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Research Article

An Analysis of Household Borrowing Behavior: Evidence on Institutional Choice, Mobile Money, and Credit Demand Drivers in Ethiopia

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Abstract

This study investigates household borrowing behavior in Ethiopia using data from the 2025 Global Findex Survey. The analysis employs Generalized Structural Equation Modeling (GSEM) to examine five financial inclusion outcomes: mobile money account ownership, receipt of mobile money credit, formal borrowing, borrowing from friends and family, and participation in informal savings groups (iqub/ROSCAs). The results reveal a segmented financial ecosystem in which access to financial services is shaped by education, borrowing purpose, and demographic characteristics. Mobile money account ownership is strongly associated with higher educational attainment, active saving behavior, urban residence, and female gender, while age and income exert relatively limited effects. In contrast, receipt of mobile money credit is only weakly related to socioeconomic characteristics and is primarily associated with health- and business-related borrowing needs, suggesting that digital credit functions mainly as a liquidity management tool. Formal borrowing is driven largely by business-related financing needs rather than demographic factors, indicating that formal financial institutions primarily support productive investments. Borrowing from friends and family serves as a key source of financing for health, food, and business expenditures, highlighting the continued importance of informal networks in household risk management and consumption smoothing. Participation in informal savings groups is more common among younger individuals and is positively. Therefore, expanding digital financial inclusion, strengthening access to formal credit, and leveraging informal financial institutions as complementary channels could contribute to a more inclusive and resilient financial system.

Keywords

Formal, Informal, Family, Friends, Digital, Mobile Money

1. Introduction

Household borrowing is an important economic activity, especially in low- and middle-income countries, where income uncertainty is high, social protection is lacking, and financial infrastructure is incomplete. Credit is not only important as an instrument for smoothing consumption but is also an important avenue for asset formation, enterprise development, and risk protection against health and environmental shocks [6, 33]. Yet, despite the best efforts of financial inclusion over the last few decades, a large number of households in developing economies are still un- or under-banked, and are hence forced to put together credit from an uncohesive and often expensive array of sources.

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Household sources of borrowing can be categorized into formal, informal, and mobile sources. Formal sources include bank, microfinance, credit union, and government sources. While they often offer large loan sizes and formal repayment conditions, they are accompanied by high transaction costs (e.g., documentation, collateral, and travel) and stringent eligibility conditions [9]. Informal sources, on the other hand, include borrowing from family, friends, moneylenders, shopkeepers, and rotating savings associations. While they are convenient and have little or no transaction costs, they are accompanied by extremely high interest rates in the case of moneylenders, as well as social and loan amount constraints [20]. Mobile sources, on the other hand, have emerged as an important source of credit over the last decade, with platforms such as M-Pesa's M-Shwari, Fuliza, and other standalone mobile apps offering algorithmic creditworthiness assessment and quick disbursement of short-term, small loan sizes [21, 31].

The increasing body of literature also points to the fact that the underlying purpose for borrowing is a significant factor that determines the type of credit that households choose to use. For instance, a medical emergency or a need for food, especially if time-sensitive and for a relatively smaller amount may require households to use mobile or informal credit, even if formal credit is available [29]. On the other hand, a need to pay school fees or to make improvements to a house, especially if a relatively larger amount is required, may require households to use formal loans, even if these are costlier [4]. The need to invest in a business is an intermediate category, where a micro-enterprise may start off with informal or mobile credit and move to formal sources as its need for capital increases [23].

The introduction of mobile financial services has impacted household borrowing behavior through a number of channels. First, mobile credit significantly reduces transaction costs, both monetary and time-related, and hence may reduce the cost of borrowing for households [32]. Secondly, mobile financial services may help households to build a digital footprint that may help to build a formal credit history and hence potentially become a means for households to access formal loans [26]. Thirdly, mobile financial services may also contribute to over-borrowing, especially if the ease of getting a loan is presented as a one-click process [14]. As a consequence, an important debate is ongoing regarding the extent to which mobile financial services act as a complement or a substitute for formal finance.

Despite extensive literature on household credit, some gaps still remain. In particular, most existing literature considers borrowing decisions in a pairwise approach, i.e., between formal and informal credit or between formal and mobile credit, without considering all three channels simultaneously as competing choice variables [33-35]. However, it is likely that households consider multiple choice variables at once, and considering mobile credit would affect the relative attractiveness of both formal and informal channels. In addition, although loan purpose is often included as a control variable, it is rarely considered as a main moderating variable, which can reverse the direction of influence of household characteristics. For instance, a rich household may prefer to use informal credit for its ease of access in emergency situations but may prefer to use formal credit for its longer-term investment plans. Further, it is often considered that mobile access is independent of household borrowing decisions, but it is correlated with income, financial literacy, and risk-taking behavior.

Ethiopia, the second most populous nation in Africa, has one of the fastest-growing mobile money markets on the continent, and its conditions are uniquely instructive for analyzing household borrowing behavior. Financial exclusion among adults in Ethiopia is widespread, with more than half of the population lacking access to formal financial services [57].

In Ethiopia, the formal financial sector includes commercial banks, microfinance institutions, and savings and credit cooperative societies. However, access to financial credit is limited. Commercial bank credit is dominated by large collateralized loans, with limited access to the majority of the population. A study on small firms in Addis Ababa found that borrowing from formal financial institutions is the least frequently used source of start-up capital for small firms. The study found that small firms cited underdeveloped financial systems, high collateral demands, high interest rates, and complex application procedures as major obstacles to accessing financial credit. Microfinance institutions are the second most frequently used source of financial credit for small firms. Microfinance institutions have partially filled the gap created by commercial banks. Recent policy reforms, including Proclamation No. 1282/2023, have liberalized the financial sector to foreign firms. The National Bank of Ethiopia has also developed a National Digital Payment Strategy for the period 2026-2030. However, the financial sector is dominated by commercial banks with limited access to financial credit.

In the absence of formal credit, Ethiopian households have relied on a variety of informal credit instruments. Borrowing from friends, relatives, and family member's ranks as the third most common source of startup capital. However, Ethiopia has two traditional institutions, namely, iddir (burial associations) and iqub (rotating savings and credit associations), which are deeply rooted in its culture and tradition. Iqub is a rotating savings and credit association formed by a group of voluntary members, where contribution to the fund is a necessity, and members receive money on a rotating basis. On the other hand, iddir is a burial association formed among neighbors or co-workers, providing mutual benefits, credit, and insurance-like benefits to its members. Both institutions are culturally appropriate, flexible, accessible, and cost-effective, and therefore attract members from all socioeconomic groups in Ethiopia. Most interestingly, a recent study has shown a significant effect of mobile financial services on iddir, implying a dynamic relationship between informal and digital finance instruments.

The most significant and transformative change in the financial sector in Ethiopia is the growth and expansion of mobile money services. Mobile money accounts have increased from 12.2 million in 2020 to 139.5 million in 2025, while mobile banking accounts have increased from 9.1 million to 54 million over the same period. By early 2026, Prime Minister Abiy Ahmed announced that 58 million citizens are using mobile wallet services, while digital payments have increased by 60 percent over the last six months. The mobile money market is dominated by two major players, namely Telebirr, owned by state-owned Ethio Telecom, which was launched in 2021, and M-Pesa, owned by Safaricom Ethiopia, which was launched after the company was issued a mobile money license in 2023. Telebirr now boasts over 51.5 million customers and processed 1.03 trillion Ethiopian Birr in transactions in the first half of the 2025/26 financial year, while M-Pesa's active customer base increased by 258.5 percent year-on-year to 5.2 million by December 2025 [45].

Despite sustained global and national efforts to expand financial inclusion in Ethiopia, a substantial gap remains in understanding how households navigate and choose among competing sources of credit. In practice, borrowing is not a uniform behavior: households may rely on formal financial institutions, informal networks such as family and friends, rotating savings and credit associations (ROSCAs), or increasingly, digital platforms enabled by mobile money services. Yet, the determinants guiding these choices at the household level remain insufficiently explored.

This study is motivated by four interrelated gaps. First, there is a clear empirical gap in the literature. Existing studies tend to examine mobile money adoption or access to formal credit in isolation, often treating borrowing as a homogeneous outcome. As a result, limited attention has been given to institutional choice across multiple credit sources simultaneously, particularly using nationally representative datasets such as the Global Findex [58] compiled by the World Bank.

Second, a policy gap persists. Financial inclusion strategies in Ethiopia have largely emphasized expanding formal banking systems and increasing account ownership. However, anecdotal and localized evidence suggests that households continue to depend heavily on informal financial arrangements. The extent of this reliance—and how it varies according to specific needs such as health expenses, food consumption, business investment, or education—remains poorly quantified, raising concerns about potential mismatches between policy priorities and actual financial behavior.

Third, there is a purpose gap in the literature. The motivation behind borrowing—why households seek credit in the first place—is rarely incorporated as a key determinant in empirical models of financial behavior. Without accounting for borrowing motives, it becomes difficult to understand why households select particular financial channels, limiting the ability of policymakers and financial service providers to design targeted, purpose-specific credit products.

Finally, a context-specific gap underscores the importance of this study. Ethiopia presents a unique case characterized by rapid expansion in digital financial services, particularly following the introduction of platforms such as Telebirr, alongside a predominantly young, rural, and low-education population. Compared to other East African countries, these structural features may shape financial behavior in distinct ways. However, recent nationally representative evidence capturing these dynamics remains scarce. The 2025 Global Findex survey provides a timely opportunity to examine these issues using up-to-date data and to generate insights into how evolving financial ecosystems influence borrowing decisions across different segments of the population. Compared to other East African countries, these structural features may shape financial behavior in distinct ways. However, recent nationally representative evidence capturing these dynamics remains scarce. The 2025 Global Findex survey provides a timely opportunity to examine these issues using up-to-date data and to generate insights into how evolving financial ecosystems influence borrowing decisions across different segments of the population.

2. Literature Review

2.1. Theoretical Literature

Household borrowing decisions are not simply an expression of credit availability but are influenced by more profound theories of household economic behavior, including theories of intertemporal choice, transaction costs, risk management, and behavioral theories. In order to understand household decisions regarding borrowing from different sources of credit, whether formal, informal, or mobile, it is essential to integrate various theories. In this section, we discuss the basic theories underlying household borrowing decisions, with special emphasis on how they address loan purposes and mobile financial services.

2.1.1. The Permanent Income Hypothesis and Consumption Smoothing

The permanent income hypothesis (PIH) [27], and its extended version, the life cycle hypothesis [39], assume that households engage in consumption-smoothing behavior, borrowing in times of income shortfalls and saving in times of income surpluses. In the case of perfect credit markets, households have the opportunity to borrow against their future income to support their current consumption and investment. However, in the case of developing countries, the credit market is imperfect, and households are unable to access credit because of the high transaction costs and lack of sufficient collateral. Therefore, they are forced to use informal credit as an alternative to consumption-smoothing [22, 57, 59]. According to the theory, households that face negative income shocks, such as crop failure and illness, are likely to seek credit sources that are easily accessible and convenient, even if they are expensive. The Permanent Income Hypothesis provides a foundational theoretical framework for understanding consumption choices, empirical evidence consistently shows that consumer behavior often deviates from its strict predictions due to liquidity constraints, income volatility, impatience, and behavioral factors. These deviations manifest as excess sensitivity of consumption to current income and the use of savings as precautionary buffers, necessitating nuanced models that accommodate these complexities for accurate representation of real-world consumption dynamics.

2.1.2. Liquidity Constraints and Buffer Stock Behavior

In line with the PIH, the buffer stock model of savings [22, 15] focuses on the behavior of households with binding liquidity constraints and hence borrows to smooth consumption in the face of unexpected shocks. The integration of these insights leads to several implications for understanding consumer behavior. First, liquidity constraints and borrowing restrictions cause consumption to be more responsive to current income changes than predicted by the PIH. Second, income uncertainty and the desire for precautionary savings encourage buffer-stock saving behavior rather than the smooth consumption path the PIH suggests. Third, behavioral biases and varying confidence levels introduce systematic deviations from rational, forward-looking consumption. Finally, generalized equilibrium models incorporating impatience, precautionary motives, and liquidity constraints have shown that the PIH consumption rule can still be optimal when these real-world frictions are properly modeled, reconciling some theoretical and empirical inconsistencies [54],. In the absence of formal credit, which is often the case in Ethiopia and other developing countries, households are likely to exhaust informal sources before moving to more costly and less accessible formal sources. The theoretical implication is the hierarchical nature of borrowing, where households are likely to first turn to informal sources (family, friends, iddir, iqub), and then mobile credit, and finally formal credit, depending on the nature and severity of the liquidity constraint and the urgency of the borrowing need.

2.1.3. Transaction Cost Economics and Credit Source Choice

Transaction Cost Economics (TCE), developed by Coase [18] and further developed by Williamson [55, 56], is a useful tool for analyzing and comparing different sources of credit. TCE theory suggests that individuals tend to select governance structures that have the lowest possible production and transaction costs. In terms of credit markets, different sources of credit—banks, moneylenders, and mobile credit—represent different governance structures with different levels of transaction costs. Formal credit sources have high levels of ex-ante transaction costs, including documentation, collateral assessment, travel, and waiting. In contrast, they have low levels of ex-post transaction costs. Informal sources have low levels of ex-ante transaction costs but high levels of ex-post transaction costs, including social costs such as strained relationships and loss of reciprocation. Mobile credit sources have low levels of both ex-ante and ex-post transaction costs, thanks to automation and computer-based credit scoring and payment systems. However, they have high levels of interest rates for small, short-term loans [31, 32]. According to TCE theory, loan purposes—measured by loan urgency and loan amounts—will determine which governance structure minimizes transaction costs. In terms of emergency medical expenses, the high levels of ex-ante transaction costs for formal credit sources mean that individuals will seek alternative sources of credit—mobile or informal credit sources. In terms of business investment, the low levels of interest rates for formal credit sources may be worth the high levels of ex-ante transaction costs.

2.1.4. Information Asymmetries and Credit Rationing

The Stiglitz-Weiss model of credit rationing [48], provides an explanation for the formal lender's reluctance to provide credit, even to creditworthy borrowers willing to pay high interest rates. The problem of adverse selection and moral hazard is caused by the inability of the lender to observe the risk and efforts of the borrower. The formal lender, in an attempt to mitigate the problem, asks for collateral, enforces repayment schedules, and screens the credit applicants, thereby denying credit to many households, especially the ones with unstable income and/or no formal assets. The informal lender, on the other hand, is able to overcome the problem of information asymmetry through social proximity and monitoring [11, 14]. The mobile lender, instead, uses transactional data, mobile money, and airtime data to algorithmically evaluate the creditworthiness of the borrower, thereby partly mitigating the problem of information asymmetry, without the need to ask for physical collateral [14, 26]. The theoretical model indicates that households that are less creditworthy from the formal lender's perspective, especially the ones without formal documentation (e.g., no bank account, no land title), will be rationed out and instead use the informal or mobile lender. The loan purpose is another factor that is taken into consideration, and the formal lender might be more willing to provide credit for investment in business than for consumption, while the mobile lender does not make this distinction.

2.1.5. Social Capital and Informal Credit Theory

In other words, informal credit markets are not just a second-best solution to formal credit markets, but they are also deeply embedded in social relationships. Social capital theory [19, 44], highlights how trust, norms, and networks facilitate informal credit markets. In the Ethiopian context, iddir and iqub, which refer to burial and rotating savings and credit associations, respectively, are examples of how social capital substitutes for formal contracting [3, 24]. Social capital in this context relies on enforcing repayment through social sanctions, such as exclusion, loss of reputation, and shame, rather than legal means. The theory on rotating savings and credit associations [12, 2] highlights how these types of informal credit markets efficiently allocate credit among members with symmetric information and minimal transaction costs, although they are often limited in size and require regular contributions. Mobile credit, on the other hand, relies on no such relationships, and indeed, no such informal repayment mechanisms, and therefore, we can expect a different behavior from households depending on whether they have a strong or weak social capital structure.

2.1.6. Behavioral Economics of Borrowing

However, recent behavioral theories also question the rational actor approach underlying classical models. Present bias, or hyperbolic discounting, implies that households overborrow for consumption and under-save for future needs [38, 42]. Mental accounting theory, on the other hand, implies that households use different borrowing objectives for different "mental accounts" and, therefore, different credit instruments [52]. For instance, borrowing for a "luxury" item might be allocated to informal credit markets, avoiding formal scrutiny, while borrowing for "necessities" might be allocated to mobile credit, given its speed. The framing effects of digital credit, such as one-click approval or daily repayment amounts, might also influence borrowing from mobile credit platforms, especially if they overcome a rational transaction cost analysis [10, 14]. This behavioral approach might be especially relevant when considering mobile credit markets, given the digital interface and its ability to reduce cognitive costs and induce immediate borrowing.

2.1.7. Complementarity vs. Substitution in Credit Sources

One of the most interesting theoretical debates relates to the complementarity or substitutability of new forms of credit (mobile credits) in relation to existing forms of credit (both formal and informal). The complementarity hypothesis posits that new forms of credits, i.e., mobile credits, will complement existing forms of credits, i.e., formal and informal credits, in the sense that they will provide new access to credits to those households which were otherwise excluded from accessing credits, and these households will eventually graduate to formal credits [26, 31]. Mobile credits can complement informal credits, i.e., iddir, in the sense that they can facilitate the flow of credits in these informal institutions (as the study from Ethiopia indicates). On the other hand, the substitution hypothesis argues that new forms of credits, i.e., mobile credits, will attract the market share of informal credits, which will eventually lead to a loss in market share for these informal credits, and in addition, mobile credits can attract the market share of formal microfinance credits, which are otherwise slower in disbursal, even if they are offered at a higher rate [32]. The segmentation hypothesis argues that the complementarity of the three types of credits—formal, informal, and mobile credits—lies in the fact that they cater to different types of loans, i.e., different loan sizes, which minimizes the scope of competition among them [20]. Formal credits cater to large loans, while informal credits cater to small loans, and mobile credits cater to very small loans.

2.2. Empirical Literature

The empirical literature on household borrowing behavior reveals distinct patterns across formal, informal, and digital credit markets, with each study offering specific methodological and geographic contributions. Beginning with Southeast Asia, Pham and Lensink [43] used regression-based methods in Vietnam to demonstrate that formal credit—requiring collateral, guarantors, and a business motive—is predominantly used by richer households, with formal credit uptake tapering off beyond a certain welfare threshold. In contrast, Tressel [53] developed a theoretical model of formal enforcement mechanisms, showing how interest rates and repayment schedules affect default risk. Moving to Thailand, Siamwalla et al. [46] employed descriptive statistics to document how informal lenders solve information asymmetries through social networks, enabling their persistence even alongside formal credit expansion.

In South Asia, Banerjee et al. [7] used a randomized controlled trial (RCT) in rural India (Karnataka and Hyderabad) to show that introducing formal microfinance can shrink informal risk-sharing networks, disproportionately harming households that never take up formal credit. Similarly, Sinha and Matin [47] applied qualitative and quantitative micro-level analysis in a Bangladeshi village to critique rigid microfinance lending technologies—fixed, increasing loan sizes that ignore income variability—leading borrowers to resort to cross-financing strategies that undermine economic stability. In Southeast Asia, Floro and Ray [25] developed a game-theoretic model applied to the Philippines, showing that vertical linkages between formal and informal lenders can worsen borrower terms depending on competition dynamics.

Turning to technology-enabled credit, Bjorkegren and Grissen [13] used machine learning on mobile phone call detail records in an unspecified middle-income South American country to create alternative credit scores that predict repayment as accurately as traditional histories, extending access to unbanked populations. In China, Chen et al. [17] applied regression and machine learning methods to data from the peer-to-peer platform Renrendai, finding that linguistic and cultural diversity correlates with smaller loan amounts and varying default rates. Nayaka et al. [40] advanced machine learning for risk assessment and portfolio management on a prominent P2P lending platform, though their country context remains unspecified. Tang [50] proposed a conceptual framework on how P2P lending and mobile payments decentralize financing and enable inclusive growth, while introducing regulatory and data-security risks.

On the African continent, several studies provide critical insights. In Kenya, Ntwiga, Ogutu, and Kirumbu [41] analyzed the M-Shwari micro-credit lending using a Hidden Markov Model coupled with multinomial logistic regression, drawing on 2016 FinAccess Household Survey data. Their approach predicted the odds of credit use based on consumer perceptions categorized as "have credit," "used to have credit," and "never had credit." This study offers methodological guidance for modeling mobile credit adoption in Ethiopia, particularly following the launch of digital credits via M-Pesa (known as Ezz be M-Pesa) and Telebirr, which has disbursed over 31.6 billion ETB in digital credits to over 57 million users. In Nigeria, Kofarmata [36] provided evidence on the suitability of the multinomial logit model for estimating factors that determine credit rationing across different credit types in rural developing contexts. In Ghana, Kumar [37] employed a treatment effect model using data from the seventh round of the Ghana Living Standards Surveys, finding that mobile money has a positive effect on the probability of accessing credit (extensive margin) but no effect on the loan amount received (intensive margin).

Several studies have empirically modeled borrowing decisions from multiple sources specifically for Ethiopian households. The foundational study is that of Castellani [16], who investigated the role of shocks on borrowing decisions and source choice for 350 households in rural Southern Ethiopia. Using a multinomial logit approach specifying four possible sources—formal only, informal only, formal and informal, and non-borrowing—Castellani found that negative asset shocks (e.g., seizure of farmland, theft) and human capital shocks (e.g., death of household head) significantly reduced the probability of borrowing from formal sources or both formal and informal sources. The results offered little support for the presumption that informal credit effectively smooths consumption, while networking effects were highly significant in explaining interactions between formal and informal credit markets. Castellani concluded that formal financial institutions are unwilling to offer contingent credit because they cannot assess and diversify risk, and that formal credit products are not suited to long-term risk management.

Abay, Kahsay, and Berhane [1] analyzed the role of iddir (an indigenous social network in Ethiopia) in facilitating factor market transactions. Using fixed effects estimation and difference-in-difference methods, they found that iddir membership increased the likelihood of land, labor, and credit transactions by 7 to 11 percentage points. The results revealed that iddir networks negatively affected borrowing from local moneylenders (Arata Abedari, an informal credit source), while formal credit was left unaffected. This implies that social networks serve as an alternative to expensive informal credit but not as a substitute for formal financial services.

Ayele [5] offered a detailed analysis of rural credit markets in Ethiopia using panel data collected over seven rounds (1994–2009) across 15 villages, averaging 1,500 households per round. Employing panel logit, dynamic probit, and dynamic multinomial logit models, the study examined factors influencing simultaneous borrowing and lending. Key findings include: households engaging in simultaneous borrowing and lending are relatively better off; positive duration dependence exists in borrowing behavior (the longer a household borrowed, the higher its probability of exiting; the longer it did not borrow, the higher its probability of re-engaging). Poverty status, flood shocks, labor sharing, mutual help association membership, oxen ownership, crop storage, off-farm activities, and fertilizer use were key determinants of borrowing behavior. Using a panel Tobit model to correct for data truncation, Ayele found that initial asset endowments, household size, household head's age, transitory income, and real per capita consumption were the most significant determinants of credit demand.

The purpose of borrowing has been recognized as a crucial factor influencing credit source choice. Castellani [16] showed that the nature of shocks—distinguishing asset shocks, health shocks, and idiosyncratic versus covariate shocks—has differential effects on the probability of borrowing from formal versus informal sources. Households experiencing severe negative shocks are more likely to be rationed out of the formal credit market, as lenders view them as riskier borrowers. This supports the prediction that formal credit is more suitable for productive purposes, while informal and mobile credit respond more to unanticipated needs. Similarly, Kofarmata [36] examined credit rationing among rural farmers in Kano State, Nigeria, using a multinomial logistic model, finding that loan purpose (e.g., borrowing for oxen fattening and productive agricultural activities) significantly affects credit market participation and rationing in the formal credit market. Although conducted in Nigeria, this study has methodological and contextual relevance for Ethiopia.

The contribution of social networks to credit access has been extensively documented in Ethiopia. The iddir (burial association) and iqub (rotating savings and credit association) are traditional practices deeply rooted in Ethiopian culture, playing vital roles in credit provision, savings, and insurance. Abay, Kahsay, and Berhane [1] provided robust quantitative evidence that iddir membership increases credit access by 7–11 percentage points, with a stronger impact on informal credit sources and a reduction in dependence on predatory informal lenders.

Gebremariam [28] contributed to the literature by investigating the link between mobile phones and credit uptake among rural households in Ethiopia. Employing a special regressor approach to control for endogeneity (given that both dependent and endogenous variables were binary), the study provided robust evidence that mobile phones are positively related to credit uptake, especially from informal sources. Rural households with mobile phones had 4–14 percent higher probabilities of credit uptake overall and 6–17 percent higher probabilities from informal sources. Mobile phones were also associated with larger loan sizes—by 65 ETB (USD 3.42) overall and 78 ETB (USD 4.11) from informal sources—demonstrating how mobile phones facilitate credit access by reducing information and transaction costs, even before the emergence of formal digital credit products.

Baraki [8] evaluated the contribution of the Oromia Credit and Savings Share Company (OCSSC) microfinance institution to rural livelihoods in the Sabata Hawas Woreda (Southwestern Shewa Zone). Using a mixed-methods approach among 130 sample borrowers, the study found that the microfinance institution improved clients' income, assets, and social services. However, the requirement that borrowers form self-selected groups before accessing loans excluded the poor. Short loan repayment periods, high interest rates, low loan amounts, and low savings interest rates were identified as main challenges.

Tarozzi, Desai, and Johnson [51] implemented a randomized controlled trial in rural Amhara and Oromiya regions between 2003 and 2006 to study the impact of increased microcredit access through two institutions—OCSSC and the Amhara Credit and Savings Institute (ACSI). The intervention targeted poverty status with special attention to women, and the study measured impacts on household welfare using an instrumental variable approach.

Hussen [30] examined the determinants and causal impact of financial inclusion on household welfare in Ethiopia using data from the 2018 Ethiopian Socioeconomic Survey and an endogenous switching regression approach. The study established that households with older, more educated heads working in non-agricultural wage employment or self-employment, and non-Muslim households, have a greater probability of accessing financial services. Financial inclusion—measured through iddir membership, mobile phones, credit information, and knowledge of bank account procedures—was positively correlated with distance to the nearest formal financial institution, suggesting that households face proximity constraints and thus opt for alternative channels. Financial inclusion was confirmed to have a positive and statistically significant impact on various dimensions of household welfare.

The rapid growth of mobile money and digital credit in Ethiopia has spawned a nascent but increasing body of empirical evidence. Gebremariam [28] provided the most direct evidence on the relationship between mobile phones and credit uptake in rural Ethiopia, finding a strong positive relationship between mobile phone adoption and the probability of informal credit uptake.

Sulle Joseph, Chegere, and Mdadila [49] explored the impact of mobile money adoption on credit access across 25 Sub-Saharan African countries using the 2021 Global Findex survey and a binary probit regression model. After controlling for location, education, wage employment, gender, age, socioeconomic status, and COVID-19 effects, the study found that mobile phone ownership, the number of mobile money accounts, and a financial inclusion index significantly and positively influence the probability of credit access. The study recommended developing regulatory guidelines on mobile money lending to set favorable interest rates and protect consumers from debt cycles.

From the World Bank's Global Findex Database 2025, cross-country analysis indicates that even as mobile money accounts in Africa rose to 40% in 2024 (from 27% in 2021), the share of adults using mobile credit remains at just 7%, unchanged from 2021. However, 59% of adults access credit overall, mostly from informal sources. In leading mobile money markets such as Kenya, Ghana, and Uganda, 22% to 32% of adults use mobile operators to borrow, but these are small amounts due within 30 days or less, with annual interest rates exceeding 100%. Regulatory prudence, low digital literacy (especially among women), limited credit bureau coverage, and business models focused on deposits rather than lending are cited as reasons for the slow uptake of mobile credit.

Taken together, this body of evidence—from Vietnam, Thailand, India, Bangladesh, the Philippines, China, Nigeria, Ghana, Kenya, and cross-Saharan Africa—provides a robust foundation for understanding Ethiopia's evolving credit landscape. Ethiopian studies by Castellani [16], Abay et al. [1], Ayele [5], Gebremariam [28], and others have confirmed many international patterns while revealing unique local dynamics, particularly the role of iddir and iqub social networks, the impact of covariate versus idiosyncratic shocks, and the rapid diffusion of mobile-enabled credit through platforms such as Telebirr, Michu, and Tila. The unanswered question—whether digital credit replaces, supplements, or restructures traditional informal arrangements—remains a critical avenue for future research in Ethiopia and beyond.

3. Methodology

3.1. Research Design

This study uses a quantitative approach with a cross-sectional research design to investigate the determinants of borrowing behavior among households with regards to formal, informal, and mobile-based sources of credit. This type of research design is appropriate to study the joint effects of various factors on the probability of using different sources of credit among households. Since the decision to use different sources of credit is likely to be correlated with the interdependence of the decision to use a mobile account, the decision to use mobile credit, and the decision to use traditional sources of credit due to the presence of correlated effects of factors like risk tolerance and financial literacy on these decisions, the study uses a Generalized Structural Equation Model (GSEM) to simultaneously estimate the relationships between the use of mobile financial access and multiple borrowing behavior.

3.2. Data Source and Sample

This study utilizes secondary data from the 2025 wave of the Global Findex database, developed by the World Bank. The Global Findex is a nationally representative survey that provides detailed information on individuals' access to and use of financial services, including savings, borrowing, and digital payments.

The 2025 Global Findex survey for Ethiopia includes approximately 1,001 respondents, covering both rural and urban populations. The dataset captures recent developments in the country's financial landscape, particularly the rapid expansion of mobile money services following key innovations such as the launch of Telebirr in 2021 and M-Pesa Ethiopia in 2023.

The analysis focuses on adult individuals (aged 15 and above), consistent with the Global Findex sampling framework. After excluding observations with missing values for key variables, the final analytical sample remains close to the original survey size due to the relatively limited incidence of missing data. Sampling weights provided within the dataset are applied to ensure national representativeness of the findings.

3.3. Variable Definition and Measurement

3.3.1. Dependent Variables (Endogenous Outcomes)

The model includes five binary dependent variables, each measured at the household level:

Table 1. *Dependent Variables (Endogenous Outcomes).*

Variable	Definition	Role in GSEM
account_mob	Household owns a mobile money account (e.g., Telebirr, M-Pesa, HelloMoney)	Equation (1) outcome
mobile_received	Household received credit through a mobile money platform in the past 12 months	Equation (2) outcome; also appears as predictor in Equation (1)
formal_bank	Household borrowed from a formal financial institution (commercial bank, microfinance institution, SACCO)	Equation (3) outcome
friend_family	Household borrowed from friends or relatives (informal social lending)	Equation (4) outcome
informal_saving	Household borrowed from an informal savings group or rotating scheme (iddir, iqub, local moneylender)	Equation (5) outcome

Source; Stata Compution (findex, 2025)

3.3.2. Independent Variables

The independent variables include demographic, economic, geographic, loan purpose, and financial inclusion controls. All categorical variables are entered as factor variables (i.e., dummy-coded) in the GSEM.

Table 2. *Independent Variables.*

Category	Variable	Measurement
Demographic	Age group	Categorical: 15–24, 25–34, 35–44, 45–54, 55–64, 65+ (dummy-coded, reference category typically 15–24)
	Gender	1 = female, 0 = male (note: original coding shown as 2 = female, but standard is 1 = female)
	Education level	Categorical: primary or less, secondary, tertiary (dummy-coded)
Economic	Income quintile	1 (poorest) to 5 (richest) based on total consumption expenditure or income (dummy-coded)
	Urban/rural	1 = urban, 0 = rural
Financial behavior	Has debit card	1 = yes, 0 = no
	Any deposits/withdrawals	1 = made any deposit or withdrawal from a formal account, 0 = no

Category	Variable	Measurement
	Stores money in account	1 = uses bank or mobile account for saving, 0 = no
	Any digital payment (anydigpayment)	1 = paid bills or sent money via mobile phone or digital means, 0 = no
Loan purpose	Borrowed for health	1 = borrowed to cover medical/health expenses, 0 = no
	Borrowed for business	1 = borrowed for business purposes, 0 = no
	Borrowed for food	1 = borrowed to purchase food or basic consumption, 0 = no
	Borrowed for any reason	1 = borrowed for any purpose (composite indicator), 0 = no
	Paid credit card	1 = has paid a credit card bill, 0 = no
Credit access outcomes	Mobile account	1 = owns a mobile money account (e.g., Telebirr), 0 = no
	Mobile received	1 = has received a mobile-based loan or digital credit, 0 = no
	Formal borrowing	1 = borrowed from bank or microfinance institution, 0 = no
	Friends/family borrowing	1 = borrowed from friends or relatives, 0 = no
	Informal club borrowing	1 = borrowed from informal club (iddir, iqub, moneylender), 0 = no

Source; Stata Compution (findex, 2025)

3.4. Model Specification

The empirical analysis is structured as a system of five probit equations estimated jointly using a Generalized Structural Equation Model (GSEM). This approach allows for correlation among the error terms across equations, capturing unobserved household characteristics (e.g., financial literacy, risk preference, trust in institutions) that simultaneously influence multiple financial behaviors—mobile account ownership, mobile credit receipt, and the choice of borrowing from formal banks, friends/family, or informal savings groups.

All five equations are estimated simultaneously with probit links (binary outcomes). The general form for each equation is:

$$y_{im}^{*} = X_i\beta_m + \epsilon_{im,}$$

$$y_{im} = \begin{cases} 1 & y_{im}^{*} > 0 \\ 0 & otherwise \end{cases}$$

Where, y_{im} is the observed binary outcome for household i on outcome m, and

$$\epsilon_{im,} \sim (N, 1)$$

With correlated error terms:

$$\text{Cov}\,(\epsilon_{im,}\epsilon_{ik,}) = p_{mk,}\ \ m \neq k$$

Equation (1): Mobile Money Account Ownership

$$account_{mobi} = \ \beta 10 + \beta 11 mobile_{receivedi} + \beta 12 age_{groupi} + \beta 13 edu_{leveli} + \beta 14 income_{quintilei} + \beta 15 urbani + \beta 16 female_{indi} + \beta 17 creditcardi + \beta 18 depo\_withi + \beta 19 stormoneyi + \varepsilon 1i \tag{1}$$

Equation (2): Mobile Credit Receipt

$$mobile_{receivedi} = \ \beta 20 + \beta 21 age_{groupi} + \beta 22 edu_{leveli} + \beta 23 income_{quintilei} + \beta 24 urbani + \beta 25 female_{indi} + \beta 26 borrowed_{healthi} + \beta 27 borrowed_{businessi} + \beta 28 borrowed_{foodi} + \beta 29 borrowed\ \ anyrei + \beta 30 paid_{creditcardi} + \varepsilon 2i \tag{2}$$

Equation (3): Formal Bank Borrowing

$$formal_{banki} = \ \beta 30 + \beta 31 age_{groupi} + \beta 32 edu_{leveli} + \beta 33 income_{quintilei} + \beta 34 urbani + \beta 35 female_{indi} + \beta 36 borrowed_{healthi} + \beta 37 borrowed_{businessi} + \beta 38 borrowed_{foodi} + \beta 39 borrowed\ \ anyrei + \beta 310 paid_{creditcardi} + \varepsilon 3i \tag{3}$$

Equation (4): Friend/Family Borrowing

$$friend_{familyi} = \beta 40 + \beta 41 age_{groupi} + \beta 42 edu_{leveli} + \beta 43 income_{quintilei} + \beta 44 urbani + \beta 45 female_{indi} + \beta 46 borrowed_{healthi} + \beta 47 borrowed_{businessi} + \beta 48 borrowed_{foodi} + \beta 49 borrowedanyrei + \beta 410 paid_{creditcardi} + \varepsilon 4i \quad (4)$$

Equation (5): Informal Saving Group Borrowing (e.g., *Iddir*, *Iqub*)

$$informal\_savingi = \beta 50 + \beta 51 age_{groupi} + \beta 52 edu_{leveli} + \beta 53 income_{quintilei} + \beta 54 urbani + \beta 55 female_{indi} + \beta 56 borrowed_{healthi} + \beta 57 borrowed_{businessi} + \beta 58 borrowed_{foodi} + \beta 59 borrowedanyrei + \beta 60 paid_{creditcardi} + +\varepsilon 5i \quad (5)$$

Where,

1) $account\_mobi$ – represents ownership of a mobile money account (e.g., Telebirr) i.
2) $mobile\_receivedi$ – represents receipt of a mobile-based loan or digital credit i.
3) $formal\_banki$ – represents borrowing from a formal financial institution (bank or microfinance) i.
4) $friend\_familyi$ – represents borrowing from friends or family members i.
5) $informal\_savingi$ – represents borrowing from an informal savings group i (e.g., *iddir*, *iqub*, or local moneylender).
6) age_group – represents the age category of the household head i (e.g., 15–24, 25–34, …, 65+).
7) edu_leveli – represents the education level of the household head (primary or less, secondary, tertiary) I.
8) $income\_quintilei$ – represents the household's income rank (1 = poorest, 5 = richest) i.
9) $urban$ i– represents urban residence (1 = urban, 0 = rural) i.
10) $female\_indi$ – represents gender of household head (1 = female, 0 = male) i.
11) $creditcardi$ – represents possession of a debit card (has debit card = 1) i.
12) $depo\_withi$ – represents having made any deposit or withdrawal from a formal account i.
13) $stormoneyi$ – represents storing money in a bank or mobile money account i.
14) $borrowed\_healthi$ – represents borrowing for health or medical expenses i.
15) $borrowed\_businessi$ – represents borrowing for business purposes i.
16) $borrowed\_foodi$ – represents borrowing for food or basic consumption i.
17) $borrowedanyi$ – represents borrowing for any reason (composite indicator) i.
18) $paid\_creditcardi$ – represents having paid a credit card bill i.

3.5. Descriptive Statistics

Table 3. Descriptive Statistics.

Variables	Obs	Mean	Std. dev.	Min	Max
Mobile account	1,001	0.1299	0.3363	0	1
mobile_received	1,001	0.03	0.1706	0	1
Formal borrowing	1,001	0.033	0.1786	0	1
Friends/family borrowing	1,001	0.4066	0.4914	0	1
Informal club borrowing	1,001	0.0679	0.2518	0	1
Age group (dummies)					
15–24	1,001	0.3267	0.4692	0	1
25–34	1,001	0.2977	0.4575	0	1
35–44	1,001	0.1998	0.4	0	1
45–54	1,001	0.0919	0.289	0	1
55–64	1,001	0.041	0.1983	0	1

Variables	Obs	Mean	Std. dev.	Min	Max
65+	1,001	0.043	0.2029	0	1
Education level (dummies)					
Primary or less	1,001	0.6224	0.485	0	1
Secondary	1,001	0.3287	0.47	0	1
Tertiary	1,001	0.049	0.2159	0	1
Income quintile (dummies)					
1 (lowest)	1,001	0.1768	0.3817	0	1
2	1,001	0.1678	0.3739	0	1
3	1,001	0.1828	0.3867	0	1
4	1,001	0.2078	0.4059	0	1
5 (highest)	1,001	0.2647	0.4414	0	1
Urban (1 = urban)	1,001	0.1798	0.3842	0	1
Female (2 = female)	1,001	0.4486	0.4976	0	1
Financial behaviors					
has debit card	1,001	0.2118	0.4088	0	1
any deposits/withdrawals	1,001	0.1728	0.3783	0	1
Stores money in account)	1,001	0.2997	0.4584	0	1
Borrowing reasons					
Borrowed_health	1,001	0.2068	0.4052	0	1
Borrowed_business	1,001	0.0939	0.2918	0	1
Borrowed_food	1,001	0.2677	0.443	0	1
Borrowed for any reason	1,001	0.0549	0.228	0	1
paid_creditcard	1,001	0.001	0.0316	0	1

Source; Stata Compution (findex, 2025)

The table above gives a description of the 1,001 participants that are part of the regression model. The sample is made up of a relatively young population that is mainly from the rural areas. They have low levels of formal education and have no access to banking facilities. There is very low adoption rate of mobile money of 13.0 percent. Even lower is that for receiving mobile money at 3.0 percent.

There are clear dichotomies in relation to borrowing sources. While there are low rates of borrowing from institutions like banks at 3.3 percent, most of the people borrow money from friends and relatives accounting for 40.7 percent. This clearly shows that the support system comes from within the social system. People also borrow money from informal savings clubs of 6.8 percent.

The income distribution pattern shows that there is fair distribution in all the five quintiles. However, the largest proportion of the sample is in the highest quintile at 26.5 percent. Females make up 44.9 percent of the respondents. On matters financial inclusion beyond mobile money, 21.2 percent have debit cards. Also, 17.3 percent of the people deposit and withdraw money. On the contrary, 30.0 percent have saved money in the bank account. On the contrary, however, 30.1 percent use digital payment methods. The percentage of digital payment methods is higher than that of mobile money accounts. This means that some people use digital payments but do not have mobile money accounts. This might be because of the existence of debit cards.

Lending reasons provide a basis for determining determinants of credit demand. Health problems cause 20.7 percent of borrowing, food causes 26.8 percent, and business causes 9.4 percent. From the high numbers, it is apparent how vulnerable consumers are and their dependence on borrowing as consumption smoothing mechanisms. The total number of borrowers is just 5.5 percent. Possibly, there can be more than one lending purpose or possibly the question was posed to another subsample. The low credit card users arise because only one observation represents credit card users (0.1 percent).

On balance, this descriptive study highlights an under banked section of the population that relies on the informal social structures within society to obtain loans. At the same time, there is a developing trend toward the use of mobile money and electronic money transfers. The above information creates a background of understanding the factors behind certain financial behaviors.

4. Regression Results and Discussion

4.1. Diagnostic Tests

a. Variance inflation factors (VIF)

Variance inflation factor (VIF) was used to measure the amount of multicollinearity among the variables used to explain the phenomenon. According to the outcome, there is very minimal multicollinearity among the independent variables; VIFs were found to range between 1.02 and 1.19, with an average VIF of 1.10. With none of the VIF exceeding the generally accepted upper limit of 5 and the critical value of 10, one can conclude that the independent variables have little correlation among them.

Table 4. *Variance inflation factors (VIF).*

Variable	VIF	1/VIF
edu_level	1.19	0.839
borrowed_health	1.18	0.846
borrowed_food	1.16	0.863
deposit/withdraw	1.15	0.868
income_quintile	1.14	0.876
urban	1.08	0.926
stores	1.07	0.932
borrowed_business	1.06	0.945
age_group	1.06	0.948
female_ind	1.04	0.960
mobile_received	1.03	0.973
paid_credit_card	1.02	0.980
Mean VIF	1.10	

b. AIC / BIC test

The second model exhibits a slight gain in terms of goodness-of-fit according to the Akaike Information Criteria, hence better explanatory power. On the other hand, the Bayesian Information Criteria marginally increases, hence a slight increase in the penalty due to the increase in model complexity. The overall change is quite insignificant, thus implying that both models have similar performance.

Table 5. *AIC / BIC test.*

Statistic	Value
Observations	1,001
Log-likelihood	-1139.262
AIC	2468.523
BIC	2934.855

c. Likelihood Ratio Test and Pseudo R^2

The estimation of the model is based on 1,001 observations. According to the likelihood ratio test, the model is statistically significant (LR $\chi^2(17) = 274.12$, $p < 0.001$), meaning that the explanatory variables affect the dependent variable as a group. Moreover, the pseudo R^2 coefficient equals 0.3547, which means that the explanatory power of the model is high, as about 35.5% of the variance in the dependent variable can be explained by it.

Table 6. *Likelihood Ratio Test and Pseudo R^2.*

Number of obs = 1,001
LR chi2 (17) = 274.12
Prob > chi2 = 0.0001
Pseudo R2 = 0.3547

4.2. Regression Results

Table 7. Regression Results.

Variable	Account_ mobile (Coef)	Account_ mobile (ME)	Mobile_ received (Coef)	Mobile_ received (ME)	Formal borrowing (Coef)	Formal borrowing (ME)	Friends/ family (Coef)	Friends/ family (ME)	Informal club (Coef)	Informal club (ME)
mobile_received	1.083*** (0.267)	0.162*** (0.0391)								
Age group (base = 0)										
1	0.305** (0.150)	0.0494** (0.0243)	–0.117 (0.207)	–0.00753 (0.0133)	0.404 (0.257)	0.0185 (0.0116)	0.0446 (0.109)	0.0146 (0.0359)	0.463*** (0.170)	0.0529*** (0.0194)
2	–0.0113 (0.181)	–0.00160 (0.0255)	–0.101 (0.248)	–0.00657 (0.0158)	0.421 (0.285)	0.0196 (0.0140)	–0.00954 (0.124)	–0.00311 (0.0406)	0.298 (0.196)	0.0299 (0.0206)
3	0.0187 (0.239)	0.00268 (0.0344)	–0.151 (0.344)	–0.00942 (0.0198)	0.825*** (0.318)	0.0547** (0.0275)	–0.381** (0.168)	–0.117** (0.0491)	0.441* (0.238)	0.0496 (0.0314)
4	–0.679 (0.544)	–0.0699* (0.0402)	–4.224 (705.4)	–4.224 (705.4)	0.466 (0.558)	0.0226 (0.0359)	0.0466 (0.227)	0.0153 (0.0748)	0.227 (0.363)	0.0214 (0.0392)
5	–0.410 (0.402)	–0.0480 (0.0398)	0.492 (0.353)	0.0526 (0.0488)	0.775* (0.426)	0.0492 (0.0394)	–0.462* (0.243)	–0.139** (0.0676)	0.547* (0.306)	0.0667 (0.0485)
Edu (base = 1)										
2	0.500*** (0.134)	0.0762*** (0.0214)	0.322* (0.184)	0.0221 (0.0136)	0.358* (0.207)	0.0220 (0.0139)	–0.0625 (0.0993)	–0.0200 (0.0316)	–0.0354 (0.146)	–0.00433 (0.0177)
3	1.411*** (0.218)	0.315*** (0.0656)	0.333 (0.377)	0.0231 (0.0329)	0.642* (0.359)	0.0494 (0.0388)	–0.195 (0.216)	–0.0609 (0.0656)	–0.0443 (0.323)	–0.00538 (0.0382)
Income quintile (base = 1)										
2	0.0874 (0.251)	0.0108 (0.0310)	–0.616* (0.332)	–0.0378* (0.0198)	–0.0489 (0.305)	–0.00323 (0.0201)	0.0552 (0.149)	0.0173 (0.0468)	0.0144 (0.214)	0.00174 (0.0259)
3	0.208 (0.234)	0.0273 (0.0304)	–0.287 (0.266)	–0.0228 (0.0214)	–0.154 (0.312)	–0.00939 (0.0192)	0.103 (0.147)	0.0327 (0.0463)	0.0295 (0.210)	0.00360 (0.0256)
4	0.143 (0.226)	0.0182 (0.0283)	–0.240 (0.255)	–0.0198 (0.0215)	0.0472 (0.281)	0.00334 (0.0198)	0.119 (0.142)	0.0378 (0.0449)	0.146 (0.198)	0.0193 (0.0259)
5	0.590*** (0.208)	0.0931*** (0.0300)	–0.236 (0.252)	–0.0195 (0.0215)	–0.298 (0.303)	–0.0164 (0.0176)	0.132 (0.141)	0.0418 (0.0444)	–0.0863 (0.211)	–0.00970 (0.0239)
Urban (base = rural)	0.487*** (0.142)	0.0833*** (0.0272)	–0.0102 (0.232)	–0.00066 (0.0151)	–0.115 (0.252)	–0.00642 (0.0133)	0.0164 (0.117)	0.00525 (0.0376)	–0.257 (0.196)	–0.0279 (0.0186)
Female (base = male)	0.549*** (0.124)	0.0831*** (0.0186)	0.104 (0.171)	0.00688 (0.0113)	–0.176 (0.188)	–0.0103 (0.0109)	–0.0197 (0.0882)	–0.00629 (0.0282)	0.0243 (0.129)	0.00300 (0.0159)
Anydeposits/with-drawals	0.0177 (0.143)	0.00264 (0.0213)								
Stores money in ac-count	0.639*** (0.124)	0.0953*** (0.0181)								
Borrowed for health			0.419** (0.200)	0.0275** (0.0136)	–0.168 (0.226)	–0.00988 (0.0133)	0.951*** (0.115)	0.304*** (0.0332)	0.326** (0.151)	0.0401** (0.0187)
Borrowed for business			0.394* (0.229)	0.0259* (0.0153)	1.366*** (0.197)	0.0803*** (0.0141)	0.802*** (0.156)	0.257*** (0.0482)	0.503*** (0.176)	0.0619*** (0.0218)

Variable	Account_ mobile (Coef)	Account_ mobile (ME)	Mobile_ received (Coef)	Mobile_ received (ME)	Formal borrowing (Coef)	Formal borrowing (ME)	Friends/ family (Coef)	Friends/ family (ME)	Informal club (Coef)	Informal club (ME)
Borrowed for food			0.0487 (0.203)	0.00320 (0.0134)	0.087 (0.203)	0.00511 (0.0119)	0.635*** (0.102)	0.203*** (0.0307)	0.112 (0.146)	0.0138 (0.0180)
Borrowed for any reason			–0.436 (0.474)	–0.0286 (0.0314)						
Constant	–2.56*** (0.235)		-1.950*** (0.239)		–2.530*** (0.304)		-0.696*** (0.134)		–1.96*** (0.213)	
Observations	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source; Stata Compution (findex, 2025)

The above table reveals distinct patterns across five financial inclusion outcomes, each of which aligns with established literature in development economics and financial inclusion.

a. Mobile Account Ownership

In Table 7 (colum 1), mobile account ownership and receiving credit from the mobile money platform have a strong positive relationship. Among individuals who applied for credit through mobile money platforms (Telebirr, M-Pesa), 16.2 percentage points of those who own mobile money account actually receive credit. This finding mirrors Jack and Suri [31], who demonstrate that mobile money adoption in Kenya reduced transaction costs and expanded financial access, and Suri and Jack [31], who show that exposure to mobile money ecosystems deepens inclusion over time.

Age differences are modest, with only younger adults (15–24) showing slightly higher ownership of a mobile money account 4.9 percentage points and those aged 45–54 showing lower ownership than the 15–24 group, with a −7.0 percentage points. In Ethiopia, the older age group does not have a mobile money account compared to the younger group. Aker and Mbiti [26] similarly argue that mobile technology reduces traditional demographic barriers, leading to relatively flat adoption across age groups.

Education exhibits a strong graded effect: secondary education raises ownership by 7.6 percentage points, while tertiary education raises it by 31.5 percentage points. As people become more educated, mobile account ownership has been increasing. Beck, Demirgüç-Kunt, and Honohan [9] identify human capital as a key determinant of financial inclusion, improving financial literacy and digital capability. Demirgüç-Kunt et al. [57] report that in low-income countries, adults with higher education are significantly more likely to hold mobile money accounts.

Income effects are weak; only the top (richest) quintile shows a positive effect of 9.3 percentage points. If people are poor, the probability of having a mobile money account is lower compared to rich people in Ethiopia. This aligns with Demirgüç-Kunt et al. [57], who find that mobile money reduces income-based exclusion by lowering entry barriers. Urban residence (8.3 percentage points) and female gender (8.3 percentage points) both increase ownership. GSMA [48] documents stronger mobile money infrastructure in urban areas, while Suri and Jack [31] find that mobile money can reduce traditional gender gaps. Finally, storing money in an account (9.5 percentage points) predicts ownership, consistent with Dupas and Robinson [23], who emphasize that active saving behavior reinforces formal financial participation.

b. Receiving Mobile Money (borrowing from mobile money)

Receipt of mobile money is only weakly associated with socio-economic characteristics; age, education, income, urban residence, and gender are mostly insignificant. This finding is consistent with Jack and Suri [31], who observe that once mobile money networks are established, usage becomes widespread across demographic groups. Demirgüç Kunt et al. [57] similarly report that digital payment receipt is less stratified by income or education than traditional banking. The only notable effects are small positive associations with borrowing for health (2.8 percentage points) and for business (2.6 percentage points), which align with Cull, Ehrbeck, and Holle [21], who argue that mobile money is often used as a liquidity management tool for shocks and productive needs. In Ethiopia, people who have a mobile money account are not determined by age, gender, residence, or income, but some people have taken money from mobile money to finance health and business (see Table 7, column 2).

c. Formal sector Borrowing (Traditional financial institutions)

Formal borrowing is primarily driven by borrowing purpose rather than socio-economic characteristics. Only the 35–44 age groups show a significant positive effect of 5.5 percentage points. Education, income, urban residence, and gender are insignificant, echoing Karlan and Zinman [33], who find that in developing contexts, formal credit access is often constrained by institutional factors (credit history, collateral) rather than by standard demographic characteristics. Most importantly, borrowing for business increases formal borrowing by 8.0 percentage points, while borrowing for health or food does not. This strongly aligns with Banerjee and Duflo [6] and Armendáriz and Morduch [4], who show that formal credit institutions primarily lend for productive investments rather than consumption or emergency needs. In Ethiopia, formal sector borrowing has been directed toward business rather than food and health, and the 35–44 age groups are also able to access it (see Table 7, column 3).

d. Friends and Family Borrowing

Informal borrowing from friends and family is dominated by borrowing purpose, with large effects for health (+30.4 pp), business (+25.7 pp), and food (+20.3 pp). These magnitudes reflect the central role of informal networks as a financial safety net, consistent with Fafchamps and Lund [29], Dercon et al. [24], and Townsend [22], who document that friends and family are the primary source of consumption smoothing and emergency funds in the absence of formal insurance. Age also matters: individuals aged 35–44 and 55+ are 11.7 pp and 13.9 pp less likely to rely on informal borrowing, which aligns with Collins et al. [20] and Rosenzweig [59], who find that reliance on informal finance declines as individuals gain financial stability over the life cycle. Education, income, urban residence, and gender show no significant effects (see Table 7, column 4).

e. Informal Club Borrowing

Participation in informal clubs (e.g., ROSCAs, iqub) is moderately influenced by age and borrowing purpose. The youngest age group (15–24) is 5.3 pp more likely to participate, consistent with Besley, Coate, and Loury [12] and Gugerty [44], who show that informal clubs serve as entry points into financial systems for younger individuals with limited formal access. Borrowing for health (+4.0 pp) and borrowing for business (+6.2 pp) increase participation, reflecting findings by Anderson and Baland (2) that informal clubs are used for both emergency financing and productive investment. Borrowing for food is not significant, suggesting that informal clubs are less oriented toward routine consumption needs. Education, income, urban residence, and gender are insignificant; highlighting the socially inclusive nature of these institutions (see Table 7, column 5).

Overall, Mobile account ownership is strongly associated with education (especially tertiary) and active saving behavior, while age differences are modest. Income effects are weak, with only the wealthiest group showing an advantage. Urban residence and female gender also positively predict ownership. This suggests mobile accounts lower entry barriers and are accessible across broad demographics, though education remains key. Receiving credit via mobile money platforms is only weakly tied to standard socio-economic characteristics (age, education, income, residence, gender). Instead, it is mildly associated with borrowing for health and business purposes, positioning mobile credit as a flexible liquidity tool for shocks and productive needs rather than being strongly segmented by social status. Formal borrowing is driven primarily by borrowing purpose, not demographics. Only one middle-aged group shows a slight positive effect. Business-related borrowing increases formal credit access, whereas borrowing for health or food does not. This reflects the formal sector's focus on productive investments. Informal borrowing from family and friends serves as the primary financial safety net, covering a wide range of needs including health, business, and food. Older individuals are less likely to rely on such networks, indicating a life-cycle shift toward greater financial stability. This channel dominates consumption smoothing and emergency funding. Informal club borrowing (ROSCAs, iqub) is moderately influenced by age—younger individuals are more likely to participate—and by borrowing for health and business, but not for routine food needs. Education, income, urban residence, and gender are insignificant, highlighting the inclusive nature of clubs.

5. Conclusion

This study examines household borrowing behavior in Ethiopia using data from the 2025 Global Findex survey conducted by the World Bank. The analysis is based on a nationally representative sample of 1,001 respondents and employs Generalized Structural Equation Modeling (GSEM) to estimate five key financial inclusion outcomes: mobile money account ownership, receipt of mobile money credit, formal borrowing, and borrowing from friends. The descriptive statistics reveal a financially constrained population with limited access to formal financial services. Mobile money ownership remains relatively low at 13.0%, and only 3.0% of respondents reported receiving mobile money. Formal borrowing is similarly limited (3.3%), while informal borrowing particularly from friends and family dominates at 40.7%, followed by informal savings groups at 6.8%. The sample is predominantly rural (82.0%), young (over 60% under age 35), and characterized by low educational attainment (62.2% with primary education or less), which helps explain the heavy reliance on informal financial networks.

The regression results are broadly consistent with these descriptive patterns. The empirical findings from this study demonstrate that households in the sample rely on a segmented financial ecosystem, where the choice of financial mechanism formal borrowing, family/friends loans, informal club participation, or mobile money services depends critically on the household's purpose, age profile, education, and access to digital infrastructure.

Mobile account ownership is strongly associated with education (especially tertiary) and active saving behavior, while age differences are modest. Income effects are weak, with only the wealthiest group showing an advantage. Urban residence and female gender also positively predict ownership. This suggests mobile accounts lower entry barriers and are accessible across broad demographics, though education remains key. Receiving credit via mobile money platforms is only weakly tied to standard socio-economic characteristics (age, education, income, residence, gender). Instead, it is mildly associated with borrowing for health and business purposes, positioning mobile credit as a flexible liquidity tool for shocks and productive needs rather than being strongly segmented by social status. Formal borrowing is driven primarily by borrowing purpose, not demographics. Only one middle-aged group shows a slight positive effect. Business related borrowing increases formal credit access, whereas borrowing for health or food does not. This reflects the formal sector's focus on productive investments. Informal borrowing from family and friends serves as the primary financial safety net, covering a wide range of needs including health, business, and food. Older individuals are less likely to rely on such networks, indicating a life-cycle shift toward greater financial stability. This channel dominates consumption smoothing and emergency funding. Informal club borrowing (ROSCAs, iqub) is moderately influenced by age younger individuals are more likely to participate and by borrowing for health and business, but not for routine food needs. Education, income, urban residence, and gender are insignificant, highlighting the inclusive nature of clubs.

Overall, Ethiopian, Borrowing from financial institutions such as banks and microfinance institutions is associated with business. However, borrowing from friends and family is associated with food, health, and business. The informal sector, such as iqub, does not lend for food but rather focuses on business and health. Receiving credit via mobile money platforms is only weakly tied to standard socio-economic characteristics (age, education, income, residence, gender).

6. Recommendations

Based on the empirical findings derived from the 2025 Global Findex data compiled by the World Bank, several policy and practical recommendations emerge to improve financial inclusion and household financial resilience in Ethiopia.

1) First, policymakers should expand formal financial products beyond business-oriented lending to include consumption-smoothing instruments, particularly for health and food emergencies. The results show that formal credit is primarily used for productive purposes, while households rely heavily on informal networks for essential needs. Financial institutions should therefore design flexible, low-collateral microcredit and emergency loan products tailored to short-term consumption shocks.
2) Second, there is a need to formally recognize and complement informal financial systems rather than attempting to replace them. Given the dominant role of borrowing from friends and family, policies could focus on integrating informal networks into the broader financial ecosystem for example, by linking community-based groups to formal institutions or providing guarantees and support mechanisms that strengthen these networks without undermining their accessibility.
3) Third, targeted interventions are required to increase mobile money account ownership. While digital financial services such as Telebirr have expanded rapidly, access remains highly unequal. Investments in digital literacy, particularly among rural, less-educated, and older populations, are essential. In addition, simplifying account registration processes and reducing transaction costs could help broaden adoption.
4) Fourth, financial inclusion strategies should prioritize youth and rural populations by leveraging informal savings groups as entry points into the formal financial system. Since younger individuals are more likely to participate in informal clubs, these groups can serve as effective channels for introducing formal savings, credit, and digital financial services.
5) Fifth, policymakers should promote purpose-driven financial product design. The findings demonstrate that borrowing motives such as health, food, and business needs—significantly influence the choice of financial source. Financial service providers should therefore tailor products to specific use cases, such as health emergency loans, agricultural input financing, or education loans, rather than offering generic credit products.
6) Finally, improving financial infrastructure and regulatory support is critical. Expanding mobile network coverage, strengthening consumer protection frameworks, and enhancing trust in formal institutions will be key to ensuring that digital and formal financial services become viable alternatives to informal borrowing.

Abbreviations

ETB	Ethiopian Birr
ROSCA	Rotating Savings and Credit Association
PIH	Permanent Income Hypothesis
TCE	Transaction Cost Economics
RCT	Randomized Controlled Trial

Author Contributions

Tesema Tadesse Milkano: Conceptualization, Methodology, Formal Analysis, Data curation, Investigation, Validation, Writing – original draft, Writing – review & editing

Conflicts of Interest

The author declares no conflicts of interest.

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