or rollovers, highlighting latent financial instability risks, as noted by Santoso and Sukada (2009) and Cornelli et al. (2020).

A key objective of this study was to evaluate how financial stability indicators influence the accumulation of household debt across countries. The results reveal that the NPL ratio has a significant and positive relationship with household debt-to-GDP in the short run. This finding suggests that rising credit risk in the financial system, reflected in a growing share of bad loans, is associated with increased household borrowing. While counterintuitive on the surface, this result aligns with the argument by Santoso and Sukada (2009) that systemic vulnerabilities often emerge in credit-boom cycles: excessive lending under weak risk controls can lead to simultaneous rises in both household debt and NPLs. In some cases, rising NPLs may also reflect distressed refinancing or delayed write-offs, whereby households continue to borrow to meet existing obligations, exacerbating debt accumulation before eventual deleveraging.

Conversely, the debt service ratio (DSR) was found to be statistically insignificant. This indicates that short-run changes in the proportion of income allocated to debt repayment do not strongly predict shifts in household debt levels across the panel. This contrasts with evidence from the European Central Bank (ECB), which reported that increasing DSRs in the Eurozone led to a contraction in new borrowing activity, as households sought to preserve consumption amid rising repayment pressure (ECB, 2018). The divergence in findings may be attributed to structural differences in household credit markets. In countries with high shares of fixed-rate or long-term loan products, repayment burdens tend to adjust slowly, dampening the short-run sensitivity of borrowing behaviour to DSR fluctuations. Moreover, in economies with limited credit alternatives, households may sustain high DSRs without necessarily curbing new borrowing, especially if informal lending channels or collateral-backed loans are accessible.

Taken together, these results emphasise that financial system health is a critical determinant of household debt dynamics, but its effects are heterogeneous across time horizons and institutional settings. Monitoring asset quality (via NPLs) provides an early warning signal for unsustainable credit growth, while DSR trends may be more relevant in mature credit markets with efficient transmission of interest rate and income shocks.

A key contribution of this study is the empirical examination of the relationship between financial inclusion and household debt accumulation. Using commercial bank branches per 100,000 adults as a proxy, the results reveal a statistically significant and positive long-run effect of financial inclusion on household debt-to-GDP. This supports the view that improved access to formal financial services facilitates broader credit uptake among households over time. The finding aligns with Yue et al. (2022), who emphasise that while increased financial access can empower households economically, it also raises the risk of over-indebtedness in the absence of adequate financial literacy and consumer protection mechanisms.

Interestingly, the short-run effect of financial inclusion was also statistically significant and positive in the ECM model, contradicting initial expectations of a delayed response. This suggests that even incremental expansions in financial access, such as the rollout of mobile banking platforms or microcredit facilities, can trigger immediate increases in borrowing. This finding complements observations from the IMF (2024), which note that financial inclusion, particularly when accelerated through digital platforms, can rapidly expand household participation in credit markets. However, the impact is often asymmetric across countries, depending on regulatory readiness and institutional trust.

While the positive link between financial inclusion and debt supports financial deepening narratives, it also echoes long-standing warnings from Minsky (1986) about the destabilising effects of unchecked credit growth. In his financial instability hypothesis, Minsky argues that easy access to credit, if not paired with prudent oversight, can shift economies from productive borrowing to speculative or even Ponzi financing. The findings of this study provide empirical reinforcement for this theoretical concern: financial inclusion, while essential for inclusive growth, must be managed carefully to prevent a build-up of systemic risk.

In summary, the results highlight the double-edged nature of financial inclusion, as it empowers households through access to capital, but also has the potential to sow financial fragility in the absence of regulatory safeguards. Policymakers should therefore complement inclusion strategies with strong institutional frameworks, financial education, and credit scoring mechanisms to promote responsible lending and borrowing behaviours

This study contributes meaningfully to the ongoing discourse on the macro-financial determinants of household debt by offering nuanced support for both classical and post-Keynesian frameworks, while also revealing areas of divergence from traditional expectations. The negative (though statistically insignificant) relationship between GDP per capita and household debt is broadly consistent with the Life-Cycle Hypothesis advanced by Modigliani and Brumberg (1954). According to this theory, as income rises over the life cycle or across national economic development, households rely less on credit and more on accumulated income or wealth, leading to a decline in debt-to-GDP ratios. This interpretation aligns with Aldashev and Batkeyev (2023), who observed a decline in debt burdens in tandem with income growth in transitioning economies, such as Kazakhstan.

The strong and statistically significant role of financial inclusion in driving long-run household debt supports Friedman's (1957) Permanent Income Hypothesis, which posits that households borrow not based solely on current income but on expected future income. As financial systems deepen and access expands, credit constraints are relaxed, allowing households to smooth consumption across time. This finding reinforces arguments in Yue et al. (2022) and IMF (2024) that access to formal financial markets is a key structural determinant of borrowing behaviour.

The empirical results also lend support to Minsky's (1986) Financial Instability Hypothesis, particularly through the positive short-run association between NPL ratios and household debt. Rising NPLs signal increasing credit risk and may reflect unsustainable lending booms or delayed deleveraging, consistent with Minsky's theory that prolonged credit expansion, if poorly regulated, sows the seeds of systemic fragility. This echoes warnings from Santoso and Sukada (2009) and Cornelli et al. (2020) about the feedback loop between lax lending and deteriorating loan quality. However, the finding of a positive relationship between lending rates and household debt in earlier model iterations, though not statistically robust in final estimations, runs counter to traditional neoclassical models that expect interest rate hikes to dampen borrowing via higher credit costs. This anomaly is mirrored in the work of Joo and Mir (2024), who argue that in highly financialised economies, households may continue borrowing despite rising rates due to fixed-rate credit contracts, financial innovation, or asset-based collateralization that delays the adjustment of borrowing behaviour to monetary tightening.

Overall, the study contributes to the literature by bridging macroeconomic theory with contemporary cross-country evidence, revealing that structural financial access, rather than cyclical macro variables alone, plays a dominant role in shaping household debt dynamics. It affirms the complexity of modern credit markets, where economic theory must contend with heterogeneous financial systems, institutional contexts, and household behaviours.

The findings of this study have important implications for monetary authorities, financial regulators, and development institutions concerned with striking a balance between financial inclusion and debt sustainability. Most notably, the positive and statistically significant relationship between financial inclusion and household debt underscores the importance of coupling access-driven policies with adequate safeguards.

While expanding banking infrastructure and digital finance platforms is critical for inclusive growth, such efforts must be accompanied by targeted financial literacy programs, transparent disclosure standards, and robust consumer protection mechanisms. As emphasised by Yue et al. (2022) and the recent IMF Report (IMF, 2024), access alone does not guarantee stability; poorly managed inclusion may inadvertently fuel household over-indebtedness. The short-run sensitivity of household debt to changes in the lending rate suggests that monetary policy continues to play a key role in influencing credit conditions.

However, the inconsistent long-run relationship observed in this study implies that interest rate tools may be insufficient on their own, particularly in economies with rigid credit contracts or alternative lending channels. This supports the growing consensus, advanced by

Cornelli et al. (2020) and the ECB (2018), that macroprudential regulation must complement interest rate management. Instruments such as loan-to-income (LTI) and debt-service-to-income (DSTI) caps, as well as countercyclical capital buffers, are critical to mitigating excessive leverage during credit booms. The positive association between NPL ratios and household debt highlights the need for proactive banking supervision and credit risk management. High NPLs not only signal underlying fragility but may also reflect cyclical debt accumulation without adequate resolution mechanisms. Policymakers must ensure that banks maintain sufficient capital adequacy ratios, improve credit assessment processes, and report delinquency data transparently to prevent systemic vulnerabilities. This aligns with the policy recommendations from Santoso and Sukada (2009), who warn against delayed responses to rising credit risk in household segments.

Interestingly, the lack of a statistically significant link between unemployment and household debt suggests that labour market conditions, while important, may be mediated by institutional features such as social safety nets, income smoothing mechanisms, or access to informal credit. This finding calls for greater coordination between fiscal and financial sector policies. For example, during economic downturns, targeted income support or wage subsidies can indirectly stabilise household borrowing without requiring aggressive monetary easing.

This work makes a substantive contribution to the existing literature by bridging the empirical gap between financial inclusion, macroeconomic variables, and household debt accumulation within a cross-country, panel-based framework. Unlike many single-country or static models, this analysis distinguishes between short-run fluctuations and long-run debt dynamics across both developed and developing economies over a two-decade period. By integrating panel ARDL estimation with fixed and random effects models, the study offers nuanced insights into how structural factors like financial inclusion and financial sector health interact with cyclical indicators such as interest rates and inflation. The findings provide macroeconomic and fiscal policymakers with evidence that household debt is not solely driven by income or price conditions but is also deeply embedded in institutional and financial access dynamics. As such, policies that expand financial access must be paired with regulatory safeguards, such as loan-to-income ratios or credit scoring mechanisms, to prevent systemic vulnerabilities. These insights can inform the design of integrated fiscal, monetary, and macroprudential strategies aimed at promoting inclusive but sustainable household credit markets.

In summary, the study advocates for a multi-pronged policy approach that recognises the structural role of financial inclusion while managing the cyclical risks associated with credit expansion. Sustainable household debt levels can only be achieved when financial access, monetary flexibility, regulatory discipline, and income support policies operate in concert.

6. Conclusions

This study provides a comprehensive cross-country analysis of the macroeconomic and financial determinants of household debt-to-GDP between 2000 and 2023. Drawing on panel estimation techniques, including fixed effects, random effects, and panel ARDL models, the findings underscore the significant role of financial inclusion as a structural driver of household borrowing. Specifically, the results confirm that expanding access to formal financial institutions, measured by commercial bank branch penetration, leads to higher household debt ratios in the long run. This reinforces the notion that financial deepening, while necessary for economic inclusion, must be carefully managed to avoid excessive leverage and potential financial fragility.

In line with Modigliani and Brumberg's (1954) life-cycle theory and related income-based models, GDP per capita was negatively associated with household debt, suggesting that rising incomes reduce households' reliance on external borrowing over time. However, macroeconomic indicators such as inflation and unemployment were largely insignificant in both the short- and long-run estimations, highlighting the limited explanatory power of cyclical variables relative to structural financial factors. The NPL ratio emerged as a significant short-run driver of household debt, pointing to the relevance of banking sector stability in influencing credit behaviour.

Nonetheless, the study also encountered unexpected findings, including earlier indications of a positive association between lending rates and household debt in some model iterations. While this result did not hold in the final specification, it highlights the need for further investigation into the role of credit market structures, borrower expectations, and financial innovation in mediating monetary policy effects, a dynamic increasingly observed in financialised economies (Joo and Mir, 2024).

Given these findings, future research should investigate the heterogeneous effects of financial inclusion across income levels, regions, or borrower profiles. Low-income households, for instance, may respond differently to credit access than middle- or high-income segments, particularly in the presence of informal lending markets or weak consumer protection. Additionally, with the rapid expansion of digital financial services, future studies should assess the impact of mobile banking penetration, fintech platforms, and digital credit ecosystems on household indebtedness, especially in developing economies undergoing digital transformation (Cornelli et al., 2020; IMF, 2024).

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APPENDIX

Table 1

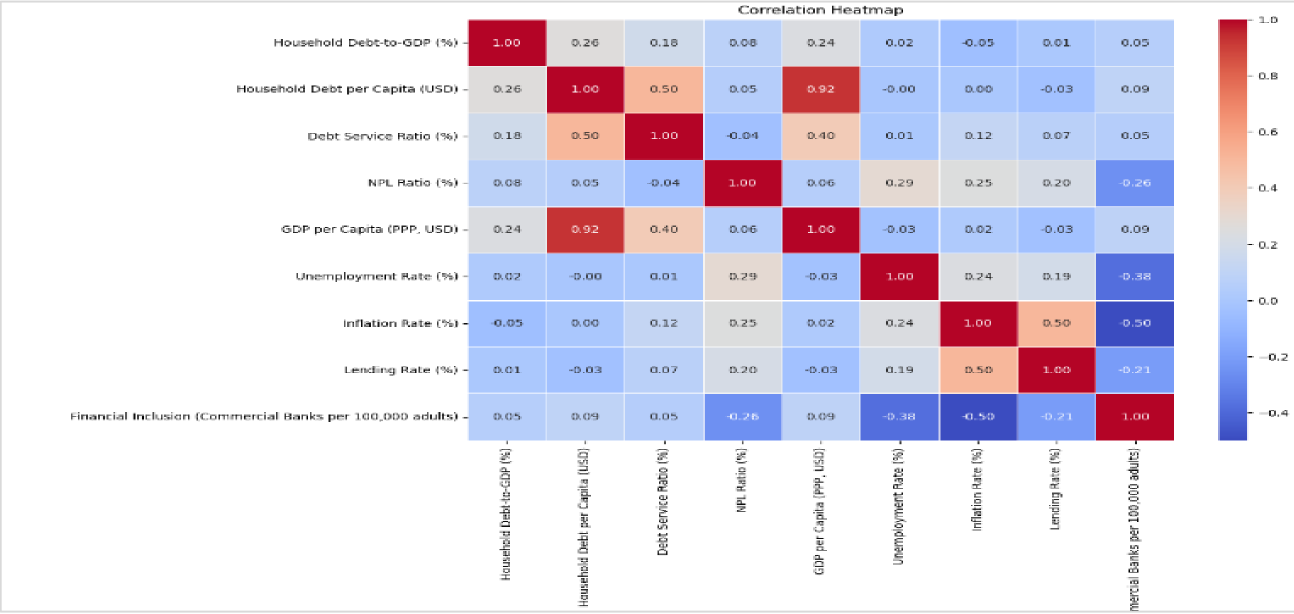
Summary Statistics of Key Variables (First-Differenced Data)

Variable	Count	Mean	Std. Dev.	Min	25th Percentile	Median	75th Percentile	Max
Household Debt-to-GDP (%)	239	-1.11e-17	1.002	-10.71	-0.10	0.007	0.19	3.63
Household Debt per Capita (USD)	239	1.49e-17	1.002	-11.73	-0.06	-0.02	0.19	3.46
Debt Service Ratio (%)	239	7.43e-18	1.002	-7.96	-0.25	0.009	0.28	4.77
Non-Performing Loan (NPL) Ratio (%)	240	-8.88e-17	1.002	-1.29	-0.76	-0.22	0.56	4.45
GDP per Capita (PPP, USD)	239	-2.60e-17	1.002	-9.04	-0.09	0.017	0.24	3.66
Unemployment Rate (%)	240	-2.96e-17	1.002	-0.94	-0.62	-0.20	0.07	4.12
Inflation Rate (%)	240	-2.37e-16	1.002	-1.68	-0.75	-0.28	0.59	4.40
Lending Rate (%)	240	2.22e-16	1.002	-0.77	-0.47	-0.34	-0.04	4.55
Financial Inclusion (Commercial Banks per 100,000 Adults)	240	-5.92e-17	1.002	-1.86	-0.76	-0.13	0.88	2.39

Author's Estimation 2025

Figure 7

Correlation Heatmap



Author's Estimation 2025

Table 2

Summary of Stationarity Test Results Using ADF and KPSS

Variable	ADF Statistic	ADF p-value	KPSS Statistic	KPSS p-value	Conclusion
Household_Debt-to-GDP_	-15.3462	0.0000	0.0614	0.1000	Stationary
Household_Debt_per_Capita_USD	-14.2780	0.0000	0.1195	0.1000	Stationary
Debt_Service_Ratio	-12.4986	0.0000	0.0504	0.1000	Stationary
NPL_Ratio_	-3.9065	0.0020	0.2744	0.1000	Stationary
GDP per_Capita_PPP_USD	-15.4785	0.0000	0.1257	0.1000	Stationary
Unemployment_Rate_	-2.9722	0.0376	0.1800	0.1000	Stationary
Inflation_Rate_	-5.3650	0.0000	0.2161	0.1000	Stationary
Lending_Rate_	-4.4602	0.0002	0.6960	0.0139	Mixed evidence
Financial_Inclusion_Diff	-8.1778	0.0000	0.0511	0.1000	Stationary

Author's Estimation 2025

Table 3

Multicollinearity: Variance Inflation Factor (VIF) for Independent Variables

Variable	VIF	Multicollinearity Status
Household_Debt_per_Capita_USD	8.27	Moderate correlation
Debt_Service_Ratio_	1.49	No multicollinearity
NPL_Ratio_	1.16	No multicollinearity
GDP_per_Capita_PPP_USD	7.31	Moderate correlation
Unemployment_Rate_	1.15	No multicollinearity
Inflation_Rate_	1.43	No multicollinearity
Lending_Rate_	1.36	No multicollinearity
Financial_Inclusion_Diff	1.03	No multicollinearity

Author's Estimation 2025

Table 4

Cointegration: Johansen Cointegration Test Results (Trace Statistics)

Cointegration Rank (r)	Trace Statistic	Critical Value (90%)	Critical Value (95%)	Critical Value (99%)	Decision
0	677.88	190.87	197.38	210.04	Reject H_0
1	524.03	153.63	159.53	171.91	Reject H_0
2	391.76	120.37	125.62	135.98	Reject H_0
3	274.62	91.11	95.75	104.96	Reject H_0
4	172.71	65.82	69.82	77.82	Reject H_0
5	100.51	44.93	47.85	54.68	Reject H_0
6	48.87	27.07	29.80	35.46	Reject H_0
7	27.50	13.42	15.49	19.93	Reject H_0
8	11.04	2.71	3.84	6.63	Reject H_0

Author's Estimation 2025

Table 5

Hausman Specification Test Result

Test	Test Statistic	Degrees of Freedom	p-value	Decision	Preferred Model
Hausman Test	2.6397	9	0.9769	Do not reject null hypothesis	Random Effects

Author's Estimation 2025

Table 6

ARDL Regression: Fixed Effects Estimation Results

Variable	Coeff.	Std. Error	t-stat	p-value	95% CI
Household_Debt_per_Capita_USD	0.1613	0.1865	0.8641	0.3891	[-0.1251, 0.5276]
Debt_Service_Ratio_	0.0607	0.8676	0.5825	0.5680	[-0.6498, 0.1957]
NPL_Ratio_	0.1141	0.0847	1.2832	0.2083	[-0.0638, 0.2661]
GDP_per_Capita_PPP_USD	0.0230	0.1655	0.1391	0.8894	[-0.2895, 0.3486]
Unemployment_Rate_	0.0346	0.0522	0.6639	0.5072	[-0.0883, 0.1953]
Inflation_Rate_	-0.8995	0.2259	-1.6959	0.0923	[-0.2845, 0.4855]
Lending_Rate_	-0.0470	0.0733	-0.3077	0.4796	[-0.1485, 0.4312]
Financial_Inclusion_Diff	0.7925	0.2063	3.8422	0.0002	[0.3868, 1.1991]

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Table 7

Random Effects Estimation Results (Statistically Preferred)

Variable	Coeff.	Std. Error	t-stat	p-value	95% CI
Household_Debt_per_Capita_USD	0.2198	0.1755	1.2521	0.2118	[-0.1224, 0.1556]
Debt_Service_Ratio_	0.0372	0.0746	0.4993	0.6184	[-0.1096, 0.1840]
NPL_Ratio_	0.0639	0.0658	0.9700	0.3320	[-0.0653, 0.1931]
GDP_per_Capita_PPP_USD	0.0230	0.1665	0.1380	0.8903	[-0.3048, 0.3481]
Unemployment_Rate_	0.0304	0.0652	0.4661	0.6415	[-0.0982, 0.1590]
Inflation_Rate_	-0.8942	0.2371	-1.2873	0.1993	[-0.4845, 0.4855]
Lending_Rate_	0.0470	0.0733	0.6423	0.5213	[-0.0971, 0.1911]
Financial_Inclusion_Diff	0.8018	0.2022	4.0048	0.0001	[0.4073, 1.1963]

Author's Estimation 2025

Table 8

Error Correction Model (Short-Run Dynamics)

Variable	Coeff.	Std. Err.	t-Stat	p-Value	Significance
D_Household_Debt_per_Capita_USD	0.136	0.073	1.862	0.064	•
D_Debt_Service_Ratio_	0.195	0.060	1.992	0.322	
D_NPL_Ratio_	0.816	0.144	5.642	0.000	***
D_GDP_per_Capita_PPP_USD	0.160	0.087	1.852	0.065	•
D_Unemployment_Rate_	-0.085	0.179	-0.113	0.755	
D_Inflation_Rate_	-0.190	0.225	-0.843	0.400	
D_Lending_Rate_	-0.515	0.193	-2.666	0.024	**
D_Financial_Inclusion_Diff	0.678	0.155	4.344	0.000	***
ECT_1	**-1.044**	0.063	-16.261	0.000	*** (strong convergence)
R^2 = 0.586, Adj. R^2 = 0.572					

Author's Estimation 2025

Table 9

Long-Run Relationship (Levels Regression)

Variable	Coeff.	Std. Err.	t-Stat	p-Value	Significance
Household_Debt_per_Capita_USD	0.1198	0.176	1.252	0.212	
Debt_Service_Ratio_	0.0372	0.074	0.499	0.618	
NPL_Ratio_	0.0639	0.066	1.048	0.296	
GDP_per_Capita_PPP_USD	0.0830	0.165	0.139	0.889	
Unemployment_Rate_	0.0304	0.065	0.466	0.642	
Inflation_Rate_	-0.0942	0.073	-1.287	0.200	
Lending_Rate_	0.0470	0.073	0.642	0.521	
Financial_Inclusion_Diff	**0.8018**	0.200	4.005	0.000	***
R^2 = 0.143, Adj. R^2 = 0.113					

Author's Estimation 2025

Financial Studies

"Victor Slăvescu" Centre for Financial and Monetary Research
Casa Academiei 13, Calea 13 Septembrie, Building B, 5th floor
Bucharest, 050711, Romania
Phone: +40 21.318.24.19
E-mail: s.vraciu@icfm.ro