Enhancing Global Financial Inclusion Through Fintech: The Importance of Connectivity

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Abstract

Building on the established link between financial inclusion and sustainable economic growth, this study examines the role of connectivity, a key enabler of fintech, in advancing financial inclusion across four dimensions: account ownership, digital payments, savings, and credit. A financial connectivity index is developed using principal component analysis (PCA) to consolidate multiple access channels into a single, comprehensive indicator. Incorporating control variables identified in the literature, panel data models reveal that connectivity promotes financial inclusion at all its stages. However, as individuals deepen their engagement with financial services, factors such as education, cultural traits, and regulatory quality become increasingly influential. Stable, high-quality employment also emerges as a critical determinant, particularly for long-term financial commitments. Despite limitations in data quality, the consistency and explanatory power of the models across all dimensions support the robustness of the study's hypotheses. Overall, the findings underscore that, while financial connectivity is essential, advancing global financial inclusion requires cultural sensitivity and a robust regulatory framework.

Keywords: financial inclusion, fintech, cultural traits

JEL classification: G20, O16, P34

1 Introduction

Acknowledging the vital role of financial inclusion in promoting sustainable economic growth has underscored the importance of considering monetary development in formulating policies and development strategies. Despite historical investigations into the connections between savings, loans, investment, and economic growth, dating back to Bagehot (1873), Schumpeter (1934), and subsequent researchers such as McKinnon (1973), it was only with the advent of endogenous growth theories (Levine, 1991) that a more detailed analysis of the significance of financial development emerged.

The Great Recession of 2007 prompted a reassessment of the presumed benefits of financial deepening, suggesting a possible relationship consistent with a Gompertz curve. Initially, financial development significantly fostered growth by easing liquidity constraints and reinforcing savings, investments, and formality. However, beyond a certain threshold, the impact of this development on growth could decelerate due to diminishing returns and challenges in resource allocation. Moreover, excessive financialization could divert resources from other sectors, potentially leading to over-indebtedness and recurring financial crises (Minsky, 1982). This shift in perspective required moving away from traditional indicators of financial development, such as financial depth, measured by credit or deposits as a percentage of GDP, and toward metrics that assess access to and usage of financial services. In essence, it marked a transition toward prioritizing financial inclusion.

With the rise of endogenous growth and conditional convergence in specialized literature, the recognition of environmental care and equity as fundamental factors for long-term economic sustainability gained prominence. Sustainable development goals (SDGs) emphasized the role of financial inclusion in mobilizing resources to achieve these goals, facilitating productive engagement, expanding opportunities for family savings and consumption, and enhancing investment prospects for businesses (United Nations [UN], 2015).

Financial inclusion, a broad objective aimed at expanding access to affordable and appropriate financial services for individuals and businesses, is widely recognized as a key driver of economic development and poverty reduction (Roa et al., 2014; World Bank Group, n.d.).

From a banking perspective, financial inclusion constitutes a strategic opportunity for business development and long-term growth. By expanding services beyond saturated markets and engaging underserved populations, financial institutions can access new customer segments. This approach not only promotes innovation and competitiveness but also reinforces the sector's contribution to inclusive economic progress.

Financial inclusion initiatives aim to enhance the financial well-being of economic agents by empowering them to navigate economic uncertainties, break the cycle of poverty, and advance their entrepreneurial activities. Innovation in access to financial services plays a crucial role in the effectiveness and impact of these initiatives, transforming financial products into tools that are more accessible, user-friendly, relevant, and affordable. However, such innovation requires a robust digital infrastructure, with connectivity being a fundamental prerequisite (Demirgüç-Kunt et al., 2022).

This study builds on a conceptual framework of financial inclusion to estimate different empirical models assessing the impact of digital connectivity on financial product usage across the stages: account ownership, digital payments, savings, and credit. Connectivity facilitates the adoption of innovative digital financial technologies while enhancing responsible practices and consumer protection. The overarching goal is to deepen the understanding of the determinants of financial service access and the conditions necessary to advance inclusion. A financial connectivity index is constructed using principal component analysis (PCA), integrating variables such as automated teller machines (ATM) and bank branch density, fixed and mobile phone subscriptions, and broader information and communication technology (ICT) indicators. The study further identifies key drivers of financial inclusion, emphasizing the roles of education, individual motivation, information asymmetries, and institutional quality.

The hypotheses to be tested are:

H0a: The ownership of savings accounts within a country is influenced by financial connectivity, educational attainment, and individual motivations related to consumption, saving, and endowment. Additionally, effective ownership depends on reducing information asymmetries and having a strong institutional framework.

H0b: The use of digital payments within a country is influenced by financial connectivity, educational level, and individual motivations related to saving and credit. Successful adoption also requires addressing information asymmetries and ensuring a supportive institutional environment.

H0c: The number of individuals within a country who own a savings account is influenced by financial connectivity, educational attainment, and individual motivations related to consumption, saving, and endowment. Moreover, broader coverage depends on addressing information asymmetries and ensuring a strong institutional framework.

H0d: Access to credit at the national level depends on the quality of financial connectivity, and is further shaped by educational attainment, individual motivations for consumption and investment, information availability, and the robustness of institutional structures.

The paper is divided into four sections. It starts by highlighting the importance of financial inclusion, then explores the role of infrastructure, especially connectivity, in facilitating access to financial technologies. A review of existing literature comes next, focusing on savings, credit, and digital infrastructure. The third section presents the empirical data and macroeconomic methodology. Finally, the conclusion summarizes the main findings, provides recommendations, and suggests future research directions.

2 Conceptual Framework

The first section lays the foundation by outlining the key elements of financial inclusion across its four main stages: account ownership, digital payments, savings, and credit. These elements are later incorporated as explanatory variables in the empirical models. This approach centers the analysis on the study's main variable of interest, connectivity as a gateway to financial products, particularly those enabled by fintech, while also accounting for control variables identified in specialized literature as critical to financial inclusion.

2.1 Financial Inclusion: Micro and Macro Perspectives

Financial inclusion refers to the widespread availability, active use, and meaningful engagement with formal financial services, such as bank accounts, digital payments, savings mechanisms, and credit, across all segments of society.

These services, provided by institutions such as banks or mobile platforms, enable individuals to manage their resources, plan for life events, and mitigate financial risks (Allen et al., 2016). For inclusion to be significant, services must be affordable, accessible, and tailored to user needs within a transparent financial ecosystem (Kumar & Joshi, 2016).

This study uses a multi-step, sequential framework for financial inclusion, progressing through the following stages: account ownership, digital payments, savings, and credit. These stages, based on empirical research (Demirgüç-Kunt et al., 2022), guide the structure of the explanatory variables in the econometric models. For example, while owning an account provides a starting point, true inclusion occurs when individuals actively engage with a variety of financial services. In developing countries, 13 percent of bank accounts held by adults show no activity (Demirgüç-Kunt et al., 2022), underscoring that financial inclusion is a continuous process rather than a one-time achievement.

At the microeconomic level, traditional models such as the permanent income hypothesis (Friedman, 1957) and life cycle theory (Modigliani & Brumberg, 1954) explain individual financial decisions based on income expectations and life stages. Savings are key not only for smoothing consumption but also for capital formation. While early perspectives highlighted their economic importance (Kuznets et al., 1946), Keynes (1936) argued that excessive saving could suppress overall demand. Later research on financial intermediation (Kashyap et al., 1993) reaffirmed the role of savings in supporting investment.

Behavioral finance offers valuable insights by highlighting how financial literacy, trust, and psychological factors influence decision-making (Lusardi & Mitchell, 2014; Kumar, 2013; Kumar & Joshi, 2016). Empirical evidence shows that financial education improves the individuals' ability to manage their finances effectively (Cole et al., 2011). Still, rising income volatility, growing inequality, and institutional imbalances challenge traditional assumptions, underscoring the need for more comprehensive, adaptive approaches.

From a macroeconomic perspective, financial inclusion depends on factors such as institutional quality, digital infrastructure, labor conditions, and cultural norms (Sarma, 2008; Allen et al., 2016). Strong institutions lower transaction costs and expand financial services (La Porta et al., 1997), while digital infrastructure broadens access (Suri & Jack, 2016). Human capital is vital for ensuring ongoing and meaningful engagement. Macroeconomic cycles, which influence interest rates, income, and employment stability, also impact financial behavior (Ozcan et al., 2003; Roa et al., 2014).

Recent discussions on financial inclusion have shifted from traditional indicators of financial depth to a stronger emphasis on service coverage, often prioritizing access over the actual economic relevance of financial services. In this context, factors such as fintech connectivity, institutional trust, and socio-cultural characteristics have become central to advancing more meaningful and effective inclusion (Ozili, 2018; Philippon, 2016; Pavón Cuéllar, 2021).

Financial inclusion emerges from the interplay between individual behavior and structural conditions, shaped by both micro- and macro-level determinants. Connectivity, understood as access to infrastructure, institutions, and technology, is decisive in enabling inclusive financial systems. This conceptual framework informs the following section, which analyzes the technological and institutional drivers—particularly digital infrastructure and fintech innovations—that are transforming access, improving service delivery, and strengthening financial ecosystems. Additionally, the section examines the role of social capital, including cultural traits and institutional frameworks, in shaping financial inclusion.

2.2 Digital Infrastructure, Fintech, and Financial Inclusion

In the digital era, infrastructure plays a pivotal role in shaping access to financial services. Digital infrastructure (DI) refers to the foundational technological components that enable the storage, processing, and exchange of digital information, including hardware, software, data centers, cloud computing systems, cybersecurity tools, and above all, connectivity (Feyen et al., 2023). From an operational perspective, DI has traditionally been conceived as the backbone of information systems management. However, within the framework of financial inclusion, it should be understood more broadly as the connective tissue of the digital economy, shaping how individuals and institutions engage with financial services. This broader conception situates DI as an integrative element within digital ecosystems (Sussan & Acs, 2017), where connectivity, comprising access to reliable internet, mobile and broadband networks, and digital devices such as smartphones and computers, emerges as a threshold condition for digital engagement.

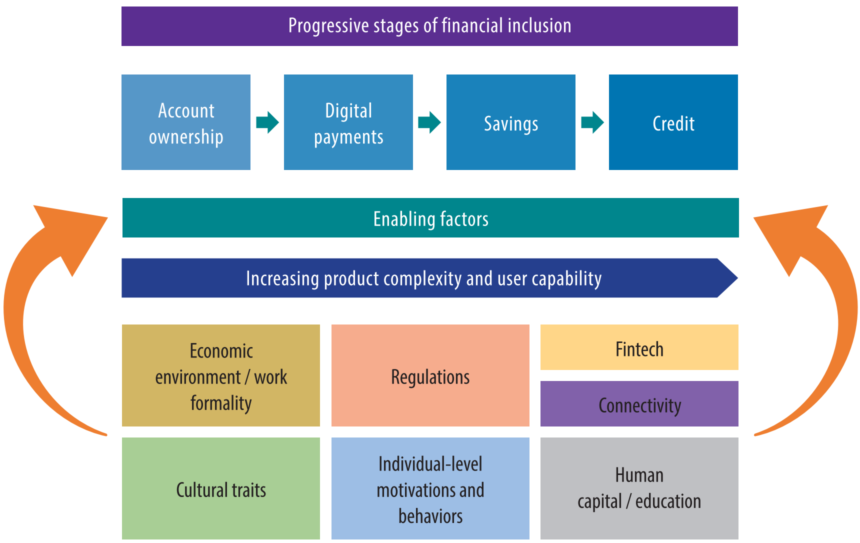
While digital infrastructure supports a wide range of digital systems and services, its role in enabling the deployment of financial technology (fintech) is especially critical. Fintech encompasses innovative solutions such as mobile banking, digital payments, blockchain, artificial intelligence (AI), big data analytics, cloud computing, regulatory technology (regtech), and insurance technology (insurtech) (Amnas et al., 2024; Alliance for Financial Inclusion [AFI], 2022), which enhance service efficiency, reduce costs, and broaden access to formal finance, particularly for underserved groups. These applications help overcome barriers such as geographic remoteness and limited branch networks (Philippon, 2016).

However, their benefits depend on enabling infrastructure, most notably affordable and stable connectivity. In many low-income and rural areas, mobile phones serve as the primary gateway to financial services (Suri & Jack, 2016); yet, affordability of smartphones, data plans, and electricity access remains a key constraint, leading to stratified digital inclusion.

Moreover, infrastructure alone does not ensure adoption. Behavioral responses vary by context and are shaped by factors such as education, regulation, trust, and cultural attitudes toward technology, formality, and finance (Eldomiaty et al., 2020; Demirgüç-Kunt et al., 2022).

The technology acceptance model (TAM) (Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) can explain how enabling infrastructure interacts with user perceptions and social norms to influence fintech adoption.

Figure 1: *Conceptual Diagram*



Source: Author.

Financial inclusion should be understood as a dynamic process that requires not only access but also the meaningful and sustained use of digital financial services. To strengthen the analytical framework, this study adopts the logic of progressive inclusion, positioning connectivity as a strategic factor at each stage of the inclusion ladder, from account ownership to digital payments, savings, and credit. Figure 1 illustrates a conceptual framework that links the progressive stages of financial inclusion with a set of enabling factors. A horizontal arrow indicates that advancing through these steps requires increasing user capability and access to more complex financial products. This framework connects macro-level enablers with individual behavioral decisions, highlighting how technological infrastructure and sociocultural contexts interact to shape financial inclusion. The integration of cultural traits into empirical models enriches the analysis of adoption patterns. This conceptual structure forms the basis for the models estimated in the subsequent sections of the article.

3 Research Method

3.1 The Models

Following the conceptual framework, this section develops a model to test the relevance of the previously identified determinants of financial inclusion. It begins by addressing the representative variables. While account ownership is a necessary first step, it is not sufficient to drive development unless accompanied by policies, products, and incentives that promote active use (Allen et al., 2016). The goal of financial inclusion is not merely to expand the formal financial system, but to ensure that account holders benefit from digital payments, savings, and appropriate credit, ultimately supporting income-generating investment. To capture this, four models are proposed, each representing a level of financial inclusion: account ownership, digital payments, savings, and borrowing. The latter two serve as proxies for the effective use of financial services:

- *Account ownership.* While traditional banking remains common, there has been a significant shift toward digital banking and non-bank financial products. Globally, account ownership reached 76 percent in 2021, up from 51 percent in 2011, a 50 percent increase. Developing countries experienced even faster growth, with a 30-point increase. Despite this progress, women, low-income individuals, and those with limited education remain unbanked at disproportionately high rates. The rise of mobile money accounts has expanded access for traditionally excluded groups. However, 1.4 billion adults in developing economies such as China, India, Pakistan, Indonesia, Bangladesh, Egypt, and Nigeria still lack access to formal financial services (Demirgüç-Kunt et al., 2022).

- *Digital payments.* Financial transactions conducted electronically via digital platforms eliminate the need for physical cash or checks. They offer convenience, speed, low cost, and security, making them increasingly preferred. However, their adoption introduces consumer risks, including fraud, hacking, over-indebtedness from digital credit, and a lack of transparency regarding fees and product terms, underscoring the need for innovative consumer protection measures (Organisation for Economic Co-operation and Development [OECD], 2023). Globally, 64 percent of adults, or 84 percent of account holders, made at least one digital payment. In high-income economies, this figure reached 95 percent, compared to 57 percent in developing countries. Notably, the share of adults using digital payments in developing economies doubled between 2014 and 2021 (Demirgüç-Kunt et al., 2022).

- *Savings.* In 2021, 49 percent of adults worldwide reported saving or setting aside money: 76 percent in high-income economies and 42 percent in developing countries. Globally, 31 percent of adults used formal channels such as financial institutions or mobile money accounts. In high-income economies, 58 percent saved formally, compared to 25 percent in developing countries, where formal saving became the most common method for the first time. Alternatives include savings clubs (used by 25 percent of adults in Sub-Saharan Africa) and informal methods such as keeping cash at home or investing in livestock, real estate, or financial assets (Demirgüç-Kunt et al., 2022).
- *Loans.* In 2021, 53 percent of adults worldwide reported borrowing, including via credit cards. In high-income economies, 65 percent of adults had new credit (formal or informal), compared to 50 percent in developing economies. Formal borrowing is on the rise, particularly in high-income countries, where it has become the predominant source of credit. In contrast, only 46 percent of borrowers in developing economies rely on formal credit, with a comparable proportion turning to family and friends for financial support. Semiformal borrowing (e.g., savings clubs) is more common in Sub-Saharan Africa, where 2 percent of adults reported using it (International Monetary Fund [IMF], 2024).

New data from the Financial Access Survey (FAS) reveal a global shift toward financial digitization, highlighted by a rise in mobile money agents, particularly in Africa and Asia, and a decline in commercial bank branches and ATMs per capita, both key indicators of sustainable development goals (SDGs). In Latin America, the growth of branchless banking further reinforces this trend (IMF, 2024). These changes underscore the importance of integrating digital infrastructure indicators, especially those related to connectivity, into financial access models. Alongside traditional metrics, the IMF (2024) recommends including internet access, broadband, and fixed and mobile phone subscriptions, as these reflect the connectivity essential for accessing digital financial services.

The core independent variable in this study is financial connectivity, operationalized through five infrastructure-based indicators: fixed-line telephone subscriptions, mobile cellular subscriptions, broadband internet access, ATM density, and commercial bank branch density. A financial connectivity index is constructed via principal component analysis (PCA), which aggregates these indicators into a single dimension.

PCA is a widely used dimensionality reduction technique that transforms a set of potentially correlated indicators into a smaller number of uncorrelated components, while preserving as much of the original variance as possible. This approach not only mitigates multicollinearity but also enhances interpretability by capturing the underlying structure of the data in a single index. Moreover, PCA assigns weights to each variable based on its contribution to the total variance, allowing for an objective and data-driven aggregation of indicators (Jolliffe & Cadima, 2016).

The PCA results indicate a dominant component, with an eigenvalue of 3.18, capturing 63.65 percent of the total variance, thereby validating the unidimensionality and explanatory power of the index.

***Table 1:** Factor Analysis Results and Financial Connectivity Index Validation*

Statistic	Value
Factor eigenvalue	3.18228
Explained variance (%)	63.65%
Factor loading (mobile cell)	0.3324
Factor loading (commercial bank branches)	0.4043
Factor loading (ATMs)	0.4673
Factor loading (fixed broadband)	0.4931
Factor loading (fixed telephone)	0.5143
Bartlett's test of sphericity	Chi2 = 3976.586 Degrees of freedom = 10 *p*-value = 0.000
Kaiser-Meyer-Olkin (KMO) overall index	0.8207
Cronbach's alpha (composite index)	0.7422

Source: Author.

This result confirms the suitability of combining the underlying indicators into a single index, as they share a substantial amount of common variance and reflect a cohesive dimension of financial inclusion. The factor loadings demonstrate associations with the underlying factor. The Kaiser–Meyer–Olkin (KMO) of overall sample adequacy (0.8207) is meritorious, and Bartlett's test of sphericity confirmed the pertinence of the data for this analysis. Cronbach's alpha for the items indicates moderately reliable internal consistency of the scale. The resulting component, referred to as the financial connectivity index, is defined as a linear combination of the key variables identified in the analysis, capturing the most relevant systematic variation in the dataset.

$$\text{Connectivity}_{it} = 0.3324\ X1_{it} + 0.4043\ X2_{it} + 0.4673\ X3_{it} + 0.4931\ X4_{it} + 0.5143\ X5_{it} \quad (1)$$

where *i* and *t* denote the country and year, respectively:

X1: Mobile cellular subscriptions (per 100 people)

X2: Commercial bank branches (per 100,000 adults)

X3: Automated teller machines (per 100,000 adults)

X4: Fixed broadband subscriptions (per 100 people)

X5: Fixed telephone subscriptions (per 100 people)

Studies by Asongu et al. (2021) and Chinoda and Kapingura (2024) demonstrated that digital technologies, particularly internet banking, promote financial inclusion, while Lenka and Barik (2018) found that mobile phones and the internet positively affect financial inclusion and contribute to inclusive growth. Sassi and Goaied (2013) highlighted the role of information and communication technologies in improving financial infrastructure and inclusion rates, while Mushtaq and Bruneau (2019) showed a positive relationship between ICT diffusion, financial inclusion, and poverty reduction in developing countries.

Besides connectivity, control variables indicated in the literature are other inducers or inhibitors of financial inclusion and must be included in the model. For example, use barriers derived from incomplete and asymmetric information, such as required documentation, guarantees or collateral, credit bureaus or interest rate spreads; quality and/or dynamism of the sources of income; institutional framework, human capital (education at different levels, financial education, and technological readiness), and social capital (cultural traits and institutional quality), among others. The variables finally included in the models are:

- *Bureau*: Public credit registry coverage reports the number of individuals and firms listed in a public credit registry with current information on repayment history, unpaid debts, or credit outstanding (percentage of the adult population / 100).
- *Education*1: Educational attainment, lower secondary (percentage of population 25+/100).
- *Education*2: Labor force with intermediate education (percentage of the working-age population / 100).
- *Vulnerable employment:* Contributing family workers and own-account workers. Represents self-employed or unpaid family workers. These groups

are more prone to falling into poverty due to a lack of formal employment arrangements, social protection, or safety nets to shield them from contingencies. This situation limits their ability to generate savings or qualify for credit (percentage of total employment / 100).

- *Regulations*: Regulatory quality, as measured by the Worldwide Governance Indicators (WGI), captures the perceptions of the government's ability to formulate and implement sound policies and regulations that foster private sector development. The original scores are expressed in units of a standard normal distribution, approximately ranging from -2.5 to 2.5. To ensure consistency and comparability with other variables in the analysis, particularly those expressed in percentages or larger numerical scales, this indicator was rescaled by multiplying its values by 100. This linear transformation preserves the relative differences and distributional properties of the original data while harmonizing it with the metric structure of the other indicators.
- *Cultural traits* (rescaled by dividing its values by 100).
- *Pragmatism*: Long-term orientation of a country refers to the time horizon a society displays. National scores range from 1 (lowest) to 100 (highest).
- *UncertAvoid*: Uncertainty avoidance reflects the degree to which a culture avoids risks. National scores range from 1 (lowest) to 100 (highest).

The ultimate estimated models for financial inclusion in its different dimensions are:

✓ Access dimension:

$$\text{Account ownership}_{it} = f(\text{ Connectivity}_{it}; \text{Education}_{it}) \quad (2)$$

$$\text{Account ownership}_{it} = f(\text{ Connectivity}_{it}; \text{Education}_{it}; \text{Cultural traits}_{i}) \quad (3)$$

✓ Payment dimension:

$$\text{Digital payments}_{it} = f(\text{ Connectivity}_{it}; \text{Education}_{it}; \text{Regulations}_{it}) \quad (4)$$

$$\text{Digital payments}_{it} = f(\text{ Connectivity}_{it}; \text{Education}_{it}; \text{Regulations}_{it}; \text{Cultural traits}_{i}) \quad (5)$$

✓ Use dimension:

– Savings:

$$\text{Savings}_{it} = f(\text{ Connectivity}_{it}; \text{Education}_{it}; \text{Regulations}_{it}) \quad (6)$$

$$\text{Savings}_{it} = f(\text{ Connectivity}_{it}; \text{Education}_{it}; \text{Regulations}_{it}; \text{Cultural traits}_{i}) \quad (7)$$

– Loans:

$$\text{Loans}_{it} = f(\text{ Connectivity}_{it}; \text{Education}_{it}; \text{Employment}; \text{Regulations}_{it}) \quad (8)$$

$$\text{Loans}_{it} = f(\text{ Connectivity}_{it}; \text{Education}_{it}; \text{Employment}; \text{Regulations}_{it}; \text{Cultural traits}_{i}) \quad (9)$$

i = 1…m number of countries; t = 1…T number of years.

Where:

1 Access dimension:

– *Account ownership:* Respondents reporting having an individual or jointly owned account at a regulated institution (bank, credit union, microfinance institution, post office, or mobile money service provider (% age 15+/100).

2 Payments dimension:

– *Digital payments:* Individuals who, in the past year, used digital or mobile platforms to make payments, pay bills, shop online or in-store, or conduct financial transactions, such as receiving wages, remittances, government transfers, or agricultural payments, directly through a financial institution or mobile money account (% age 15+).

3 Use dimension:

– *Savings:* Resident customers who saved at a financial institution (% age 15+).

– *Loans:* Borrowers from commercial banks (per million adults).

4 Results of Empirical Analysis and Discussion

This section examines how financial connectivity influences inclusion outcomes while accounting for other variables identified in the theoretical framework as key determinants. It also assesses whether these factors maintain a statistically significant relationship within the context of the sample and period under study.

Exploring different available databases was necessary to select the variables, group the indicators into categories, and, through correlation analysis, exclude those that seemed to capture the same information.

The model uses annual data from 2006 to 2021, covering a sample of 122 countries. Data sources include Hofstede (2001), Hofstede et al. (2010), the World Bank (WB, 2024), the International Labour Organization (ILO, 2024), the Economist Intelligence Unit (2022), and the International Monetary Fund (IMF, 2024). During the integration process, certain countries and years were excluded due to data inconsistencies, and isolated missing values were estimated using linear extrapolation techniques (Armstrong & Collopy, 1993).

To address potential endogeneity, serial correlation, and heteroskedasticity, likely resulting from the endogenous nature of certain variables, four complementary estimation techniques were applied to ensure the robustness of the results. These include: (1) the two-step system generalized method of moments (system GMM), used where panel structure permitted, with collapsed instruments and a restricted lag structure to mitigate overfitting, endogeneity, and dynamic panel bias (Arellano & Bover, 1995; Blundell & Bond, 1998; Roodman, 2006); (2) panel feasible generalized least squares (FGLS), suitable for linear models exhibiting

AR(1) autocorrelation, cross-sectional dependence, and heteroscedasticity; (3) panel-corrected standard errors (PCSE), estimated via the Prais-Winsten transformation to account for non-independence and heteroscedasticity across countries (Beck & Katz, 1995); and (4) Driscoll-Kraay standard errors, applied to credit random effects model based on the results of the Hausman test.

Tables 2-5 present the results of various models. While multiple estimation techniques were applied, specific models were identified as more suitable for each dimension, as discussed in the following sections. The Lagrange multiplier (LM) tests showed no evidence of omitted variables or model under-identification.

In its first dimension, account ownership, financial inclusion is significantly driven by digital connectivity and minimum educational attainment, confirming the findings by Demirgüç-Kunt et al. (2022). A dynamic panel model estimated via two-step system GMM with collapsed instruments highlighted the strong persistence of account ownership over time. Diagnostic tests validated the model (AR(2) $p = 0.177$; Hansen $p = 0.198$), and showed that regulatory quality loses significance, likely due to its effect being captured by the lagged dependent variable. According to information criteria, the dynamic model excluding cultural traits and regulatory quality was chosen.

Table 2: *Financial Inclusion: Access Dimension Panel Results*

	Model 1		**Model 2**		**Model 3**
Dependent variable: Account ownership	Prais-Winsten regression	FGLS	Prais-Winsten regression	FGLS	Two-step system GMM
Coefficients					
Explanatory					
L.Accountowners$_{it}$					0.8050**
Connectivity$_{it}$	0.3245**	0.3633***	0.2971**	0.3496***	0.0652**
Education1$_{it}$	0.0048***	0.0037***	0.0042***	0.0032***	0.0010***
Regulations$_{it}$	0.0241***	0.0399***	0.0512**	0.0624***	-
Pragmatism$_{i}$	-	-	0.0901*	0.0837**	-
Constant	-	-	-	-	0.0449*
R^2	0.9115	-	0.9253	-	-
Rho	0.9015	-	0.8745	-	-
Wald chi^2	6,288.88	733,935.29	5,569.68	31,768.32	27,657.82
Prob > chibar^2	0.0000	0.0000	0.0000	0.0000	0.0000
Breusch and Pagan Lagrange multiplier chi^2	1085.49		700.80		1259.05
Prob > chibar^2	0.0000		0.0000		0.0000
Hausman chi^2	80.84		58.74		53.86
Prob > chibar^2	0.0000		0.0000		0.0000
Kleibergen-Paap k LM statistic (underidentification test)	211.06		85.57		170.045
Chi^2 (2) *p*-value	0.0000		0.0000		0.0000
IV redundancy test (LM test of redundancy of specified instruments)	40.68		67.52		170.045
Chi^2 (1) *p*-value	0.0000		0.0000		0.0000
Hansen J test: *p*-value					0.198
Arellano-Bond AR(1) test *p*-value					0.785
Arellano-Bond AR(2) test *p*-value					0.177
Observations	605	583	426	416	541
Groups (countries)	122	100	74	64	119
Instruments					5

Information criteria for model selection					
Akaike information criterion (AIC)	-3.514066	-3.566136	-3.491319	-3.521270	**-6.784995**
Schwarz information criterion (BIC)	-3.492223	-3.544291	-3.453250	-3.483200	**-6.753251**
Hannan-Quinn criterion (HQC)	-3.505566	-3.557635	-3.476281	-3.506232	**-6.772581**

Notes: Statistically significant at 10% (*), 5% (**), and 1% (***) levels.
Source: Author.

Although the Hausman test favored fixed effects, the presence of heteroskedasticity, autocorrelation, and unbalanced panels warranted the use of PCSE and FGLS estimators. These methods, appropriate under such data conditions, address violations of classical assumptions and yield more reliable standard errors. This approach aligns with established practices in macro-panel analysis (Beck & Katz, 1995; Drukker, 2003; Wooldridge, 2010), particularly in contexts where standard estimators may be affected by complex error structures. This is particularly useful for correcting standard errors without modeling individual effects, and the consistent results across specifications reinforce the credibility of the findings despite data limitations.

Evidence indicates that account ownership remains relatively stable regardless of changes in the labor market or macroeconomic conditions. A cultural trait associated with long-term orientation modestly improves model fit. However, its exclusion is justified by its limited explanatory power, its time-invariant nature within countries despite notable variation across them, and the aim of maintaining model parsimony.

A similar pattern is observed in the second stage of financial inclusion, digital payments (Table 3), where financial connectivity remains the leading predictor within the model. This effect is reinforced by basic educational attainment, although the influence of regulatory quality appears limited. The relatively low regulatory requirements at this stage may partially explain the higher incidence of fraudulent activity within both formal and informal financial systems. In contrast to the initial stage, cultural factors begin to play a more prominent role: societies characterized by high levels of anxiety exhibit lower adoption rates of digital payments, as reflected in improved model fit based on information criteria. Given the unbalanced nature and short time cover of the panel, along with diagnostic evidence of heteroskedasticity, autocorrelation, and multicollinearity, factors that compromise the reliability of fixed-effects estimates despite the Hausman test and preclude the use of dynamic models, PCSE estimation was employed to correct for heteroskedasticity and AR(1) serial correlation in panels with a large cross-sectional and short temporal dimension. As a robustness check, FGLS was also applied. The consistency of results across both methods reinforces the credibility of the findings, despite the dataset's current limitations.

The savings models (Table 4) are primarily estimated using a two-step system GMM dynamic panel approach, which serves as the core of the analysis. This specification employs collapsed instruments and a restricted lag structure to mitigate overfitting and instrument proliferation.

Table 3: *Financial Inclusion: Digital Payments Dimension Panel Results*

	Model 1		Model 2	
Dependent variable: Digital payments	Prais-Winsten regression	FGLS	Prais-Winsten regression	FGLS
Coefficients				
Explanatory				
Connectivity$_{it}$	0.2331**	0.2396**	0.2561**	0.3023**
Education1$_{it}$	0.0038***	0.0034***	0.0047***	0.0041***
Regulations$_{it}$	-	-	-	-
Uncertainty avoidance$_{i}$	-	-	-0.1416**	-0.1756**
Constant	-	-	-	-
R^2	0.6830	-	0.6898	-
Rho	0.7129	-	0.6983	-
Wald chi^2	925.75	153,505.46	811.93	132,750.26
Prob > chibar^2	0.0000	0.0000	0.0000	0.0000
Breusch and Pagan Lagrange multiplier chi^2	28.84		3.44	
Prob > chibar^2	0.0000		0.0318	
Hausman chi^2	87.11		84.27	
Prob > chibar^2	0.0000		0.0000	
Kleibergen-Paap k LM statistic	160.68		116.33	
Chi^2 (2) *p*-value	0.0000		0.0000	
IV redundancy test (LM test of redundancy of specified instruments)	160.68		114.93	
Chi^2 (1) *p*-value	0.0000		0.0000	
Observations	593	571	482	468
Groups (countries)	119	97	88	74
Information criteria for model selection				
Akaike information criterion (AIC)	-2.685628	-2.685920	-2.694726	**-2.706082**
Schwarz information criterion (BIC)	-2.670838	-2.671130	-2.668722	**-2.680078**
Hannan-Quinn criterion (HQC)	-2.679868	-2.680160	-2.684506	**-2.695862**

Notes: Statistically significant at 10% (*), 5% (**), and 1% (***) levels.

Source: Author.

Table 4: *Financial Inclusion: Use Dimension (Savings) Panel Results*

	Model 1		**Model 2**	**Model 3**
Dependent variable: Savings	Prais-Winsten regression	FGLS	Two-step system GMM	Prais-Winsten regression
Coefficients				
Explanatory				
$L.Savings_{it}$			0.6665*	
$Connectivity_{it}$	0.0898**	0.0859***	0.0285**	0.0735**
$Education1_{it}$	0.0020***	0.0018***	0.0007***	0.0020***
$Regulations_{it}$	0.0871***	0.0813***	0.0390**	0.1041**
$Pragmatism_{i}$	-	-	-	0.0834*
$Uncertainty\ avoidance_{i}$	-	-	-	-0.0857**
R^2	0.7537	-	-	0.7693
Rho	0.9214	-	-	0.913649
Wald chi^2	1,241.44	13,596.57	-	1,104.22
Prob > $chibar^2$	0.0000	0.0000	-	0.0000
Breusch and Pagan Lagrange multiplier chi^2		1272.98		795.38
Prob > $chibar^2$		0.0000		0.0000
Hausman chi^2		63.89		43.06
Prob > $chibar^2$		0.0000		0.0000
Kleibergen-Paap k LM statistic		160.689		78.484
Chi^2 (2) *p*-value		0.0000		0.0000
IV redundancy test (LM test of redundancy of specified instruments)		160.689		64.487
Chi^2 (1) *p*-value		0.0000		0.0000
Hansen J test: *p*-value			0.821	
Arellano-Bond AR(1) test *p*-value			0.960	
Arellano-Bond AR(2) test *p*-value			0.970	
Observations	593	571	530	421
Groups (countries)	119	97	116	74
Instruments			5	
Information criteria for model selection				
Akaike information criterion (AIC)	-4.034704	-4.032007	**-6.15049**	-4.085227
Schwarz information criterion (BIC)	-4.012519	-4.009822	**-6.118242**	-4.058030
Hannan-Quinn criterion (HQC)	-4.026063	-4.023366	**-6.137868**	-4.078645

Notes: Statistically significant at 10% (*), 5% (**), and 1% (***) levels.

Source: Author.

The use of system GMM is further supported by the higher quality and consistency of the data available for savings and credit variables, which allows for more robust dynamic panel estimation. This model confirms the significance of the lagged dependent variable, indicating persistence in saving behavior, and shows that digital connectivity, educational attainment, and regulatory quality have positive and statistically significant effects. Diagnostic tests support the validity of the specification. The results indicate no evidence of serial correlation, and the instruments are found to be valid. Moreover, this dynamic model outperforms alternative specifications based on information criteria, reinforcing its relevance for understanding the determinants of formal saving.

As shown in Table 4, robustness checks using panel-corrected standard errors and feasible generalized least squares confirm the direction and significance of the main predictors. Financial connectivity consistently drives saving behavior, controlled by education or labor conditions. However, concerns persist regarding the need for proper financial regulation. Consistent with Pavón Cuéllar (2024), a pragmatic, future-oriented mindset appears to encourage frugality.

As expected, Table 5 reveals that more advanced stages of financial inclusion are associated with more complex determinants (Kumar & Joshi, 2016). While financial connectivity remains relevant, borrowing from commercial banks requires formal labor market participation, higher education levels, and a strong regulatory framework. Advanced credit information systems, such as credit bureaus, help mitigate information asymmetries, reduce excessive spreads, and prevent adverse selection and moral hazard, thereby enhancing systemic stability.

To address potential endogeneity in borrowing behavior, a two-step system GMM estimator was employed using collapsed instruments and a restricted lag structure. The model satisfies key diagnostics, including the Hansen test for instrument validity and the absence of second-order autocorrelation.

Table 5: *Financial Inclusion: Use Dimension (Loans) Panel Results*

	Model 1			**Model 2**		
Dependent variable: Borrowers from commercial bank	Prais-Winsten regression	Driscoll-Kraay standard errors	Two-step system GMM	Prais-Winsten regression	Feasible generalized least squares	Driscoll-Kraay standard errors
Coefficients						
Explanatory						
$Connectivity_{it}$	0.1521**	0.1535***	0.2554**	0.1119**	0.1364***	0.1045***
$Education2_{it}$	0.0692**	0.1229**	0.0741*	0.0651**	0.0435**	0.1950**
$Regulations_{it}$	0.0754**	0.1082***	0.0862**	0.1069**	0.0760***	0.1400***
$Pragmatism_{i}$	-	-	-	0.0022***	0.0020***	0.0015***
Vulnerable employment	-0.2158**	-0.0467**	-0.0376**	-0.0852**	-0.1104**	-0.1662**
Public credit bureau	0.0763**	0.0101**	0.0559*	0.0695**	0.0064**	0.0093**
R^2	0.6977	0.8233	-	0.7369	-	0.8568
Rho	0.8689	-	-	0.8881	-	-
Wald chi^2	789.92	-	-	773.17	2569.36	-
Prob > $chibar^2$	0.0000	-	-	0.0000	0.0000	-
Breusch and Pagan Lagrange multiplier chi^2	2103.92			1246.50		
Prob > $chibar^2$	0.0000			0.0000		
Hausman chi^2	10.28			5.96		
Prob > $chibar^2$	0.0678			0.3105		
Kleibergen-Paap k LM statistic	222.35			88.568		
Chi^2 (2) *p*-value	0.0000			0.0000		
IV redundancy test (LM test of redundancy of specified instruments)	165.207			68.995		
Chi^2 (1) *p*-value	0.0000			0.0000		
Hansen J statistic (over-identification test of all instruments)	22.128			20.369		

Chi^2 (1) *p*-value	0.000			0.000		
Arellano-Bond AR(1) test *p*-value			0.217			
Arellano-Bond AR(2) test *p*-value			0.193			
Observations	664	664	664	374	373	374
Groups (countries)	83	83	83	45	44	45
Instruments			7			
Information criteria for model selection						
Akaike information criterion (AIC)	-3.977698	**-4.025066**	-4.000727	-3.673923	-3.653158	**-3.719995**
Schwarz information criterion (BIC)	-3.915581	**-3.991193**	-3.966854	-3.610967	-3.590202	**-3.657039**
Hannan-Quinn criterion (HQC)	-3.948304	**-4.011940**	-3.987602	-3.648926	-3.628161	**-3.694999**

Notes: Statistically significant at 10% (*), 5% (**), and 1% (***) levels.
Source: Author.

Additional robustness checks using PCSE and Driscoll–Kraay standard errors reinforce these findings and highlight the role of cultural traits: societies with a pragmatic orientation are more likely to borrow, possibly due to greater entrepreneurial feasibility in dynamic economies with higher-quality employment. Similar patterns have been observed by Bialowolski et al. (2023), among others.

5 Conclusions

Historically, financial development has been closely linked to economic growth, with various theoretical models emphasizing the importance of access to financial services. However, the global financial crisis of 2007–2008 exposed the limitations of traditional financial deepening, particularly in terms of resource misallocation and rising over-indebtedness. These shortcomings have prompted a shift toward multidimensional indicators that capture the quality and inclusiveness of financial systems more accurately.

In line with sustainable development goals (SDGs), financial inclusion is increasingly recognized as a vital strategy for reducing poverty and empowering historically underserved populations. Fintech, driven by digital infrastructure, has played a transformative role by expanding access to financial services. Still, its success depends on closing connectivity gaps, particularly in low-income and rural areas.

The digital transformation of financial services relies on strong and widespread connectivity, which enables real-time access to financial products through mobile devices, internet platforms, and cloud technologies. Improved connectivity lowers transaction costs and reduces information asymmetries, allowing financial institutions and fintech providers to reach previously excluded populations. It also supports real-time data exchange, enhancing credit assessments, fraud detection, and the delivery of personalized financial advice. Tools such as mobile banking, digital wallets, and electronic payments leverage this infrastructure to extend services beyond traditional banking channels. However, in less developed contexts, particularly among older populations, conventional access points, namely, ATMs, fixed-line services, and physical branches, remain essential.

Financial connectivity is also reshaping financial value chains by enabling service atomization and interoperability across providers. High-quality internet access supports these innovations, making financial services more modular, flexible, and inclusive. Nonetheless, realizing this potential requires additional investments in digital infrastructure and supportive regulatory frameworks, especially in countries where technological adoption is limited.

Although the benefits of financial inclusion are well established in the literature, the specific role of financial connectivity, particularly as a driver of fintech adoption, remains insufficiently examined. This gap can be attributed, in part, to the recent availability of standardized cross-country datasets. In response, the present study introduces a novel financial connectivity index, constructed using principal component analysis (PCA) to synthesize multiple dimensions of access into a single, composite metric. This index offers a globally comparable and methodologically streamlined alternative to prior approaches that relied on isolated proxies or region-specific constructs. Employing panel data econometric techniques, the analysis presents robust evidence that financial connectivity significantly enhances financial inclusion, controlling for structural variables such as educational attainment, labor market conditions, and institutional quality. Furthermore, the findings underscore the moderating role of cultural dimensions, specifically uncertainty avoidance and long-term orientation, in shaping the effectiveness of connectivity, thereby challenging the assumption that infrastructure alone is sufficient to ensure inclusion. Overall, the study contributes to the literature by offering both methodological innovation and empirical insights into the complex interplay among digital infrastructure, socioeconomic factors, and regulatory environments.

Nonetheless, the study has several limitations. Although panel data methods are suitable for identifying general patterns and estimating average effects, they cannot capture within-country heterogeneity or subnational dynamics. While the global scope enhances external validity, it may obscure context-specific insights. Data limitations also constrained the use of more advanced econometric techniques. Inconsistencies in the quality and coverage of cross-country data on connectivity and financial services may affect the precision of the results. In particular, integrating macro-level (FAS) and micro-level (Findex) indicators introduces potential aggregation bias, which cannot be addressed due to the lack of sufficiently detailed, harmonized datasets. Moreover, although global shocks between 2006 and 2021 likely caused cross-sectional dependence, the fragmented panel structure prevented the use of second-generation estimators accounting for unit roots, cointegration, or dynamic common factors. To partly address these issues, PCSE and FGLS estimators were applied in select models to correct for heteroskedasticity and autocorrelation. While these adjustments improve reliability, results should be interpreted cautiously.

Future research should prioritize disaggregated analyses to better capture contextual differences and guide the development of targeted policy interventions. Exploring how education and cultural values influence the adoption of digital financial services can help create more inclusive financial solutions, especially when combined with efforts to improve financial literacy among underserved groups. Additionally, the potential of emerging technologies such as artificial intelligence (AI), big data, and decentralized finance (DeFi) to promote financial inclusion deserves further investigation, particularly within strong, transparent regulatory frameworks. Future studies could deepen their analysis by incorporating technology acceptance frameworks, such as the technology acceptance model (TAM) and unified theories of technology use, to better understand how connectivity drives fintech adoption. While these models provide useful tools for analyzing digital financial behavior on a macroeconomic level, their application is limited by the current lack of granular, standardized global datasets. Progress in this area depends on enhancing data availability to better capture the complex interactions among infrastructure, individual capabilities, and sociocultural factors that shape inclusive financial ecosystems.

Expanding financial connectivity presents significant opportunities for advancing inclusive development. However, technological progress alone is insufficient. A comprehensive approach, encompassing ethical considerations, regulatory foresight, and institutional commitment, is essential to ensure equitable access and maintain public trust. Effective regulation must strike a careful balance between fostering innovation and safeguarding vulnerable users. Progress toward global financial inclusion ultimately requires coordinated efforts from governments, industry players, and civil society. Only through effective governance, participatory policymaking, and ongoing impact evaluation can we build a resilient financial system that leaves no one behind.

Notes

ChatGPT (OpenAI, 2023) was used solely to support language polishing and editorial refinement of the manuscript. All analyses, interpretations, and conclusions were developed by the author.

Literature

Allen, F., Demirgüç-Kunt, A., Klapper, L., & Martinez Peria, M. S. (2016). The foundations of financial inclusion: Understanding ownership and use of formal accounts. *Journal of Financial Intermediation*, *27*, 1–30. https://doi.org/10.1016/j.jfi.2015.12.003

Alliance for Financial Inclusion. (2022, February). *Regulatory and supervisory technologies for financial inclusion*. https://afi-global.org/wp-content/uploads/2024/10/RegTech_SupTech_special_report_isbn.pdf

Amnas, M. B., Selvam, M., & Parayitam, S. (2024). FinTech and financial inclusion: Exploring the mediating role of digital financial literacy and the moderating influence of perceived regulatory support. *Journal of Risk and Financial Management*, *17*(3), 108. https://doi.org/10.3390/jrfm17030108

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D

Armstrong, J. S., & Collopy, F. (1993). Causal forces: Structuring knowledge for time-series extrapolation. *Journal of Forecasting*, *12*, 103–115. https://doi.org/10.1002/for.3980120205

Asongu, S. A., Biekpe, N., & Cassimon, D. (2021). On the diffusion of mobile phone innovations for financial inclusion. *Technology in Society*, *65*, 101542. https://doi.org/10.1016/j.techsoc.2021.101542

Bagehot, W. (1873). *Lombard Street: A description of the money market*. Scribner, Armstrong & Co. https://fraser.stlouisfed.org/files/docs/meltzer/baglom62.pdf

Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American Political Science Review*, *89*(3), 634–647. https://doi.org/10.2307/2082979

Bialowolski, P., Xiao, J. J., & Weziak-Bialowolska, D. (2023). National culture and financial capability: A global perspective. *Social Indicators Research*, *170*, 877–891. https://doi.org/10.1007/s11205-023-03221-7

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Chinoda, T., & Kapingura, F. M. (2024). Digital financial inclusion and economic growth in Sub-Saharan Africa: The role of institutions and governance. *African Journal of Economic and Management Studies*, *15*(1), 15–30. https://doi.org/10.1108/AJEMS-09-2022-0372

Cole, S., Sampson, T., & Zia, B. (2011). Price or knowledge? What drives demand for financial services in emerging markets? *The Journal of Finance, 66*(6), 1933–1967. https://doi.org/10.1111/j.1540-6261.2011.01696.x

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Demirgüç-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). *The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. International Bank for Reconstruction and Development / The World Bank. https://openknowledge.worldbank.org/bitstreams/d36d178f-8fc4-555a-a7a6-00c1c7e70bf4/download

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *The Stata Journal*, *3*(2), 168–177. https://doi.org/10.1177/1536867X0300300206

Eldomiaty, T., Hammam, R., & El Bakry, R. (2020). Institutional determinants of financial inclusion: Evidence from world economies. *International Journal of Development Issues*, *19*(2), 217–228. https://doi.org/10.1108/IJDI-08-2019-0147

Feyen, E., Natarajan, H., & Saal, M. (2023). *FinTech and the future of finance: Market and policy implications*. The World Bank Group. https://doi.org/10.1596/978-1-4648-1914-8

Friedman, M. (1957). *A theory of the consumption function*. Princeton University Press.

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations*. Sage Publications.

Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind*. McGraw-Hill.

International Labour Organization. (2024). *Data and statistics*. Retrieved February 24, 2024, from https://www.ilo.org/data-and-statistics

International Monetary Fund. (2024). *Financial access survey (FAS)*. The World Bank Group. Retrieved February 25, 2024, from https://data360.worldbank.org/en/dataset/IMF_FAS

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *374*(2065), 20150202. https://doi.org/10.1098/rsta.2015.0202

Kashyap, A. K., Stein, J. C., & Wilcox, D. W. (1993). Monetary policy and credit conditions: Evidence from the composition of external finance. *The American Economic Review*, *83*(1), 78–98. https://www.jstor.org/stable/2117497

Keynes, J. M. (1936). *The general theory of employment, interest and money*. Harcourt & Brace.

Kumar, N. (2013). Financial inclusion and its determinants: Evidence from India. *Journal of Financial Economic Policy*, *5*(1), 4–19. https://doi.org/10.1108/17576381311317754

Kumar, S., & Joshi, H. G. (2016). Financial inclusion through financial literacy in India: Issues and challenges. *Bonfring International Journal of Industrial Engineering and Management Science*, *6*(1), 200–203. https://doi.org/10.9756/bijiems.8341

Kuznets, S., Epstein, L., & Jenks, E. (1946). *National product since 1869*. NBER Books.

La Porta, R., Lopez-De-Silanes, F., Shleifer, A., & Vishny, R. W. (1997). Legal determinants of external finance. *The Journal of Finance*, *52*(3), 1131–1150. https://doi.org/10.2307/2329518

Lenka, S. K., & Barik, R. (2018). Has expansion of mobile phone and internet use spurred financial inclusion in the SAARC countries? *Financial Innovation*, *4*(1), 5, 1–19. https://doi.org/10.1186/s40854-018-0089-x

Levine, R. (1991). Stock markets, growth, and tax policy. *The Journal of Finance, 46*(4), 1445–1465. https://doi.org/10.1111/j.1540-6261.1991.tb04625.x

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, *52*(1), 5–44. https://www.aeaweb.org/articles?id=10.1257/jel.52.1.5

McKinnon, R. I. (1973). *Money and capital in economic development*. The Brookings Institution.

Minsky, H. P. (1982). *Inflation, recession, and economic policy*. Wheatsheaf Books.

Modigliani, F., & Brumberg, R. H. (1954). Utility analysis and the consumption function: An interpretation of cross-section data. In K. K. Kurihara (Ed.), *Post-Keynesian Economics* (pp. 388–436). Rutgers University Press.

Mushtaq, R., & Bruneau, C. (2019). Microfinance, financial inclusion and ICT: Implications for poverty and inequality. *Technology in Society*, *59*, 101154. https://doi.org/10.1016/j.techsoc.2019.101154

OpenAI. (2023). *ChatGPT (GPT-4)*. https://openai.com/chatgpt

Organisation for Economic Co-operation and Development. (2023). Financial consumers and sustainable finance: Policy implications and approaches. *OECD Business and Finance Policy Papers*, *32*. OECD Publishing. https://doi.org/10.1787/318d0494-en

Ozcan, K. M., Gunay, A., & Ertac, S. (2003). Determinants of private savings behavior in Turkey. *Applied Economics*, *35*, 1405–1416. https://doi.org/10.1080/0003684032000100373

Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review*, *18*(4), 329–340. https://doi.org/10.1016/j.bir.2017.12.003

Pavón Cuéllar, L. I. (2021). Financial inclusion as a pillar of sustainable growth: International experience. *Ekonomski horizonti / Economic Horizons*, *23*(2), 107–121. https://doi.org/10.5937/ekonhor2102107P

Pavón Cuéllar, L. I. (2024). The importance of social capital in promoting financial inclusion: An international perspective. *Scientific Annals of Economics and Business*, *71*(2), 221–240. https://doi.org/10.47743/saeb-2024-0013

Philippon, T. (2016). *The FinTech opportunity* (NBER Working Paper Series, Working Paper No. 22476). National Bureau of Economic Research. https://doi.org/10.3386/w22476

Roa, M. J., Alonso Másmela, G. A., Garcia Bohórquez, N., & Rodríguez Pinilla, D. A. (2014). *Financial education and inclusion in Latin America and the Caribbean. Programs of central banks and financial superintendencies*. Center for Latin American Monetary Studies. https://www.cemla.org/PDF/otros/2014-10-Financial-Education-Inclusion-LAC.pdf

Roodman, D. (2006). *How to do Xtabond2: An introduction to difference and system GMM in Stata* (Center for Global Development Working Paper No. 103). Center for Global Development. https://doi.org/10.2139/ssrn.982943

Sarma, M. (2008). *Index of financial inclusion* (Working Paper No. 215). Indian Council for Research on International Economic Relations. https://icrier.org/pdf/Working_Paper_215.pdf

Sassi, S., & Goaied, M. (2013). Financial development, ICT diffusion, and economic growth: Lessons from MENA region. *Telecommunications Policy*, *37*(4–5), 252–261. https://doi.org/10.1016/j.telpol.2012.12.004

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. Harvard University Press.

Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, *354*(6317), 1288–1292. https://doi.org/10.1126/science.aah5309

Sussan, F., & Acs, Z. J. (2017). The digital entrepreneurial ecosystem. *Small Business Economics*, *49*(1), 55–73. https://doi.org/10.1007/s11187-017-9867-5

The Economist Intelligence Unit. (2022). *Democracy index 2022.* Retrieved January 15, 2024, from https://www.eiu.com/n/campaigns/democracy-index-2022/

The World Bank Group. (n.d.). *Financial inclusion*. https://www.worldbank.org/ext/en/topic/financial-sector/financial-inclusion

United Nations. (2015). *Transforming our world: The 2030 Agenda for Sustainable Development*, A/RES/70/1. International Trade Union Confederation. https://sdgs.un.org/2030agenda

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). The MIT Press.

World Bank. (2024). *DataBank*. The World Bank Group. Retrieved March 15, 2024, from https://databank.worldbank.org/home