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TITLE OF THE THESIS:

"Financial Inclusion through Mobile Technologies: Assessment of Socio-Economic Impact in Emerging Markets"

MASTERS THESIS

in the field of study: 38.04.08 Finance and Credit

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Moscow
2026

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1 Introduction

1.1 Problem

Financial inclusion has emerged as a key objective in development policy, particularly in emerging markets where access to formal financial services remains uneven. The ability of individuals and firms to access and use financial services is widely considered essential for economic development, poverty reduction, and social inclusion.

In recent years, mobile technologies have played a central role in expanding financial inclusion by reducing transaction costs and overcoming geographical barriers. However, despite the rapid growth of mobile financial services, their impact remains ambiguous. Increased access does not necessarily lead to effective usage or improved socio-economic outcomes, as many users remain underbanked and a significant share of accounts is inactive.

Moreover, financial inclusion is shaped not only by technological factors but also by institutional and socio-economic conditions, including regulatory quality, financial literacy, and trust in financial systems. These factors may significantly influence whether expanded access translates into meaningful economic participation.

The scientific problem addressed in this study lies in the gap between financial access and the effective use of financial services, as there is limited empirical evidence on how institutional factors influence this relationship and, consequently, the socio-economic impact of financial inclusion.

It should be noted that, due to data availability constraints and the need to increase cross-country variation within the panel dataset, the empirical sample also includes several developed economies alongside emerging markets. The inclusion of these observations improves the robustness and precision of the empirical analysis.

1.2 Goal

The goal of this study is to assess the socio-economic impact of financial inclusion through mobile technologies in developed and emerging markets, with particular attention to the role of institutional factors in shaping the effectiveness of financial service usage.

1.3 Objectives

To achieve this goal, the study pursues the following objectives:

1. To analyse the extent to which mobile technologies contribute to the expansion of financial inclusion.

2. To evaluate whether increased access to financial services translates into effective usage.

3. To examine the relationship between mobile financial inclusion and socio-economic outcomes.

4. To assess the role of institutional factorssuch as regulatory quality, financial literacy, and trustin influencing the effectiveness of financial inclusion.

5. To identify external constraints, including geopolitical risks and sanctions, that may limit the functionality of financial systems.

1.4 Object

The object of this study is financial inclusion in the developed and emerging markets.

1.5 Subject

The subject of this study is the relationship between mobile-driven financial inclusion, effective usage of financial services, and their socio-economic impact, conditioned by institutional and external factors.

1.6 Methodology

This study employs a quantitative empirical approach to examine the relationship between mobile technologies and financial inclusion in emerging markets. The analysis is based on panel data across countries and time, allowing for the evaluation of both cross-country differences and temporal dynamics.

The main empirical model is specified as follows:

$$FI_{it} = \alpha_i + \lambda_t + \beta_1 Mobile_{it} + \beta_2 Internet_{it} + \beta_3 X_{it} + \varepsilon_{it} \tag{1.1}$$

where FI_{it} represents the level of financial inclusion in country i at time t, $Mobile_{it}$ denotes mobile phone penetration, $Internet_{it}$ captures Internet

usage, and X_{it} is a vector of control variables, including GDP per capita, inequality indicators, and other socio-economic factors. The terms α_i and λ_t represent country-specific and time-specific effects, respectively.

To capture the role of institutional factors, the model is extended as follows:

$$FI_{it} = \alpha_i + \lambda_t + \beta_1 Mobile_{it} + \beta_2 Institution_{it} + \beta_3 (Mobile \times Institution)_{it} + \varepsilon_{it} \quad (1.2)$$

This specification allows for testing whether the effect of mobile technologies on financial inclusion depends on institutional conditions.

The empirical analysis is conducted in R. Panel regression techniques are applied, including fixed-effects and random-effects models. Model selection is based on statistical tests such as the Hausman test. Robust standard errors are used to account for potential heteroskedasticity and serial correlation.

In addition, exploratory data analysis and visualization are performed to identify patterns and relationships in the data. Visualization tools, including Tableau and R libraries such as ggplot2, are used to present key trends in financial inclusion and digital adoption.

The choice of methodology is motivated by its ability to capture both structural relationships and country-specific heterogeneity, while remaining suitable for the available data and the scope of the study.

Moreover, including OECD countries allows for better identification of the effect of institutional variables such as democracy and government effectiveness, since these variables exhibit limited variation within developing countries alone. Should be mentioned that since the study focuses on the relationship between governance, trust, and financial usage, including more advanced economies improves the identification of these effects across different stages of development.

1.7 Structure

This thesis consists of three main chapters, followed by appendices A and B.

The first chapter provides the theoretical and conceptual foundations of the study. It introduces the concept of financial inclusion, reviews its key determinants, and examines the role of mobile technologies and institutional factors. In addition, this chapter identifies the research gap and formulates the hypotheses of the study.

The second chapter presents the data and methodology. It describes the data sources, defines the variables used in the analysis, and outlines the econometric models applied in the study. This chapter also discusses the empirical strategy and diagnostic tests used to ensure the robustness of the results.

The third chapter is devoted to the empirical analysis and results. It presents descriptive statistics, regression results, and their interpretation. Furthermore, this chapter includes robustness checks and discusses the findings in relation to existing literature and policy implications.

The thesis concludes with appendices, which provide supplementary materials, including additional tables, regression inputs, and technical details of the analysis.

2 Theoretical Foundations & Literature Review

2.1 Literature Review

According to previous research, financial inclusion is strongly linked to a person's residence, income, education level, and gender (Demirguc-Kunt and Klapper, 2012). Researchers define financial inclusion as the ability to obtain and access a personal bank account. The authors highlight several barriers to access: lack of money, cost, distance, documentation, and trust. Demirguc-Kunt and Klapper also focus on cross-country inequality: about 90% account ownership in high-income countries, while the rate is much lower in developing economies, where informal money remains widespread.

On the other hand, the research results provided by the authors should be critically studied because of outdated data and the lack of socio-economic impact. However, it can still be used for retrospective analysis.

The other study shifts the focus from the bank services to bank access to the financial resilience and financial health (Crosignani et al., 2025). According to the research, the development of a fintech industry has greatly expanded access to personal accounts and banking services. Survey focuses on the US market. Figure 1 illustrates the portion of unbanked US citizens, which is lower than that of underbank households, but remains significant.

However, such a fintech expansion may lead to high-cost credit, BNPL[1] .Dependency, the fragmentation of regulation. According to the study, the highest financial inclusivity may contribute to the emergence of financial fragility with overexpansion of credit, and the complication of a financial system overall, leading to possible regulatory oversight.

Study approves the Demirguc-Kunt and Klapper's research observation that access to a bank account is dependent on income: the higher the income, the more likely an individual is to have a personal account, and vice versa (Figure 2).

[1]Buy Now, Pay Later — the form of credit that allows a consumer to split a retail transaction into smaller, interest-free installments and repay over time (CONSUMER FINANCIAL PROTECTION BUREAU, 2022)

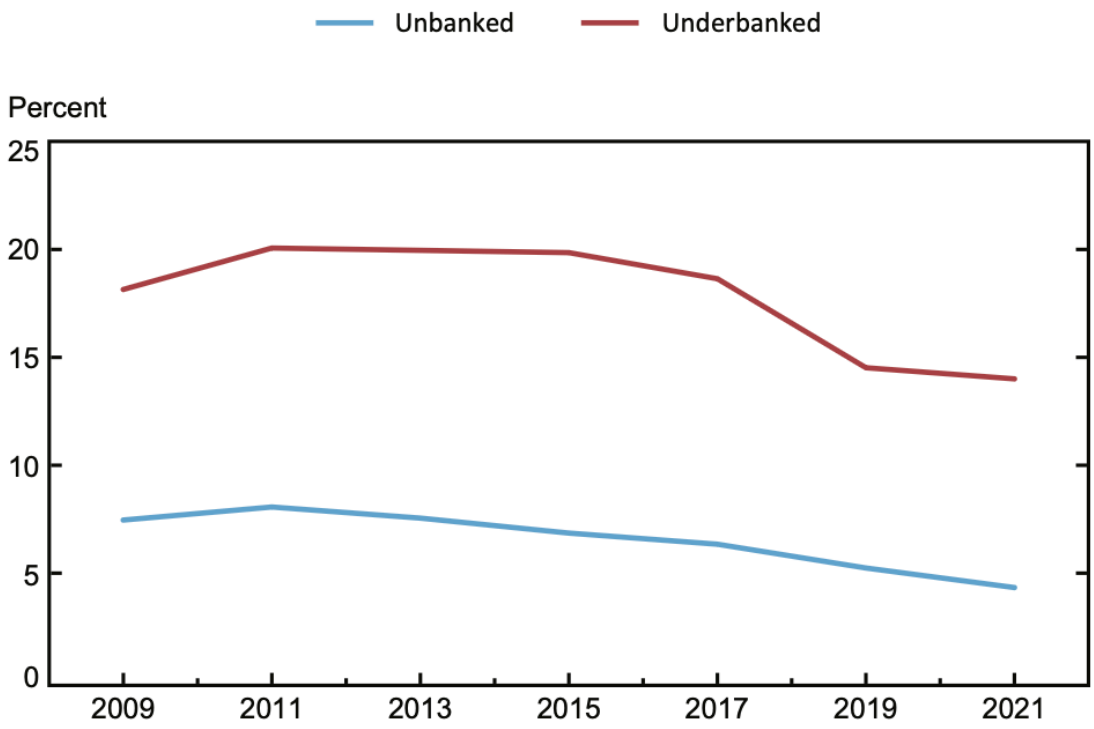


Figure 1: Shares of households that are unbanked and underbanked

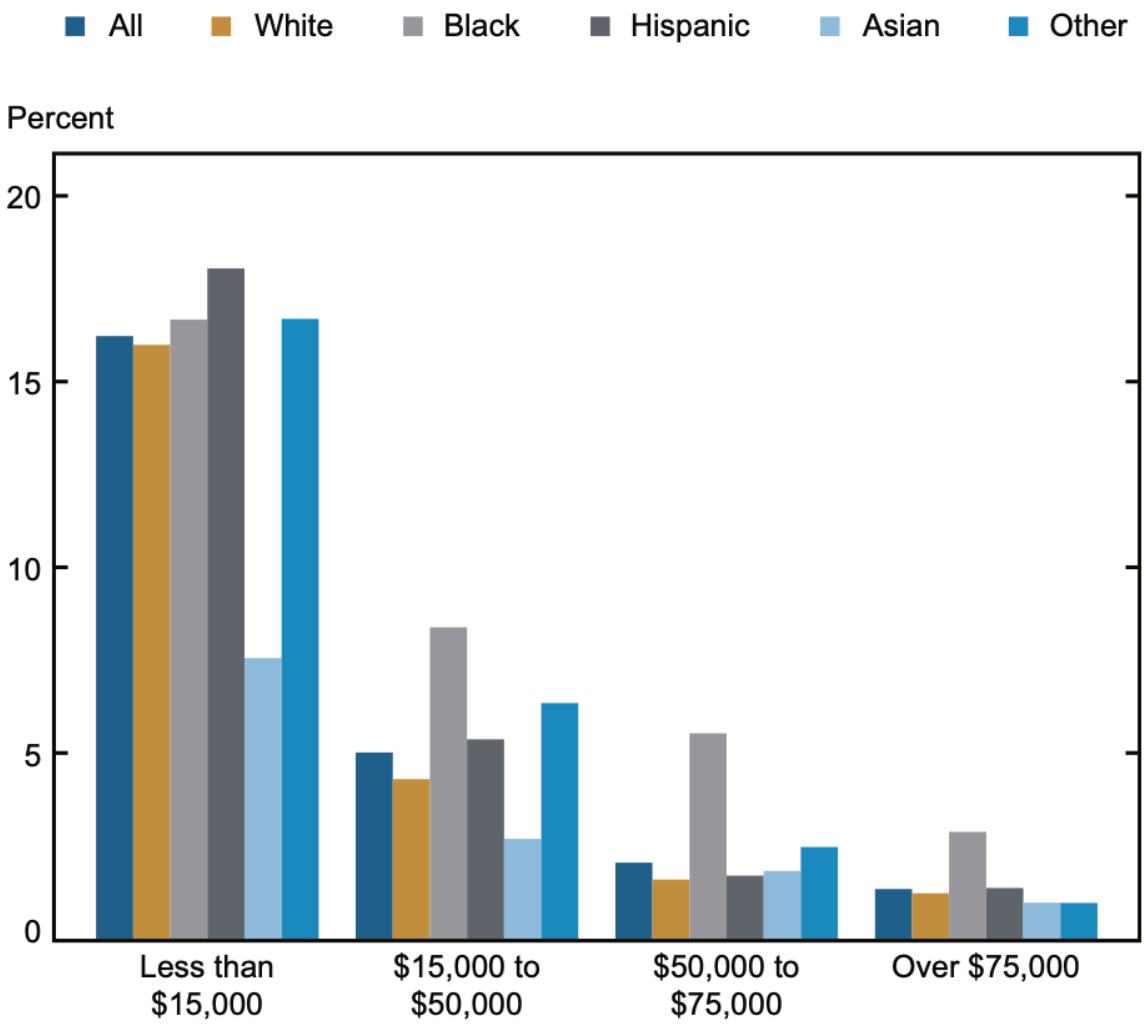


Figure 2: Share without a bank account by income and race

Income differences do not fully explain disparities in being unbanked across racial and ethnic groups. Even within the same income ranges, outcomes vary sharply. Among people making less than $15,000 per year, nearly all demographic groups had unbanked rates above 15%, except for non-Hispanic Asians, whose unbanked rate was roughly half that level. Meanwhile, for incomes above $75,000, the overall unbanked rate was 1.3%, but for non-Hispanic Black individuals it rose to 2.9%, meaning they were more than twice as likely to be unbanked as the population average in that income band.

US citizens have a few common reasons to not have a personal account, according to the survey. The most popular reason is the lack of money to meet the minimum balance requirements — 40 percent of respondents; because of privacy issues and mistrust of banks — 8.4 and 13.2 percent respectively;

The problem of this research is the centering on the US market, while the emerging markets remain unobserved. However, the research provides a powerful methodology and concepts.

The evaluation of financial inclusion by OBrien and Ulhoa (2022) opens the other perspective. According to the study, Financial inclusion is defined as the use of financial services by individuals and firms. The main question of the research is whether the rise of financial inclusion reduces poverty.

The time-scale is from 2014 to 2022. According to the study, account ownership increased significantly over the years; digital financial services (DFS) expanded rapidly; and government transfers boosted account creation (OBrien and Ulhoa, 2022).

In fact, the work describes the weak sides of such a growth: a) the poverty reduction evidence is mixed; b) the usage of personal accounts remains shallow; and c) many accounts remain dormant.

According to the study, financial inclusion increased noticeably over the time period. However, the impact on poverty and welfare remains unclear. The rise in inclusion affects welfare indeed, but it is not general, context-dependent, and heterogeneous. The work shows a strong influence of gender: the gap is global, and when access improves, the usage of accounts remains limited, and the impact is uneven.

As follows, financial inclusion may improve resilience (long-term, indirect effects), but does not consistently produce immediate, measurable welfare gains.

The Financial Action Task Force (FATF) (2025) noticed that the level of financial inclusion does not influence economic development directly.

Moreover, the authors highlighted that an active expansion of mobile banking does not translate into active usage. Figure 3 illustrates that only 26 percent of mobile money accounts are in active usage; Approximately 38 percent of mobile money accounts are active within 90 days. It could be another proof of the relatively small effect of an expansion.

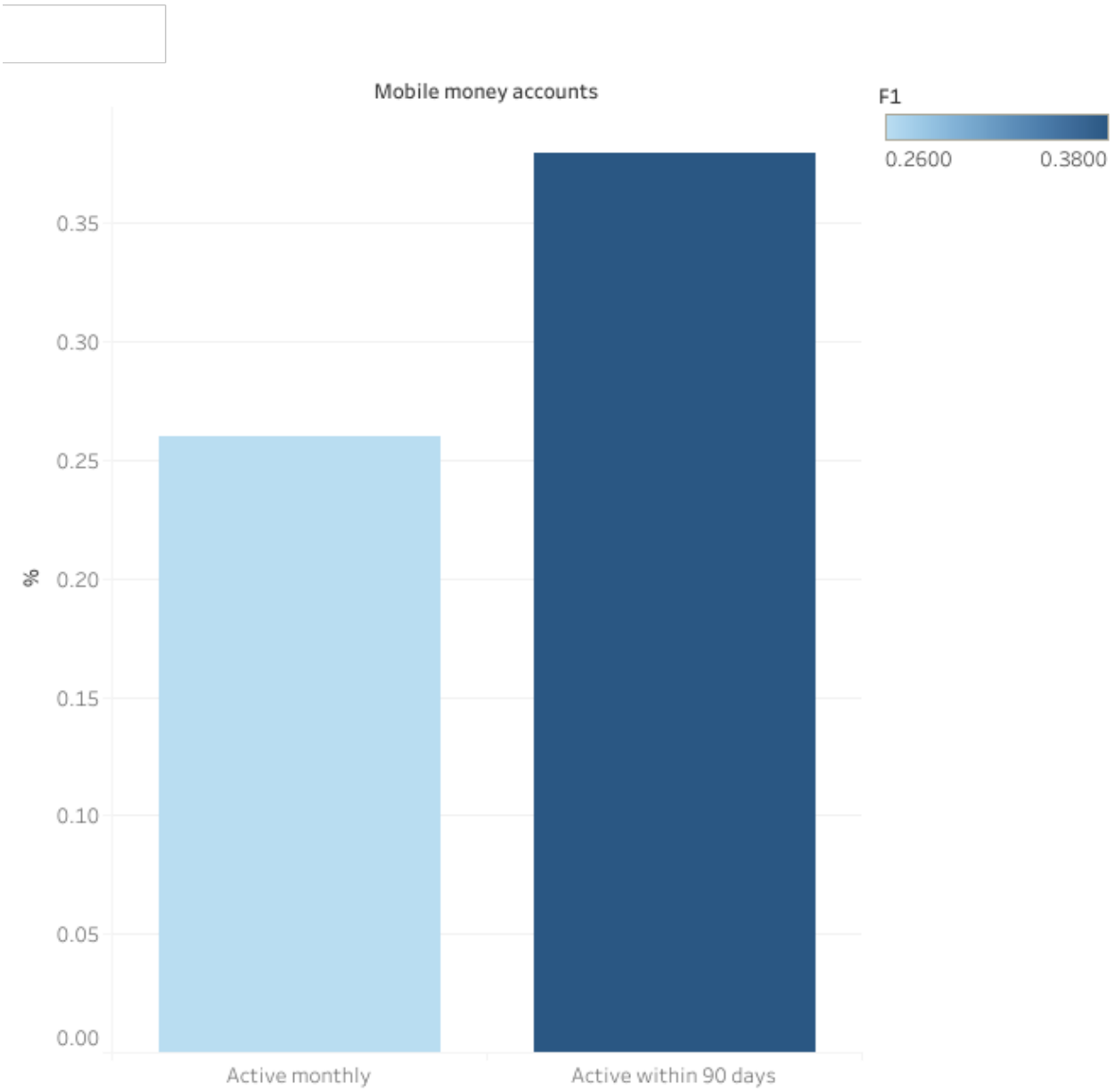


Figure 3: The activity of mobile accounts

Another finding is that the global average cost of sending $200 abroad is 6.2%, compared to a target of only 3%. Hence, it is obvious that cross-border pay-

ment inefficiencies directly limit financial inclusion outcomes, especially for low-income households.

The study confirmed the existence of a gender gap: 4% globally, 6% in developing economies, and up to 13% in Sub-Saharan Africa and MENA. Moreover, women use mobile bank accounts less actively. Mobile technologies increase access but not inequality itself: among the richest 60%, the account ownership percentage is 79 percent, while among the poorest 40%, it is slightly less: 72 percent.

COVID-19 showed that mobile financial inclusion is highly context-dependent and responsive to structural disruptions, because of that highly increased remote accounts openings and digital transactions. For instance, the amount of digital transactions in Africa rose to 35 percent of GDP by 2022.

Therefore, while mobile technologies have significantly expanded access to financial services in emerging markets, their socio-economic impact is constrained by low active usage, persistent gender and income inequalities, and structural barriers related to trust, literacy, and product design. As a result, mobile-driven financial inclusion remains incomplete and often superficial.

While mobile technologies have expanded access to financial services, institutional and regulatory constraints may limit their effectiveness. For instance, the European Banking Authority (2022) highlights that compliance with sanctions and AML/CFT [2] requirements can lead to unintended financial exclusion, particularly for vulnerable populations such as refugees.
Chilufya and Fernando C. Saldivar (2025) extends the impact of sanctions on financial inclusion. Targeted sanctions can lead banks to avoid entire regions, as in Africa. Because of the necessity of monitoring clients, avoiding sanctioned entities, and performing strict KYC [3], the common behaviour of banks is:

- reduction operations,
- avoiding new clients,
- and becoming extremely risk-averse.

The findings suggest that banks tend to withdraw from markets rather than incur the risk of regulatory penalties. Financial inclusion constitutes a critical determinant of economic development and poverty reduction; however, it

[2] AML/CFT stands for Anti-Money Laundering (AML) and Countering the Financing of Terrorism (CFT)

[3] Know Your Customer standards, which are protocols aiming to protect financial institutions from corruption, money laundering, etc.

is also significantly affected by sanctions.

Another study by Ayadi (2025) describes financial inclusion as the ability to participate confidently, not just access. According to the study, three geopolitical channels undermine financial inclusion:

1. Conflict (destroys infrastructure and confidence, systems become politicized).

2. Sanctions (disrupt payments and banking).

3. Desinformation (reduces trust in financial innovation).

Therefore, financial inclusion appears to be highly sensitive to the political and macroeconomic environment. While AML/KYC regulations have been introduced as mechanisms to safeguard financial systems, they may also constitute substantial barriers to financial inclusion.

Belozyorov and Sokolovska (2020) provides empirical evidence on the macroeconomic impact of sanctions, showing that trade and foreign direct investment declined significantly following their introduction. Importantly, the authors argue that digital transformation and financial inclusion can serve as mechanisms to mitigate these negative effects by improving payment efficiency, expanding access to financial services, and supporting income-generating activities. However, the effectiveness of such measures is uneven and depends on structural factors such as income inequality and regional disparities.

Thus, the hypothesis of a direct effect of mobile technologies on financial inclusion cannot be unequivocally confirmed, as its effectiveness depends on inequality levels (notably between capital regions and peripheral areas in Russia) and on the quality of infrastructure and institutional frameworks.

On the other hand, there is another way to increase financial inclusion. Rami (2025) noticed that FinTech can provide financial services to sanctioned populations without violating regulations with specific regulations.

Financial inclusion is not just an economic phenomenon; it is also an institutional process, especially under sanctions. In other words, the impact of financial inclusion under sanctions depends on the ability of financial technologies to operate within regulatory frameworks. By integrating AML/CFT controls, sanctions screening, and digital identity verification into platform architecture, fintech solutions can partially restore financial access without violating regulatory frameworks. However, the effectiveness of such models

depends on regulatory cooperation, infrastructure, and the ability to balance compliance costs with accessibility.

The study of Bayar et al. (2021) finds that mobile internet is a crucial factor for financial inclusion. The research highlights the correlation between mobile subscriptions and internet usage, with access to financial institutions and financial markets.

According to the study, a 1-unit increase leads to approximately a 0.0015 increase in inclusion. Hence, the effect is present but relatively small. Moreover, the impact is relative: the Czech Republic has a negative effect, while Hungary and Poland have a positive impact, which can be interpreted as the results are heterogeneous.

Important that the relationship is structural and not temporary, which supports the previous studies. Moreover, while mobile technologies drive financial inclusion, it is a one-way directional driver; the Internet itself has a two-way relationship: distribution and development of the Internet affects financial inclusion, and vice versa, inclusion improves the Internet. Therefore, the technologies.

Bayar et al. (2021) suggests using the cointegration test developed by, which takes into account cross-sectional dependence and structural breaks, while allowing for differences in variance and serial correlation (Joakim Westerlund and David L. Edgerton, 2008). It also permits structural breaks in both the intercept and trend that may vary across countries. The Equations 2.1, 2.2, and 2.3 are presented below.

$$y_{i,t} = \alpha_i + t_i + \delta_i D_{i,t} + x'_{i,t}\beta_i + (D_{i,t}x'_{i,t}y_i + z_{i,t}) \tag{2.1}$$

$$x_{i,t} = x_{i,t-1} + w_{i,t'} \tag{2.2}$$

$$D_{i,t} = \begin{cases} 1, t > T_i \\ 0, \text{other} \end{cases} \tag{2.3}$$

Where i is a cross-section, t are time period, and D are dummys.

Taken together, these results indicate that mobile phone penetration and Internet usage have a statistically significant positive impact on financial inclusion in both the short and long run. However, the magnitude of this effect is relatively small, suggesting that technological expansion alone is insufficient to generate substantial improvements in financial inclusion. Furthermore, the impact varies across countries, highlighting the importance of institutional

and structural factors.

However, Osabutey and Jackson (2024) has challenged the studies. Their study leads to the conclusion that many studies present mobile money as highly beneficial; however, this is a biased observation. So, the benefits of the expansion of mobile technologies, as a rule, go to the middle class, while the effect on the poorest is dramatically lower. Also, the benefits that are distributed across stakeholders are unequal. The main finding of the study, which is highly suitable for this thesis, is that while access rises, usage remains limited and outcomes are unclear. In other words, financial inclusion does not lead to real inclusion directly. For the improvement of inclusion, the authors highlight three vital infrastructure limitations, listed below.

1. Poor internet.
2. Weak electricity.
3. Old phones.

These barriers are especially highly relevant in emerging markets.

Recent research emphasises the growing importance of financial technology (fintech) as a tool for promoting financial inclusion in developing and emerging markets. Fintech is defined as the use of technology to simplify and automate the delivery of financial services, thereby reducing operational costs and improving accessibility (Ediagbonya and Tioluwani, 2022)

The literature suggests that fintech has the potential to address long-standing inefficiencies in traditional banking systems and expand access to financial services, particularly for low-income and unbanked populations. Digital financial solutions such as mobile payments, online banking, and automated services are seen as key drivers of financial inclusion and economic participation. However, empirical findings indicate that despite the expansion of these technologies, the financial inclusion gap remains significant in many developing economies.

Ediagbonya and Tioluwani (2022) identify multiple structural barriers that limit the effectiveness of fintech in achieving inclusive financial systems. These include widespread illiteracy, inadequate infrastructure, unreliable electricity supply, poor mobile network coverage, and frequent system failures in banking services. Additionally, high transaction costs and information asymmetry further discourage individuals from actively using financial services, even

when access is technically available.

A key contribution of the study is the application of institutional theory, which highlights the role of weak institutional environments in constraining financial inclusion. In contexts characterised by regulatory inconsistencies, insufficient consumer protection, and weak governance structures, fintech solutions struggle to achieve their full potential. The study argues that institutional voids significantly limit market participation and contribute to persistent financial exclusion.

Furthermore, the research demonstrates that access to financial services does not necessarily imply effective usage. Many individuals remain functionally excluded due to a lack of financial literacy, distrust in financial institutions, and limited ability to navigate digital platforms. In some cases, the transition toward digital financial systems may even exacerbate exclusion by marginalising individuals who lack technological skills or access to digital infrastructure.

Overall, the study concludes that while fintech offers substantial opportunities to enhance financial inclusion, its effectiveness is highly dependent on broader socio-economic and institutional conditions. Without improvements in infrastructure, regulatory frameworks, and financial education, fintech alone cannot bridge the financial inclusion gap in developing and emerging markets.

The study of Torres-Reyna (2010) employs panel data econometric techniques to analyse the relationship between financial inclusion and its determinants across countries over time. Panel data, also referred to as longitudinal or cross-sectional time-series data, allows observing the behaviour of entities (e.g., countries) across multiple time periods, thereby capturing both cross-sectional and temporal variation.

The baseline model is estimated using pooled Ordinary Least Squares (OLS). However, OLS does not account for unobserved heterogeneity across entities or over time, which may bias the estimates if omitted variables are correlated with the regressors. To address this limitation, panel data models are applied.

The fixed effects (FE) model is used to control for unobserved heterogeneity that is constant over time within each country. This approach allows isolating the within-country variation by removing time-invariant characteristics, such as institutional or structural differences between countries.

Formally, the FE estimator captures how changes in the explanatory variables

over time within a given country affect the dependent variable. The coefficients, therefore, reflect within-entity effects, meaning that the estimated relationship represents how the dependent variable changes over time when an independent variable increases by one unit, holding constant country-specific effects.

In contrast to fixed effects, the random effects (RE) model assumes that unobserved heterogeneity is uncorrelated with the explanatory variables. This model incorporates both within-entity and between-entity variation, allowing more efficient estimation when its assumptions hold.

The coefficients in the RE model reflect a combination of cross-sectional and time-series variation. Therefore, their interpretation differs from FE, as they capture the average effect of explanatory variables both across countries and over time.

To determine the appropriate specification between fixed and random effects, the Hausman test is employed. The null hypothesis states that the random effects model is consistent and preferred, while the alternative hypothesis favours the fixed effects model.

If the p-value of the Hausman test is below the conventional significance level (e.g., 0.05), the null hypothesis is rejected, indicating that the random effects estimator is inconsistent due to correlation between unobserved effects and regressors. In this case, the fixed effects model is preferred.

Moreover, the author suggests that several additional diagnostic tests be conducted to ensure the validity of the econometric results:

1. Breusch-Pagan LM test is used to determine whether random effects are preferable to pooled OLS by testing for the presence of panel effects,
2. Tests for time-fixed effects assess whether time-specific shocks should be included in the model,
3. Cross-sectional dependence tests (Breusch-Pagan LM and Pesaran CD) evaluate whether residuals are correlated across entities,
4. Serial correlation tests (Breusch-Godfrey/Wooldridge) check for autocorrelation in panel data,
5. Unit root tests (ADF) are applied to verify stationarity of the variables,

6. Heteroskedasticity tests (Breusch-Pagan) detect non-constant variance of residuals

However, it should be noted that the study reflects only on the methodology of the data analysis, not financial inclusion itself.

Despite significant growth in mobile financial inclusion, there is limited evidence that such expansion leads to consistent socio-economic improvements in markets, particularly under institutional constraints such as regulatory frameworks and geopolitical factors.

To sum up, the literature observed provides relevant evidence that mobile technologies improve access to financial services, leading to the expansion of financial inclusion. However, the existing studies clearly indicate that an increase in access does not directly lead to an active usage of financial services or a meaningful socio-economic impact.

The studies show that financial inclusion is a context-dependent process. While technological advancements reduce barriers related to distance and transaction costs, structural constraints such as income inequality, financial literacy, infrastructure limitations, and institutional quality significantly influence the effectiveness of mobile-based financial systems. Moreover, regulatory frameworks, including AML/KYC requirements and sanctions, may unintentionally restrict access and contribute to financial exclusion, particularly for vulnerable populations.

Therefore, the key finding is that the relationship between mobile technologies and inclusion with its socio-economic outcomes cannot be established and fully explained by access-based indicators alone. This gap motivates the present study, which aims to assess not only the expansion of financial inclusion through mobile technologies but also its actual effectiveness and impact under varying structural and institutional conditions in emerging markets.

2.2 Research Gap

Several contradictions were observed in the literature. On the one hand, mobile technologies are widely recognized as a key driver of economic development and financial inclusion. On the other hand, some research provides empirical evidence that the influence of mobile technologies' penetration is quite limited, heterogeneous, and unevenly distributed across different population groups. That suggests that the persistence of inactive accounts, low usage rates, and the benefits indicate that financial inclusion driven by mo-

bile technologies remains incomplete.

3 Methodology & Data

3.1 Hypotheses

H_1: **Mobile penetration increases the probability of active financial account usage, controlling for income and infrastructure** (Equation 3.1)

$$Y_{it} = \beta_1 X_{mob_{it}} + \beta_2 X_{dem_{it}} + \beta_3 X_{GDP_{it}} + \beta_4 X_{br_{it}} + \alpha_i + \chi_t + \varepsilon_{it} \tag{3.1}$$

H_2: **Higher regulatory stringency reduces the effect of mobile penetration on active financial account usage.** (Equation 3.2)

$$Y_{it} = \beta_1 X_{mob_{it}} + \beta_2 X_{gov_{it}} + \beta_3 (X_{mobit} \times X_{gov_{it}}) + \gamma_1 X_{dem_{it}} + \gamma_2 X_{GDP_{it}} + \gamma_3 X_{Q_{it}} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3.2}$$

Where, where i denotes the country, and t denotes time. The terms α_i and λ_t represent country and time fixed effects, respectively. Robust standard errors are used to account for heteroskedasticity.

H_3: **In countries where the index of trust in legislation is below the sample median, the effect of increased mobile penetration on the share of active accounts is statistically significantly lower than in countries where the index is above the median.** (Equation 3.3)

$$Y_{it} = \beta_1 X_{mob_{it}} + \beta_2 (X_{mob_{it}} \times X_{Tlow_{it}}) + \gamma X_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3.3}$$

Dummy:

$$X_{T_{low}} = \begin{cases} 1, \text{if trust}_i < \text{median} \\ 0, \text{otherwise} \end{cases} \tag{3.4}$$

Equation 3.17 restates the specification in 3.3 with explicit notation of the control vector.

3.2 Variables

For the future tests and models, the following variables are used:

- Y = usage
- $X_{mob_i t}$ = mobile cellular subscriptions per 100 people

- X_{gov_it} = government effectiveness
- X_{dem_it} = democracy level
- $X_{GDP_{log_it}}$ = GDP per capita
- X_{tr_it} = trust in government
- X_{Qit} = regulatory quality
- $X_{br_{it}}$ = broadband penetration per 100 people.

The democracy variable was excluded from the final specifications due to its limited within-sample variation, particularly in the OECD subsample, where values remain within a narrow range. As a result, the variable is weakly identified in a fixed effects framework and may absorb the influence of other institutional factors, leading to unstable and economically implausible coefficient estimates.

3.3 Data tests

Before conducting a deep econometric analysis, several tests were performed to assess data quality and suitability. The tests check the data for potential violations of OLS assumptions (heteroskedasticity, serial correlation, cross-sectional dependence), panel effects, and the choice between random effects and fixed effects.

First, in chapters 3.3.1 - 3.3.3, the data overview is presented.

Also, the following tests are performed in this study:

1. LM test,
2. Time Effects test,
3. Hausman test,
4. Wooldridge test,
5. Breusch-Godfrey test,
6. Pesaran cross-sectional dependence test,
7. Breusch-Pagan test.

These tests are presented from Chapter 3.3.4 to Chapter 3.3.10.

3.3.1 Data description

Table 1: Descriptive Statistics of Variables

Variable	Min	1st Qu.	Median	Mean	Max
gov_eff	-0.1710	0.3367	1.0735	1.0292	2.2330
democracy	0.1600	0.7665	0.8530	0.8096	0.9210
mobile	80.35	111.22	122.51	124.10	178.72
trust	15.00	28.46	39.42	41.68	83.17
usage	22.63	66.59	91.28	81.34	100.00
GDP	10504	28932	43599	44946	132170
quality	14.42	67.98	84.45	79.69	99.05
broadband	1.313	22.616	29.675	28.451	47.943

End of the table

3.3.2 VIF

Table 2: Variance Inflation Factors (VIF)

Variable	VIF
mobile	1.1387
broadband	3.1633
gov_eff	8.4810
quality	4.4355
trust	2.1178
GDP	3.2635
democracy	1.7832

End of the table

3.3.3 Correlation

Table 3: Correlation Matrix

	usage	**mobile**	**broadband**	**gov_eff**	**quality**	**trust**	**GDP**	**democracy**
usage	1.0000	-0.1382	0.8201	0.8149	0.7291	0.2716	0.6961	0.4706
mobile	-0.1382	1.0000	-0.3143	-0.1998	-0.2221	0.0474	-0.2124	-0.1996
broadband	0.8201	-0.3143	1.0000	0.7664	0.6920	0.2607	0.7226	0.5102
gov_eff	0.8149	-0.1998	0.7664	1.0000	0.8685	0.5411	0.7887	0.5705
quality	0.7291	-0.2221	0.6920	0.8685	1.0000	0.3572	0.6948	0.5456
trust	0.2716	0.0474	0.2607	0.5411	0.3572	1.0000	0.5153	0.0446
GDP	0.6961	-0.2124	0.7226	0.7887	0.6948	0.5153	1.0000	0.4896
democracy	0.4706	-0.1996	0.5102	0.5705	0.5456	0.0446	0.4896	1.0000

End of the table

For a clarification of the correlation, the results were also illustrated in a graphic form in the Picture 4.

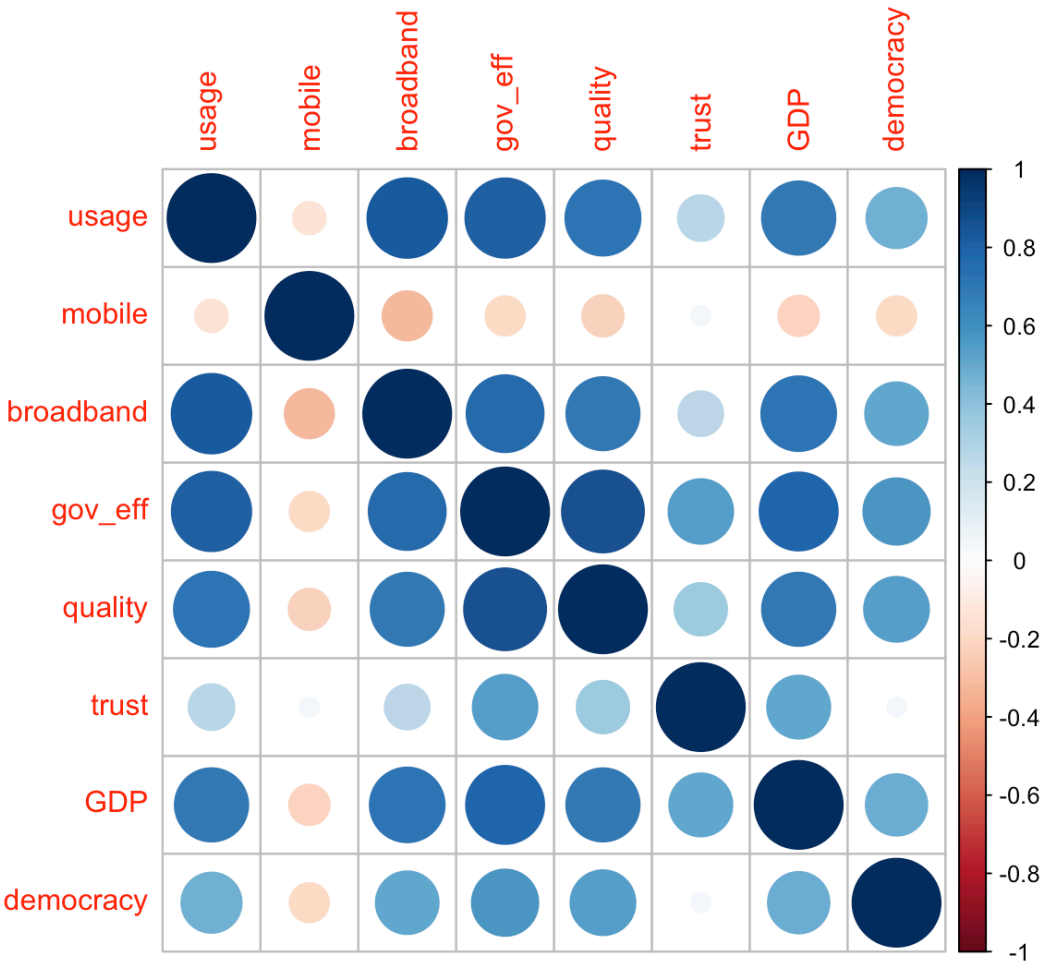


Figure 4: Correlation matrix

Descriptive statistics and correlation analysis were conducted to examine the structure of the data. The variables exhibit substantial variation across countries and over time, supporting the use of panel regression techniques.

The correlation matrix reveals strong positive relationships between financial service usage and key explanatory variables, particularly broadband penetration, government effectiveness, regulatory quality, and GDP. These results suggest that both digital infrastructure and institutional factors play an important role in explaining financial inclusion.

In contrast, mobile penetration shows a weak and negative correlation with financial service usage, indicating that mobile access alone does not necessarily translate into active use of financial services. This finding is consistent with the distinction between access and effective usage.

Some institutional variables, particularly government effectiveness and regulatory quality, exhibit relatively high pairwise correlation. However, the Variance Inflation Factor (VIF) analysis indicates that multicollinearity is not severe, with all values remaining below critical thresholds. The highest VIF is observed for government effectiveness, suggesting partial overlap with other institutional indicators, but not to a degree that compromises estimation reliability.

Overall, the diagnostic analysis supports the validity of the empirical specification and confirms that the selected variables capture distinct but related dimensions of financial inclusion and institutional development.

Moreover, additional tests were applied further:

3.3.4 LM Test

The BreuschPagan Lagrange Multiplier (Equation 3.5) test is used to determine whether panel effects are present in the data. In other words, it evaluates whether unobserved individual-specific effects exist across countries.

$$LM_n = \frac{1}{n} \nabla_{\theta,n}^t \hat{V_n} \nabla_{\theta,n} \tag{3.5}$$

Where,

$$\nabla_{\theta,n} = \nabla_\theta (ln[L(\hat{\theta}_n^R, \xi_n)]) \tag{3.6}$$

If the null hypothesis is not rejected, the data can be adequately modeled using pooled OLS, implying no significant differences across cross-sectional

units. However, rejection of the null hypothesis indicates the presence of unobserved heterogeneity, meaning that country-specific effects influence the dependent variable.

In the context of this study, rejecting the null hypothesis implies that financial inclusion differs systematically across countries due to unobserved factors such as institutional structure, culture, or economic development. Therefore, panel data models are required.
Hypotheses:

- H_0: Restrictions are valid ($Var(\alpha) = 0$),
- H_1: Dependence exists.

After the execution of the test in R, the following results were received: $\chi^2 = 36.393$ and $p_{-value} = 1.613 \times 10^{-9}$. Therefore, the Breusch-Pagan Lagrange Multiplier test strongly rejects the null hypothesis of no panel effects ($p < 0.001$). This indicates that unobserved country-specific effects are present in the data and that the use of pooled OLS would be inappropriate.

In other words, financial services significantly and systematically differ across the countries observed due to unobserved characteristics. Hence, the panel data methods are required for the study.

3.3.5 Time Effects test

The test examines whether time-specific effects affect the predictors across all the countries.

Hypotheses: H_0: $\lambda_t = 0$

If the null hypothesis is rejected, it indicates that global or common temporal factorssuch as technological progress, global financial trends, or macroeconomic shockssignificantly influence financial service usage.

The BreuschPagan test for time effects rejects the null hypothesis of no time-specific effects ($\chi^2 = 9.266$ and $p < 0.01$). This result indicates that common temporal shocks or trends significantly affect financial service usage across countries. In other words, financial inclusion is influenced not only by country-specific characteristics, but also by period-specific developments. Therefore, the inclusion of time fixed effects is empirically justified.

3.3.6 Hausman test

The Hausman test, given in Equation 3.7, is used to determine whether the fixed effects or random effects model is more appropriate.

$$H = (\hat{\beta_{FE}} - \hat{\beta_{RE}})'[\hat{V}(\hat{\beta_{FE}}) - \hat{V}(\hat{\beta_{RE}})]^{-1}(\beta_{FE} - \hat{\beta_{RE}}) \tag{3.7}$$

Where,

- β_{FE} = vector of coefficients from the Fixed Effects model (consistent)
- β_{RE} = vector of coefficients from the Random Effects model (efficient under H_0)

The key distinction between the two approaches lies in the treatment of unobserved heterogeneity. The random effects model assumes that unobserved country-specific effects are uncorrelated with the explanatory variables, while the fixed effects model allows for such correlation.

Hypotheses for the test follow:

- H_0 Re is consistent (no correlation),
- H_1 FE is consistent (correlation exists).

If the null hypothesis is rejected, it indicates that unobserved country-specific characteristicssuch as institutional quality or structural economic differencesare correlated with the regressors. In this case, the random effects estimator becomes inconsistent, and the fixed effects model is preferred.

Given the cross-country nature of the dataset, it is highly plausible that institutional and structural differences influence both financial inclusion and explanatory variables, supporting the use of fixed effects.

Table 4: Hausman test results

Statistic	**Value**
Model	usage $\sim$ mobile + broadband + gov_eff + quality + trust + GDP + democracy
Test	Hausman Test
χ^2	89.147
Degrees of Freedom	7
p-value	$< 2.2 \times 10^{-16}$
Conclusion	Reject H_0 (RE inconsistent)

End of the table

According to the results (given in the Table 4), the Hausman test very strongly rejects the null hypothesis that the random effects estimator is consistent ($\chi^2 = 89.147$ and $p < 0.001$). This indicates that unobserved country-specific effects are correlated with the explanatory variables. As a result, the random effects model is inappropriate for this dataset, and the fixed effects specification is preferred. The magnitude of the test statistic provides particularly strong evidence that structural differences across countries are systematically related to the determinants of financial inclusion and must therefore be controlled for explicitly.

3.3.7 Serial Correlation (Wooldridge test)

The Wooldridge test for serial correlation examines whether the error terms are correlated over time within each cross-sectional unit.

Serial correlation violates the classical regression assumption of independently distributed errors and may lead to biased standard errors and incorrect statistical inference.

In panel data, serial correlation is common, as economic variables tend to evolve gradually over time. For example, financial inclusion levels in a given country are likely to be persistent across periods.

Therefore, if serial correlation is detected, it is necessary to use robust estimation techniques, such as clustered standard errors, to ensure consistent inference.

According to this test, if first difference residuals are correlated:

$$\Delta y_{it} = \Delta x_{it}\beta + \Delta U_{it} \tag{3.8}$$

Then use:

$$\hat{e}_{it} = \rho \hat{e}_{it-1} + \eta_{it} \tag{3.9}$$

The test (Equation 3.9) checks if autocorrealtion coefficient $\rho = -0.5$.
The Wooldridge test indicates the presence of serial correlation in the panel model ($F = 22.373$, $p < 0.001$). This means that the residuals are correlated over time within countries, which is consistent with the persistent nature of financial inclusion indicators. Although serial correlation does not invalidate the fixed effects model, it affects the reliability of conventional standard errors. Therefore, standard errors clustered at the country level are required to obtain valid statistical inference.

3.3.8 Breusch-Godfrey test

The Breusch-Godfrey test provides an additional check for autocorrelation in panel data models. The test is presented in Equation 3.10.

$$LM = (n - p)R^2 \tag{3.10}$$

The purpose of the test is similar to the Wooldridge test. However, it is less suited for panel FE settings. Therefore, it is used as a complementary diagnostic tool rather than the primary test.

The hypotheses H_0 of no autocorrelation should be rejected if $LM > \chi^2_{crit}$.
The BreuschGodfrey test does not reject the null hypothesis of no serial correlation (($\chi^2 = 0.440$), (p = 0.507)). On its own, this would suggest that autocorrelation is not a serious issue. However, the Wooldridge test shows different results.
However, this result conflicts with the Wooldridge test, which clearly detected serial correlation. In panel data settings, the Wooldridge test is usually considered more reliable and more appropriate for fixed effects models. Therefore, the BreuschGodfrey result should be treated as a supplementary check rather than the decisive test. The main conclusion should still follow the Wooldridge result: serial correlation is present.

3.3.9 Cross-Sectional Dependence test (Pesaran CD)

The Pesaran CD test is used to detect cross-sectional dependence in panel data models.

The hypotheses of this test are as follows:

- H_0: No cross-sectional dependence,
- H_1: Cross-sectional dependence exists.

The null hypothesis assumes that residuals are independent across cross-sectional units, meaning that shocks affecting one country do not influence others.

However, in macroeconomic panel data, cross-sectional dependence may arise due to global shocks, financial integration, or regional spillovers.

If cross-sectional dependence is present, standard estimation methods may produce biased results. In this study, the absence of cross-sectional dependence suggests that country-specific shocks dominate and that the panel units

can be treated as largely independent.

The Pesaran CD test does not reject the null hypothesis of no cross-sectional dependence ($z = -1.417$, $p = 0.157$). This suggests that, after controlling for the explanatory variables and fixed effects, the residuals are not significantly correlated across countries. In substantive terms, the remaining unexplained variation appears to be primarily country-specific rather than driven by common cross-sectional shocks. Although some country pairs were omitted due to limited overlap in time periods, this does not materially alter the interpretation of the result.

3.3.10 Heteroscetasticity (Breusch-Pagan test)

The BreuschPagan test is used to detect heteroskedasticity in the error term, for instance, if the variance of residuals is constant across observations.

Heteroskedasticity violates one of the key assumptions of classical regression models and may lead to inefficient estimates and biased standard errors.

In cross-country data, heteroskedasticity is expected due to differences in economic size, institutional development, and data variability. Therefore, the Breusch-Pagan test (Equation 3.11) was executed.

$$Var(\varepsilon_{it}) = \delta^2 \neq const \tag{3.11}$$

To address this issue, robust standard errors are employed in all model specifications, ensuring valid statistical inference despite the presence of heteroskedasticity.

The studentized BreuschPagan test rejects the null hypothesis of homoskedasticity ($BP = 30.639$ and $p < 0.001$). This indicates that the variance of the residuals is not constant across observations. Such heteroskedasticity is expected in cross-country panel data, where countries differ substantially in economic scale, institutional quality, and variability of outcomes. To address this issue, robust standard errors clustered at the country level are employed in all estimated models.

3.3.11 Tests conclusions

Overall, the diagnostic tests support the use of a panel fixed effects specification with time effects and clustered standard errors. The LM test confirms the presence of panel effects, while the time effects test indicates that common temporal shocks should be taken into account. The Hausman test shows

that fixed effects are preferable to random effects, implying that unobserved country-specific heterogeneity is correlated with the explanatory variables.

However, at the same time, the results of the Wooldridge and Breusch-Godfrey tests are contradictory. While the BreuschGodfrey test does not reject the null hypothesis, the Wooldridge test strongly indicates serial correlation in the panel.

According to the previous studies by Born and Breitung (2016) and Wooldridge (2016), the Wooldridge test is specifically designed for fixed effects panel data models and remains valid in settings with a relatively small number of time periods and a large cross-sectional dimension. In contrast, traditional tests such as the BreuschGodfrey test are not well-suited for fixed effects models, as the transformation of residuals and the presence of individual-specific effects distort their statistical properties. Moreover, studies highlight that standard LM-type tests may suffer from bias and incorrect limiting distributions in panels with fixed effects and short time dimensions. Although the Wooldridge test is not derived from classical LM or Wald principles, it provides a practical and widely accepted approach in applied panel data analysis.

Therefore, the greater weight in the analysis was given to the Wooldridge test. Hence, the presence of serial correlation is concluded based on the Wooldridge test, and appropriate corrections, such as clustered standard errors, are employed in subsequent estimations.

3.4 Hypothesis 1

H_1: Mobile penetration increases the probability of active financial account usage, controlling for income and infrastructure

The hypothesis H_1 is defined as:

$$Y_{it} = \beta_1 X_{mob_{it}} + \beta_2 X_{dem_{it}} + \beta_3 X_{GDP_{it}} + \beta_4 X_{br_{it}} + \alpha_i + \chi_t + \varepsilon_{it} \tag{3.12}$$

To further examine the robustness of the results, additional model specifications are estimated.

First, a reduced model excluding mobile penetration is considered in the Equation 3.13:

$$Y_{it} = \beta_1 X_{dem_{it}} + \beta_2 X_{GDP_{it}} + \beta_3 X_{br_{it}} + \alpha_i + \chi_t + \varepsilon_{it} \tag{3.13}$$

Second, a model excluding broadband penetration is estimated in the Equation 3.14:

$$Y_{it} = \beta_1 X_{mob_{it}} + \beta_2 X_{dem_{it}} + \beta_3 X_{GDP_{it}} + \alpha_i + \chi_t + \varepsilon_{it} \tag{3.14}$$

Finally, to examine whether the effect of mobile penetration depends on the level of digital infrastructure, an interaction model is specified in the Equation 3.15:

$$Y_{it} = \beta_1 X_{mob_{it}} + \beta_2 X_{br_{it}} + \beta_3 (X_{mob_{it}} \times X_{br_{it}}) + \beta_4 X_{dem_{it}} + \beta_5 X_{GDP_{it}} + + \alpha_i + \chi_t + \varepsilon_{it} \tag{3.15}$$

This specification in the Equation 3.15 allows testing whether mobile and broadband penetration act as complements or substitutes in explaining financial service usage.

3.5 Hypothesis 2

H_2: Higher regulatory stringency reduces the effect of mobile penetration on active financial account usage. (Equation 3.2)

The primary explanatory variable is mobile penetration, which represents access to digital communication infrastructure. Institutional quality is measured by government effectiveness, indicating the states capacity to implement policies and support financial systems. Regulatory quality is incorporated as an additional control variable, reflecting the governments ability to design and enforce sound regulatory frameworks. Trust in government is introduced in the extended model to account for confidence in public institutions. Control variables include democracy and GDP, which capture broader political and economic conditions.

For a proxy of financial usage, the following dataset was used: the share of adults making or receiving digital payments, obtained from the Global Findex database, as it captures actual engagement with financial services rather than mere access. Mobile penetration is measured by mobile cellular subscriptions per 100 people, reflecting the availability of digital infrastructure (GSM Association, 2025), (ITU and World Bank, 2026), (Eurostat et al., 2026), (World Bank, 2026), (OECD, 2026), (V-Dem, 2026), and (World Bank, 2021).

This set of variables enables a comprehensive test of H_2, capturing both technological and institutional aspects of financial inclusion while controlling for key macroeconomic and socio-political factors.

For clarity and familiarization, the R code is presented in Appendix A.

The workflow and testing of the models are below.

During the work on the model, two additional specifications of the hypothesis model were created: a) Equation 3.2 and b) Equation 3.16, which is extended by trust in government as an additional variable.

$$Y_{it} = \beta_1 X_{mob_{it}} + \beta_2 X_{gov_{it}} + \beta_3 (X_{mobit} \times X_{gov_{it}}) + \gamma_1 X_{dem_{it}} + \gamma_2 X_{GDP_{it}} + \gamma_3 X_{Q_{it}} + \gamma_4 X_{T_{it}} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3.16}$$

According to the original formulation of H_2, higher regulatory stringency was expected to reduce the effect of mobile penetration on financial inclusion. However, the empirical results do not support this expectation. Instead, the findings suggest that institutional quality has a positive direct association with financial inclusion, while the moderating effect of mobile penetration remains weak and inconsistent.

The results of the analysis are presented in Chapter III (4.2).

3.6 Hypothesis 3

Econometrically, this specification can be interpreted as a heterogeneous treatment effect model, where the effect of mobile penetration is allowed to vary across institutional regimes. The inclusion of the interaction term enables the identification of differential marginal effects, capturing whether mobile technologies are more or less effective in environments characterized by low institutional trust.

This approach provides a more flexible framework compared to linear interaction models, as it does not impose a continuous relationship between institutional quality and the effectiveness of mobile financial services.

The model is presented in the Equation 3.3.

$$Y_{it} = \beta_1 X_{mob_{it}} + \beta_2 (X_{mob_{it}} \times X_{Tlow_{it}}) + \gamma X_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3.17}$$

In the Equation 3.17 γX_{it} is a vector of the other variables:
$(\gamma X_{it} = \{X_{dem_{it}}, X_{GDP_{it}}\})$.

Therefore, the expanded model is shown below (Equation 3.18):

$$Y_{it} = \beta_1 X_{mob_{it}} + \beta_2 (X_{mob_{it}} \times X_{Tlow_{it}}) + \beta_3 X_{dem_{it}} + \beta_4 X_{GDP_{it}} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3.18)$$

β_1 and β_2 depict the effect of mobile penetration in countries with a high trust index (Equation 3.19) and the difference in low-trust countries (Equation 3.20), respectively. As follows from the hypothesis H_3, the effect is lower in countries with a low trust index. Hence, $\beta_2 < 0$.

$$\frac{\partial Y_{it}}{\partial X_{mob_{it}}} = \beta_1 \quad (3.19)$$

$$\frac{\partial Y_{it}}{\partial X_{mob_{it}}} = \beta_1 + \beta_2 \quad (3.20)$$

To test H_3, a dummy variable (Equation 3.21)indicating low institutional trust is constructed based on the sample median. Countries with trust values below the median are assigned a value of one, while others are assigned zero.

$$X_{T_{low}} = \begin{cases} 1, \text{if trust}_i < \text{median} \\ 0, \text{otherwise} \end{cases} \quad (3.21)$$

Unlike the continuous interaction used in H_2, the specification of H_3 introduces a discrete institutional threshold. This approach allows the identification of non-linear effects, in which the impact of mobile penetration may differ qualitatively across groups of countries rather than changing smoothly with institutional variables.

By splitting the sample based on the median level of trust, the model captures potential regime-specific behavior. This is particularly relevant in the context of financial inclusion, where institutional constraints may generate structural differences between low-trust and high-trust environments.

Since the indicator of low institutional trust is time-invariant, its main effect is absorbed by the country fixed effects and cannot be estimated separately. However, its interaction with time-varying variables, such as mobile penetration, remains identifiable. This allows the model to capture differences in slopes across institutional regimes while controlling for unobserved country-specific heterogeneity.

Should be mentioned that under H_3, the interaction coefficient is expected to be negative, indicating that the marginal effect of mobile penetration on financial service usage is lower in countries with weak institutional trust. This reflects the idea that low-trust environments may limit the adoption and effective use of financial technologies.

Moreover, the additional split models were created (Equations 3.22 and 3.23) for in-depth analysis.

For high-trust countries:

$$Y_{H_{it}} = \beta_1 X_{mob_{it}} + \beta_2 X_{dem_{it}} + \beta_3 X_{GDP_{it}} + \beta_4 X_{br_{it}} + \beta_5 X_{gov_{it}} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3.22)$$

And for low-trust countries:

$$Y_{L_{it}} = \beta_1 X_{mob_{it}} + \beta_2 X_{dem_{it}} + \beta_3 X_{GDP_{it}} + \beta_4 X_{br_{it}} + \beta_5 X_{gov_{it}} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3.23)$$

4 Results & Analysis

4.1 Hypothesis 1

The results of the baseline H_1 models (Equations 3.12, 3.13, and 3.14) are presented in the Table 5, indicating that mobile penetration alone does not have a statistically significant effect on the usage of financial services. Across all specifications, the coefficient on mobile penetration remains positive but insignificant, suggesting that access to mobile technology does not necessarily translate into active use of financial services.

Table 5: Estimation Results for Model H1

Variable	**Model 1**	**Model 2**	**Model 3**
Dependent variable: usage			
mobile	0.0364 (0.0853)		0.0342 (0.0912)
democracy	-65.89*** (17.13)	-65.79*** (17.78)	-67.45*** (17.36)
GDP	-8.25e-5 (0.0001)	-8.72e-5 (0.0001)	-0.0001 (0.0001)
broadband	1.103** (0.3893)	1.100** (0.3871)	
Fixed Effects			
country	Yes	Yes	Yes
year	Yes	Yes	Yes
Model Statistics			
S.E.: Clustered	by: country	by: country	by: country
Observations	127	127	127
R^2	0.95859	0.95839	0.95317
Within R^2	0.28832	0.28484	0.19520
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			

End of the table

In contrast, as shown in the Table 6, broadband penetration exhibits a positive and statistically significant effect across all relevant specifications. This finding highlights the importance of digital infrastructure in facilitating financial inclusion, suggesting that access to stable internet connectivity plays a more critical role than mobile access alone.

Table 6: Estimation Results for Model H_1 (Interaction Specification)

Variable	**Model 4**
Dependent variable: usage	
mobile	0.2795· (0.1473)
broadband	2.603*** (0.6987)
democracy	-61.03** (17.98)
GDP	-8.53e-5 (0.0001)
mobile × broadband	-0.0112* (0.0053)
Fixed Effects	
country	Yes
year	Yes
Model Statistics	
S.E.: Clustered	by: country
Observations	127
R^2	0.96067
Within R^2	0.32404
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	

End of the table

The interaction model provides additional insights. The interaction term between mobile and broadband penetration is negative and statistically significant, indicating that the effect of mobile penetration decreases as broadband penetration increases. Moreover, the mobile penetration term is positive and statistically significant at the 10 percent level. This suggests a substitution relationship between mobile and broadband technologies. In countries with limited broadband infrastructure, mobile technologies may play a more important role in enabling access to financial services. Conversely, in countries with widespread broadband access, the marginal contribution of mobile penetration is reduced.

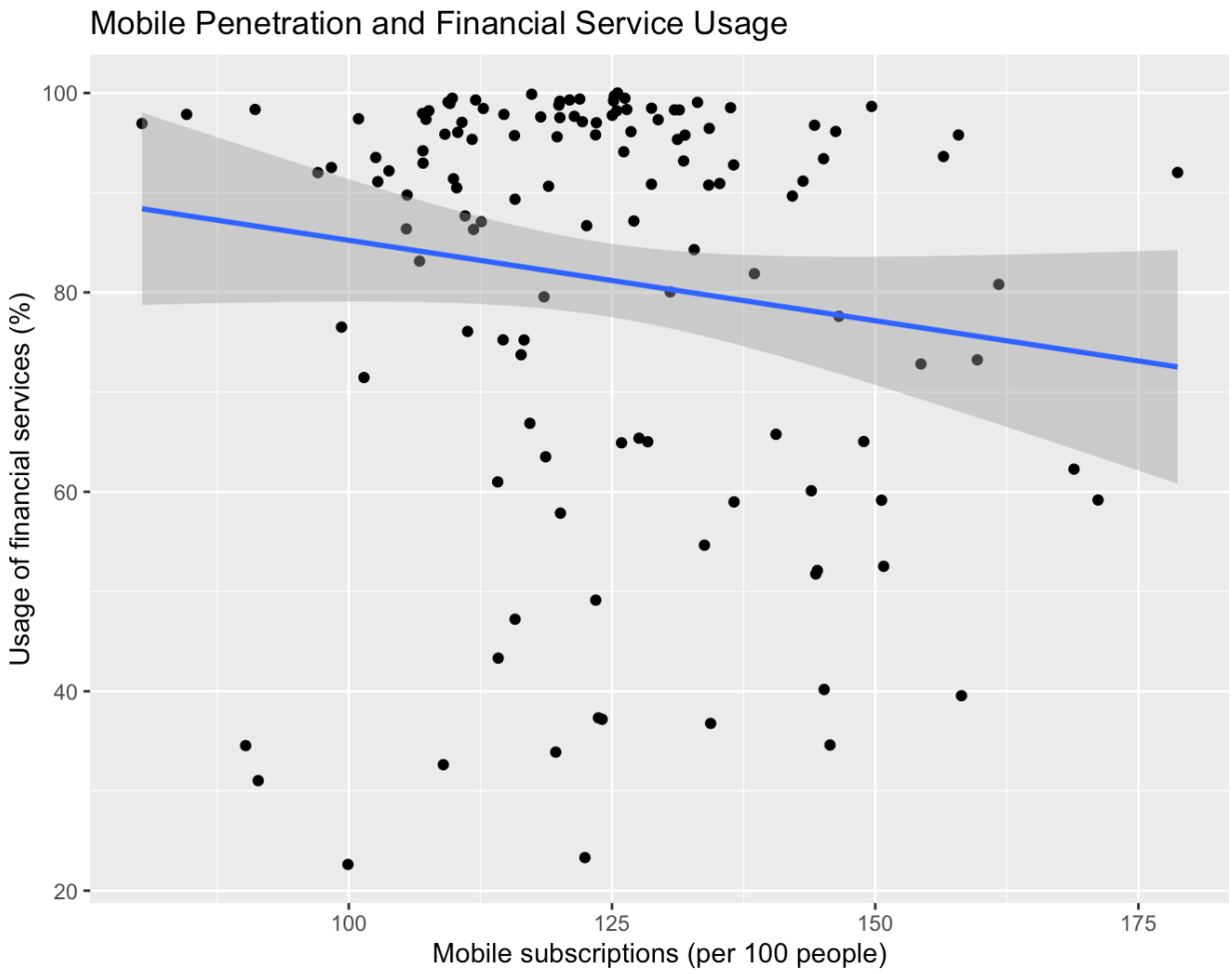


Figure 5: Mobile Penetration and Financial Service Usage

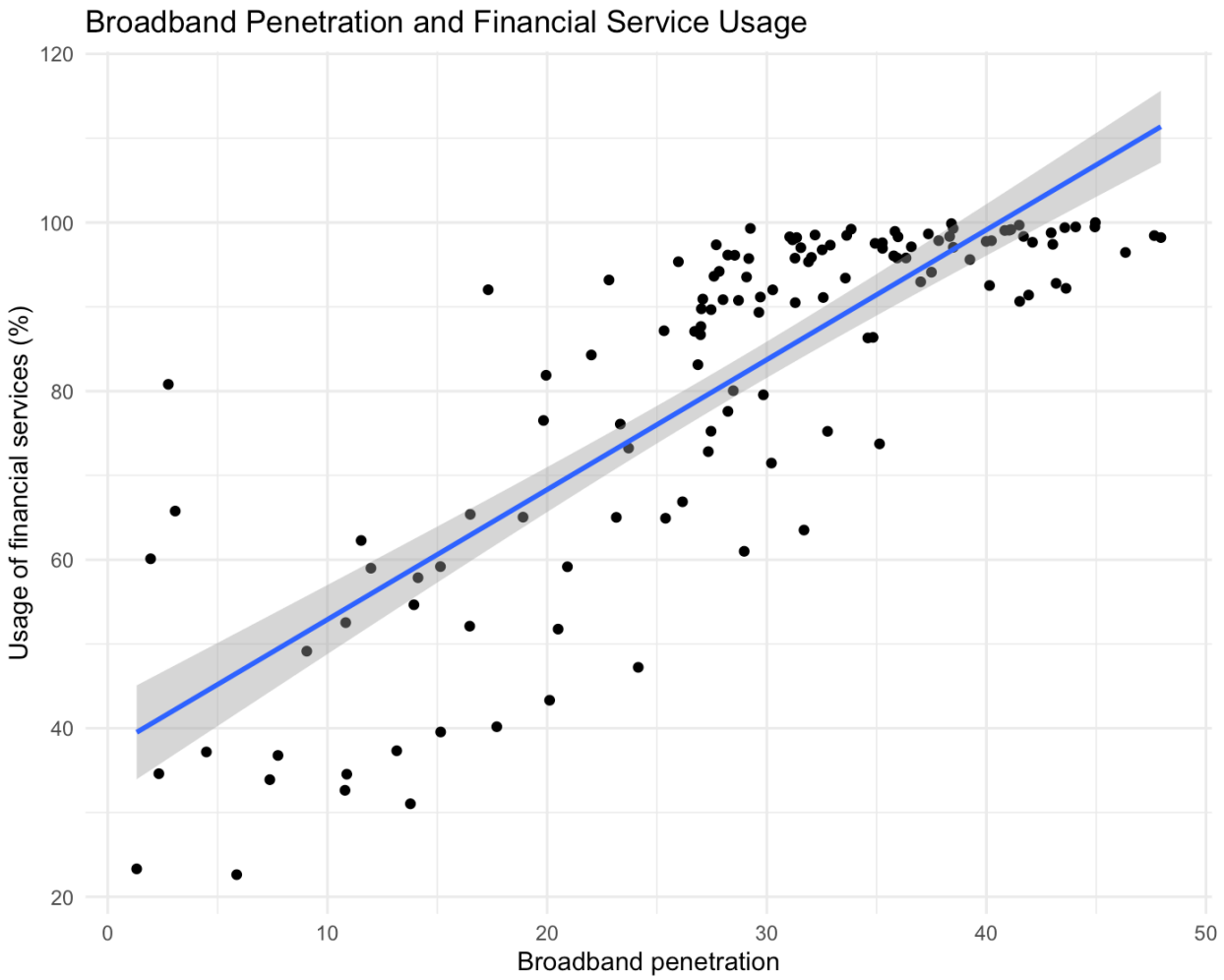


Figure 6: Broadband Penetration and Financial Service Usage

The scatter plot (Figure 5) reveals no clear positive relationship between mobile penetration and financial service usage. The wide dispersion of observations indicates that mobile access alone is insufficient to explain variation in financial inclusion.

In contrast, broadband penetration shows a strong positive relationship with financial service usage, indicating that digital infrastructure plays a key role in enabling financial inclusion, as shown in the Figure 6.

The democracy variable is retained as a control and is discussed in Section 4.4.

Overall, the results do not support Hypothesis H_1, as mobile penetration alone does not significantly increase financial service usage. Instead, the findings emphasize the importance of complementary digital infrastructure and highlight the conditional nature of mobile financial inclusion

4.2 Hypothesis 2

The results of analysis of the models (Equations 3.2 and 3.16) are presented below in the Table 7.

Table 7: Estimation Results for Model H2

Variable	**Model 1**	**Model 2**	**Model 3**
Dependent variable: usage			
mobile	0.0691 (0.1458)	0.0676 (0.1191)	0.1129 (0.3883)
gov_eff	24.02. (12.11)	27.76* (11.04)	16.04*** (3.648)
democracy	-62.87*** (16.57)	-65.58*** (16.43)	-66.55*** (16.37)
GDP	-0.0002 (0.0002)	-2.61e-5 (0.0001)	-2.22e-5 (0.0001)
quality	-0.4103* (0.2014)	-0.4203* (0.1574)	-0.2479 (0.7342)
mobile × gov_eff	-0.0971 (0.0975)	-0.0962 (0.0805)	
trust		-0.3388. (0.1776)	-0.3492. (0.1867)
mobile × quality			-0.0016 (0.0047)
Fixed Effects			
country	Yes	Yes	Yes
year	Yes	Yes	Yes
Model Statistics			
S.E.: Clustered	by: country	by: country	by: country
Observations	127	127	127
R^2	0.95836	0.96358	0.96297
Within R^2	0.28444	0.37404	0.36368
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			

End of the table

In Model 1, government effectiveness exhibits a positive and statistically significant effect on financial service usage, indicating that stronger institutional capacity contributes to higher levels of financial inclusion. This result is consistent with the expectation that effective governance facilitates the functioning of financial systems.

The interaction term between mobile penetration and government effectiveness is negative, although not statistically significant. This suggests that the marginal effect of mobile penetration may decrease as institutional quality

increases; however, the lack of statistical significance implies that this relationship is not robust in the baseline specification.

Regulatory quality enters the model with a negative coefficient, although it is not statistically significant in Model (1). This indicates that regulatory conditions may influence financial service usage, but the effect is not precisely estimated in this specification.

Model (2) extends the baseline specification by including trust in government. The inclusion of this variable leads to several important changes in the results.

First, the positive effect of government effectiveness remains stable and statistically significant, confirming the robustness of this relationship. Second, the interaction term between mobile penetration and institutional quality remains negative and becomes slightly more precisely estimated, although it remains statistically insignificant. This suggests that the potential substitution effect between mobile financial technologies and institutional quality persists even after controlling for trust, but the evidence remains weak.

Third, regulatory quality becomes negative and statistically significant in the extended specification. This result suggests that countries with higher regulatory quality tend to exhibit lower usage of mobile-based financial services. A possible explanation is that stronger regulatory environments are associated with more developed traditional financial systems, reducing reliance on mobile financial solutions.

Finally, trust in government is negative and statistically significant. This indicates that higher levels of trust are associated with lower usage of mobile-based financial services. This finding may reflect structural differences across countries, in which high-trust environments coincide with well-established financial institutions and broader access to conventional banking services.

The inclusion of trust improves the model's explanatory power, as reflected by the increase in within R. This suggests that institutional factors play a meaningful role in explaining variation in financial inclusion over time.

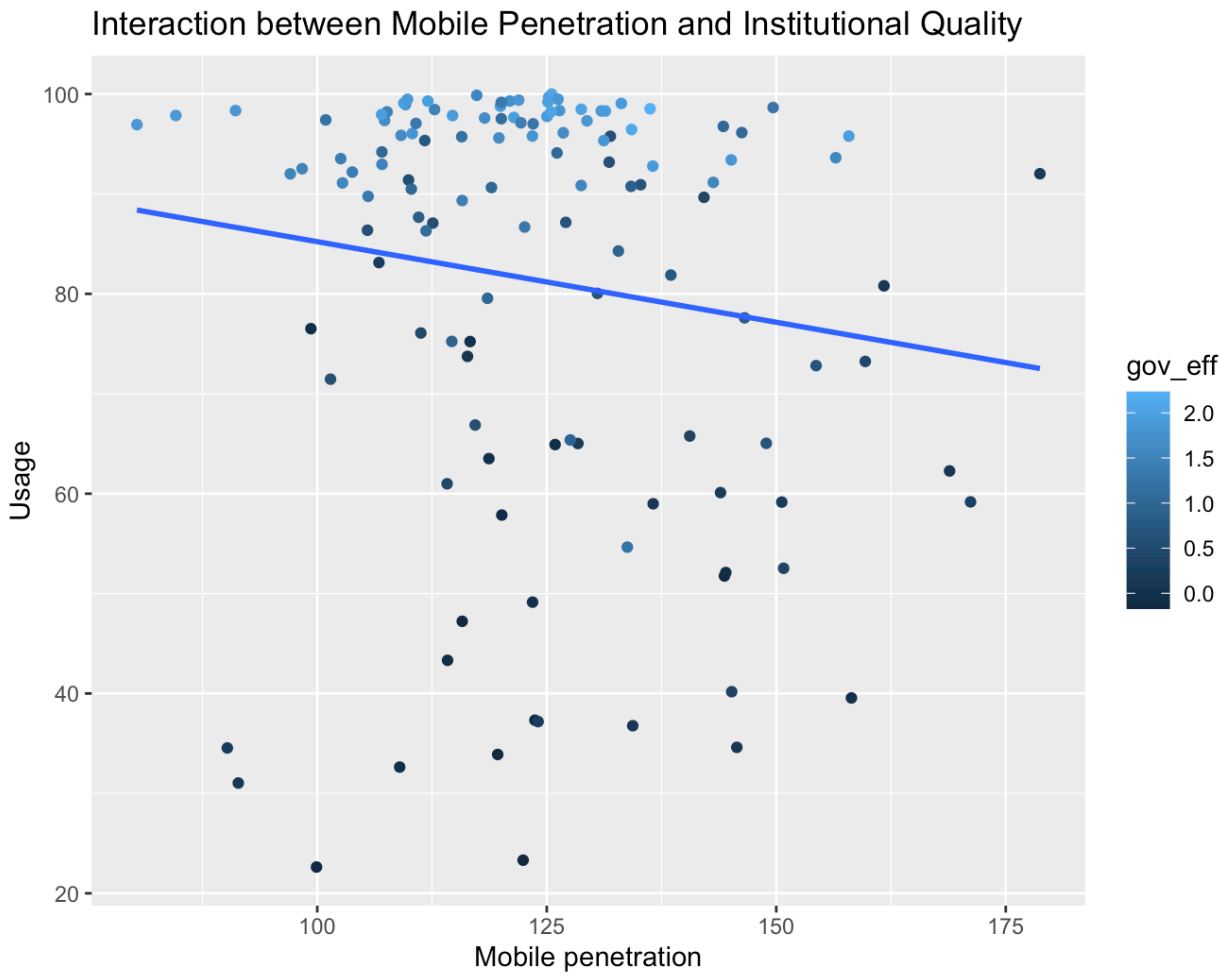


Figure 7: Interaction between Mobile Penetration and Institutional Quality

Figure 7 illustrates the interaction between mobile penetration and institutional quality in relation to financial service usage. The plot presents the relationship between mobile penetration and usage, with observations differentiated by the level of government effectiveness.

The overall relationship between mobile penetration and financial service usage appears weak and slightly negative, as indicated by the downward-sloping fitted line. At the same time, observations with higher levels of institutional quality are generally associated with higher levels of financial service usage, reflecting the positive role of institutions in supporting financial inclusion.

However, the visual evidence suggests that the marginal effect of mobile penetration does not increase with institutional quality. Instead, the relationship appears relatively flat or slightly decreasing across different levels of institutional development. This pattern is consistent with the regression results, which indicate a negative interaction between mobile penetration and institutional quality.

It should be noted that interaction effects are difficult to capture visually due to the high dispersion of the data. Therefore, the graphical analysis serves as a complementary illustration, while the formal interpretation relies on the regression estimates.

Overall, the empirical results do not support Hypothesis H_2. While institutional quality has a positive direct effect on financial service usage, there is no robust evidence that it strengthens the impact of mobile penetration. Instead, the results point to a potential substitution effect, whereby mobile financial technologies are more relevant in weaker institutional environments. However, this relationship is not statistically significant and should therefore be interpreted with caution.

Therefore, the institutional quality is a direct driver of financial inclusion, rather than a moderator of mobile-based financial access.

4.3 Hypothesis 3

The results of the analysis are presented in the Table 8.

Table 8: Estimation Results for Model H_3

Variable	**Results**
Dependent variable: usage	
mobile	0.0868 (0.1864)
trust_low	12.88 (20.45)
GDP	-5.98e-5 (0.0001)
mobile × trust_low	-0.0857 (0.1599)
Fixed Effects	
country	Yes
year	Yes
Model Statistics	
S.E.	Clustered (by country)
Observations	127
R^2	0.94337
Within R^2	0.02678
Significance levels: *** p<0.001, ** p<0.01, * p<0.05	

End of the table

Based on the results, the H_3 specification provides no strong support for the hypothesis of heterogeneous effects across institutional regimes.

The low R^2 value (0.027) indicates that the interaction specification explains only a limited share of within-country variation in financial inclusion over time. This partly explains the absence of statistically significant interaction effects in the model. Since the fixed-effects specification relies exclusively on temporal variation within countries, the explanatory power of interaction terms becomes limited when institutional indicators and trust variables exhibit relatively low variation across years.

The coefficient on mobile penetration reflects its effect in high-trust countries and is positive but not statistically significant. The interaction term between mobile penetration and the low-trust indicator is negative, suggesting that the effect of mobile technologies is weaker in countries with lower institutional trust. However, this interaction is not statistically significant.

Evaluating the marginal effects, the estimated impact of mobile penetration is slightly lower in low-trust countries compared to high-trust countries. Nevertheless, the difference is economically small and statistically indistinguishable from zero.

Overall, these findings indicate that while institutional trust may influence financial inclusion directly, there is no robust evidence that it significantly alters the effectiveness of mobile penetration. Therefore, H_3 is not supported by the empirical results.

However, to test the hypothesis H_3 more accurately and for more deep explanation was decided to resort to the split models (Equations 3.22 and 3.23). The results are presented in the Table 9.

Table 9: Fixed Effects Estimation by Trust Groups

Variable	**High trust**	**Low trust**
Dependent variable: usage		
mobile	0.2061 (0.1274)	-0.1665* (0.0796)
democracy	-93.34*** (20.76)	-41.27 (25.12)
GDP	-0.0001 (0.0002)	-0.0010 (0.0006)
broadband	0.5476 (0.8495)	0.6738 (0.4415)
gov_eff	6.287 (4.508)	-0.8219 (5.160)

Continuation on the next page

Continuation of Table 9

Variable	**fe_high**	**fe_low**
Fixed Effects		
country	Yes	Yes
year	Yes	Yes
Model Statistics		
S.E.	Clustered (by country)	Clustered (by country)
Observations	57	59
R^2	0.96990	0.97523
Within R^2	0.55758	0.33752
Significance levels: *** p<0.001, ** p<0.01, * p<0.05		

End of the table

To further examine heterogeneity in the effect of mobile penetration, the sample was divided into high-trust and low-trust countries based on the median level of institutional trust.

During estimation, a small number of observations were automatically removed by the fixed-effects estimator. These correspond to country-year observations that do not exhibit within-group variation after splitting the sample into high- and low-trust subsamples. As such observations do not contribute to the identification of coefficients in a two-way fixed effects model, their exclusion does not affect the consistency of the estimates.

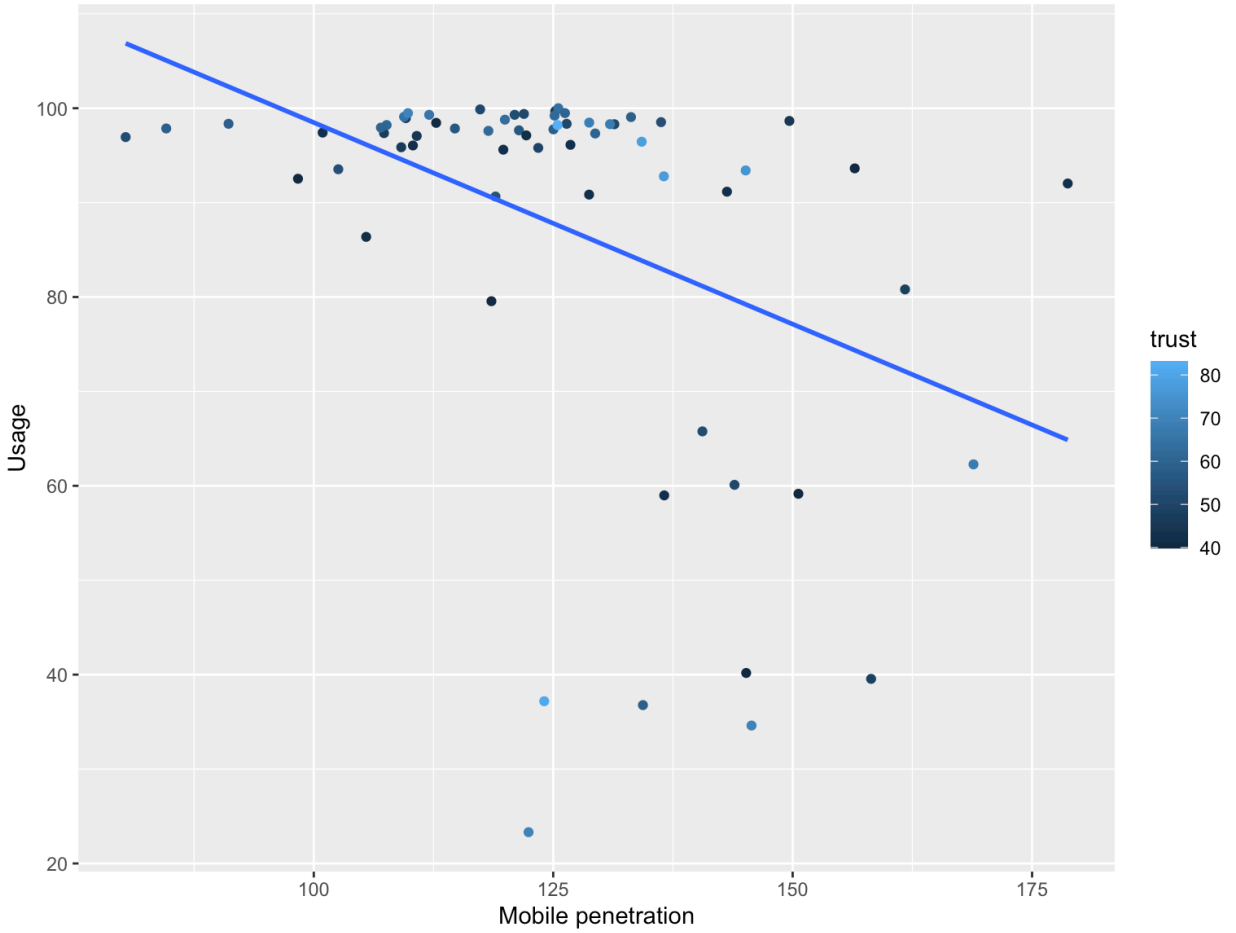


Figure 8: Relationship between mobile penetration and financial service usage in high-trust countries

Figure 8 presents the relationship between mobile penetration and financial service usage in countries with high levels of institutional trust. In contrast to the low-trust group, the fitted regression line exhibits a slight positive slope, indicating a weak positive association between mobile penetration and financial service usage.

However, the relationship appears relatively flat, and the dispersion of observations suggests that the effect is not statistically strong. This is consistent with the regression results, where the coefficient on mobile penetration in high-trust countries is positive but not statistically significant.

The visual evidence suggests that in high-trust environments, financial service usage is already well established and less dependent on mobile penetration. Instead, individuals may rely on more developed financial infrastructure, including traditional banking systems and broadband-based services.

Thus, while mobile technologies may contribute positively to financial inclusion in high-trust countries, their marginal effect is limited, as financial

participation is primarily driven by institutional quality and existing financial development.

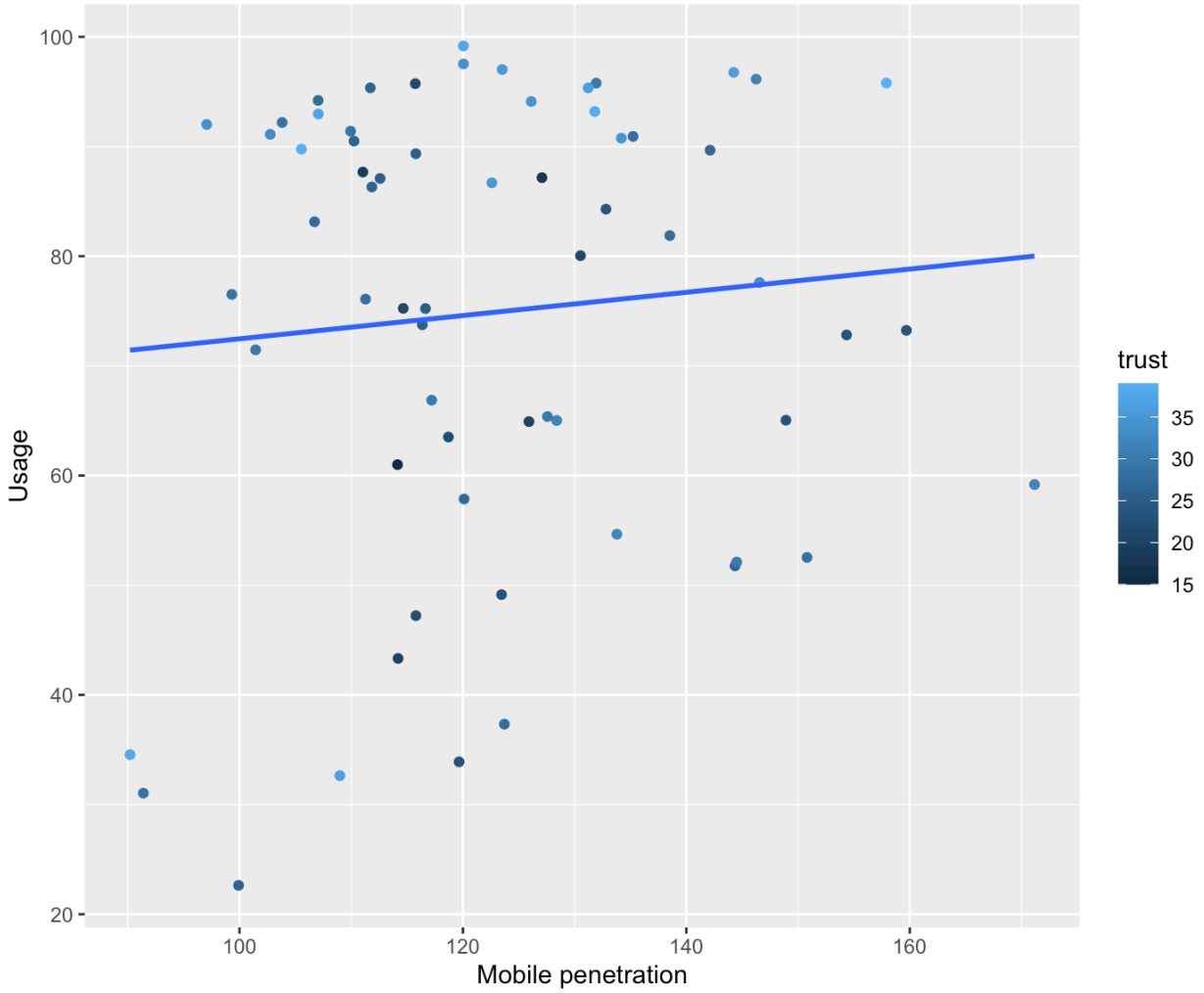


Figure 9: Relationship between mobile penetration and financial service usage in low-trust countries

Figure 9 illustrates the relationship between mobile penetration and financial service usage in countries characterized by low levels of institutional trust. The fitted regression line exhibits a clear negative slope, indicating that higher levels of mobile penetration are associated with lower levels of financial service usage.

This result suggests that in low-trust environments, the expansion of mobile technologies does not translate into increased engagement with formal financial systems. On the contrary, greater mobile access may be associated with substitution toward informal financial channels, reduced reliance on regulated institutions, or limited confidence in digital financial services.

The dispersion of observations further indicates substantial heterogeneity across countries, reflecting the influence of additional structural factors such as financial literacy, infrastructure quality, and regulatory constraints. However, the overall downward trend remains consistent with the regression results, which indicate a negative and statistically significant effect of mobile penetration in low-trust countries.

Therefore, the figure provides visual support for the hypothesis that weak institutional trust constrains the effectiveness of mobile-driven financial inclusion.

The results reveal a clear asymmetry in the relationship between mobile penetration and financial service usage. In low-trust countries, mobile penetration is associated with a statistically significant negative effect on usage, suggesting that increased access to mobile technology does not translate into higher participation in formal financial services.

In contrast, in high-trust countries, the coefficient on mobile penetration is positive but not statistically significant, indicating no clear relationship.

An additional asymmetry emerges for the democracy variable in the split-sample results. In the high-trust group, democracy has a negative and statistically significant effect ($\beta = 93.34$, $p < 0.001$), whereas in the low-trust group, the coefficient remains negative but statistically insignificant ($\beta = 41.27$, $p > 0.05$). This indicates that the negative association between democratisation and financial inclusion outcomes is concentrated in high-trust institutional environments, while it weakens and becomes statistically indistinguishable from zero in low-trust countries.

The possible explanation for this is that high-trust environments may be associated with structural or behavioural factors that affect the reliance on mobile financial services.

These findings suggest that institutional trust plays a critical role in shaping the effectiveness of mobile financial inclusion. In environments characterized by weak trust, mobile penetration alone may be insufficient and can even be associated with lower usage of formal financial services. This result provides partial support for H3, highlighting the importance of institutional conditions in determining the impact of mobile technologies.

4.4 Interpretation of results

The overall results of the empirical analysis provide several important insights into the nature of financial inclusion.

First, the findings consistently indicate that **mobile penetration** alone does not significantly increase the usage of financial services. Despite the widespread expansion of mobile technologies, the estimated coefficients remain statistically insignificant across all baseline specifications. This suggests that access to mobile infrastructure does not automatically translate into effective participation in financial systems. Instead, financial inclusion appears to be constrained by factors beyond technological availability.

Throughout the analysis, the variation in GDP across countries is captured by fixed effects in the FX-adjusted model. As a result, identification relies only on within-country changes, which are small, leading to insignificance.

Second, digital infrastructure, represented by **broadband penetration**, demonstrates a strong and robust positive effect on financial service usage. This highlights the importance of stable and high-quality connectivity, suggesting that more advanced forms of digital infrastructure play a greater role in enabling active engagement with financial services than mobile access alone.

Moreover, according to the results in Table 6, the effect of mobile penetration on financial inclusion is conditional on broadband availability. In the interaction specification (Model 4), the coefficient on mobile penetration becomes marginally significant ($p = 0.058$), indicating that its positive effect is primarily observed in environments with lower broadband penetration, while it diminishes as broadband access increases.

Third, **institutional factors** emerge as key determinants of financial inclusion. Government effectiveness consistently exhibits a positive and statistically significant effect, indicating that stronger institutional capacity facilitates the functioning and accessibility of financial systems. At the same time, the results suggest that institutional development may substitute rather than complement mobile-based financial solutions, as the interaction effects between mobile penetration and institutional variables are negative and statistically insignificant.

Fourth, the analysis reveals substantial heterogeneity in the relationship between mobile penetration and financial inclusion across countries. While in-

teraction models fail to capture statistically significant moderating effects, the split-sample analysis demonstrates a clear asymmetry between institutional regimes. In low-trust countries, mobile penetration is associated with a negative and statistically significant effect on financial service usage, whereas in high-trust countries, the effect is positive but not significant. This indicates that the impact of mobile technologies depends critically on the institutional environment and cannot be adequately described by a simple linear interaction.

Taken together, these results suggest that financial inclusion is not a purely technology-driven process. Instead, it is shaped by a complex interaction of digital infrastructure, institutional quality, and structural conditions. The expansion of mobile technologies increases access, but its effectiveness in promoting active financial participation depends on the broader institutional context.

The estimated coefficient for the democracy variable is negative across several specifications, suggesting that higher levels of democracy are associated with lower usage of financial services. This result appears counterintuitive and contradicts theoretical expectations.

Moreover, the **democracy** variable is highly correlated with other institutional and development indicators, such as government effectiveness and GDP per capita. This multicollinearity may lead to unstable coefficient estimates and incorrect signs. Also, the level of democracy's influence is quite high and negative. It happens because democracy indices capture political rights rather than state capacity, whereas financial inclusion depends heavily on the ability of governments to implement policies effectively. More democratic systems may impose stricter regulatory and compliance frameworks, potentially slowing the expansion of financial services compared to more centralized systems. Second, less democratic regimes may facilitate faster expansion of financial services through centralized, state-led initiatives, particularly in digital finance. Third, democratic systems are often associated with stricter regulatory frameworks, which may slow the expansion of financial services. Finally, within-country variation may reflect periods of institutional reform or transition associated with democratization, which can temporarily disrupt financial development. Such interpretations are supported by the previous studies. Also, the democracy index may be a proxy for other related factors such as market maturity and policy strength.

Therefore, the negative coefficient should not be interpreted as evidence of a causal relationship between democracy and financial inclusion, but rather as

a result of limited variation and model specification constraints.

Country fixed effects already capture time-invariant institutional characteristics, including political systems and long-term governance structures. As a result, the democracy variable reflects only short-term fluctuations, which are not economically meaningful.

Overall, the findings support the conclusion that financial inclusion in emerging markets remains incomplete and context-dependent. Technological expansion alone is insufficient to generate meaningful improvements in financial service usage, and policies aimed at enhancing financial inclusion should therefore focus not only on expanding access but also on strengthening institutional frameworks and improving the quality of digital infrastructure.

5 Conclusions

As follows from the literature research and the analysis, institutional quality is an independent determinant of financial inclusion, not a moderator of the effect of mobile technologies.

This study examined the relationship between mobile financial inclusion and the effective usage of financial services, with a particular focus on the role of institutional factors. Using a panel data approach with country and time fixed effects, the analysis provides several important conclusions.

First, the results confirm that mobile penetration alone is not a sufficient driver of effective financial inclusion. While mobile technologies expand access, their direct effect on usage is limited and not consistently significant across specifications. This supports the broader literature emphasizing that access does not automatically translate into meaningful participation in financial systems.

Second, the findings demonstrate that institutional proxed with quality by government effectiveness has a strong and statistically significant positive effect on financial service usage. This suggests that institutional environments play a fundamental role in enabling individuals to utilize financial services beyond mere access.

Third, the interaction effects indicate that institutional variables do not significantly amplify the marginal effect of mobile technologies. In other words, institutions do not primarily operate as moderators of mobile financial inclusion. Instead, they function as independent determinants of financial inclusion outcomes.

The heterogeneity analysis (high vs. low trust environments) suggests that the effectiveness of mobile technologies varies across institutional contexts. In the split-sample analysis, mobile penetration has a negative and statistically significant effect in low-trust countries (β = -0.17), whereas the effect is positive but statistically insignificant in high-trust countries. These results indicate that institutional trust conditions the impact of mobile technology adoption on usage outcomes. As a result, the split-sample analysis provides partial support for H_3 rather than the interaction specification. This indicates that informal institutional factors such as trust may influence financial behavior, but their role is more complex and indirect.

Overall, the study contributes to the literature by shifting the focus from

technology-driven inclusion to institutionally embedded inclusion. It aligns with recent research emphasizing that financial inclusion should be evaluated not only in terms of access, but also in terms of effective usage and financial resilience

6 Limitations

Despite the robustness of the empirical approach, several limitations should be acknowledged.

First of all, the study relies on a restricted panel dataset, covering a limited number of countries and time periods (Global Findex waves). This leads to a relatively small sample size, reducing statistical power and limiting generalizability.

Moreover, the analysis uses aggregate country-level indicators, which may obscure important micro-level dynamics. Financial inclusion is inherently heterogeneous across individuals, and aggregate measures may fail to capture distributional effects.

The variable measuring trust is based on OECD aggregate indicators, rather than individual-level survey data. This introduces potential measurement bias, as trust is a complex and multidimensional concept that may vary significantly within countries.

Also, although fixed effects models control for unobserved heterogeneity, endogeneity concerns remain, particularly regarding reverse causality between financial inclusion and institutional quality.

Finally, the study focuses primarily on access and usage indicators, without directly measuring broader welfare outcomes such as income, poverty reduction, or financial resilience. Existing evidence suggests that the link between financial inclusion and welfare outcomes is complex and not always direct.

7 Policy Recommendations

Based on the empirical findings, several policy recommendations can be suggested:

Shift focus from access to usage

Policies should move beyond expanding access to financial services and instead prioritize effective usage. This includes designing products that meet user needs, improving financial literacy, and reducing behavioral barriers.

This is consistent with the broader understanding that financial inclusion should be defined not only by access, but by actual engagement with financial services.

Strengthen institutional quality

Given the strong direct effect of government effectiveness, policymakers should prioritize:

- Improving regulatory quality
- Enhancing transparency and governance
- Reducing bureaucratic inefficiencies

Institutional reforms can significantly increase financial inclusion even without additional technological expansion.

Complement mobile expansion with institutional reforms

Mobile technologies should not be viewed as a standalone solution. Their effectiveness depends on:

- Legal frameworks,
- Consumer protection,
- Trust in financial institutions.

Without these elements, mobile-driven inclusion may remain superficial.

Target trust and behavioral barriers

In low-trust environments, policymakers should:

1. Promote financial education,
2. Improve communication between institutions and users,
3. Increase transparency in financial services.

This can help convert access into actual usage.

Develop inclusive digital ecosystems

Digital financial services should be integrated into a broader ecosystem that includes:

1. Payment infrastructure
2. Identification systems
3. Financial literacy programs

Evidence shows that removing barriers such as cost, distance, and documentation can significantly expand financial inclusion.

Tailor policies to country-specific conditions

The heterogeneity of results suggests that one-size-fits-all policies are ineffective. Policymakers should adapt strategies based on:

1. Institutional quality
2. Trust levels
3. Economic development

Summing everything up, financial inclusion is not primarily a technological phenomenon, but an institutional one. Mobile technologies expand opportunities, but institutions determine whether those opportunities are actually realized.

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9 Appendix A

R script

```
#Add essentia packages
library(readxl)
library(openxlsx)
library(writexl)
library(corrplot)
library(dplyr)
library(tidyr)
library(stringr)
library(ggplot2)
library(lmtest)
library(stargazer)
library(EnvStats)
library(RColorBrewer)
library(reshape2)
library(FinCal)
library(FinancialMath)
library(pander)
library(car)
library(lubridate)
library(readr)
#library(tidyquant)
#library(fredr)
  #fredr_set_key("b512611cc61ca15fd64ef147b22205b2")
library(sandwich)
library(plm)
library(fixest)

# DATA
active_mobile_money_accounts <- read_csv("~/Library/Mobile Documents/com~apple~Clou
                                         col_types = cols(Year = col_date(format =



government_effectiveness_vs_electoral_democracy_index <- read_csv("~/Library/Mobile
                                                              col_types = cols(


mobile_cellular_subscriptions_per_100_people <- read_csv("~/Library/Mobile Document
                                                    col_types = cols(Year = co



mobile_money_account_usage <- read_csv("~/Library/Mobile Documents/com~apple~CloudD
                                       col_types = cols(Year = col_date(format = "%
```

```
oecd_average_trust_in_governments <- read_csv("~/Library/Mobile Documents/com~apple
                                               col_types = cols(Year = col_date(form


data <- government_effectiveness_vs_electoral_democracy_index %>%
  inner_join(mobile_cellular_subscriptions_per_100_people, by = c("Code", "Year"))
  inner_join(oecd_average_trust_in_governments, by = c("Code", "Year"))
colnames(data)




data <- data %>%
  select(Entity, Year, `Government Effectiveness Index`, Code, `Electoral Democracy


findex <- read_csv("~/Library/Mobile Documents/com~apple~CloudDocs/HSE/Researches/I
                   col_types = cols(`2011 [YR2011]` = col_skip()))
findex

findex_long <- findex %>%
  pivot_longer(
    cols = starts_with("20"),   # all year columns
    names_to = "year",
    values_to = "usage"
  )


findex_long$year <- as.numeric(substr(findex_long$year, 1, 4))

findex_long
findex_long <- findex_long %>%
  rename(country = `Country Name`) %>%
  rename(code = `Country Code`) %>%
  select(country, year, code, usage)




API_RQ_PER_RNK_DS2_en_csv_v2_5299 <- read_csv("~/Library/Mobile Documents/com~apple
                                               col_types = cols(`1996` = col_n
                                                                `19
                                                                `19
                                                                `20
                                                                `20
                                                                `20
                                                                `20
                                                                `20
                                                                `20
```

```
                                                
```

```
data2 <- data %>%
  inner_join(findex_long, by = c("country", "year")) %>%
  select(-code.y) %>%
  rename(code = code.x)

data2$usage <- ifelse(data2$usage == "..", NA, data2$usage)
data2$usage <- as.numeric(data2$usage)

data2 <- data2 %>%
  filter(!is.na(usage))

colnames(data2)




# GDP

gdp_per_capita <- read_csv("~/Library/Mobile Documents/com~apple~CloudDocs/HSE/Rese
                                      col_types = cols(Year = col_number(),
                                                       `GDP per capita` = col_number
                                                       `World region according to OW

gdp_per_capita
gdp_per_capita$Year <- as.numeric(substr(gdp_per_capita$Year, 1, 4))


gdp_per_capita <- gdp_per_capita %>%
  rename(country = Entity,
         code = Code,
         year = Year,
         GDP = `GDP per capita`)


data2 <- data2 %>%
  inner_join(gdp_per_capita, by = c('country', 'year'))



dataX <- data2 %>%
  inner_join(quality, by = c('country', 'year'))



broadband_penetration_by_country <- read_csv("~/Library/Mobile Documents/com~apple~
                                                 col_types = cols(Year = col_number(),
                                                                  `Fixed broadband sub

broadband_penetration_by_country <- broadband_penetration_by_country %>%
```

```
  rename(country = Entity, year = Year, broadband = 'Fixed broadband subscriptions
  select(-Code)

dataX <- dataX %>%
  inner_join(broadband_penetration_by_country, by = c('country', 'year'))

dataX %>%
  count(country, year) %>%
  filter(n > 1)


dataX <- dataX %>%
  group_by(country, year, code.x, region) %>%
  summarise(across(everything(), mean, na.rm = TRUE))

dataX <- dataX %>%
  select(-code.y) %>%
  rename(code = code.x)
colnames(dataX)

head(dataX)

# Tests

summary(dataX)

dataX_cor <- dataX %>%
  ungroup() %>%
  select(usage, mobile, broadband, gov_eff, quality, trust, GDP, democracy)
cor_matrix <- cor(dataX_cor)
cor_matrix
corrplot(cor_matrix)


ols_check <- lm(
  usage ~ mobile + broadband + gov_eff + quality + trust + GDP + democracy,
  data = dataX
)

vif(ols_check)


pdata <- pdata.frame(dataX, index = c("country", "year"))

fe <- plm(usage ~ mobile + broadband + gov_eff + quality + trust + GDP + democracy,
          data = pdata,
          model = "within")
fe

re <- plm(usage ~ mobile + broadband + gov_eff + quality + trust + GDP + democracy,
          data = pdata,
```

```
          model = "random")
re

plmtest(fe, type = "bp")

plmtest(fe, effect = "time", type = "bp")

phtest(fe,re)


pbgtest(fe)   # Breusch-Godfrey

# or better:
pwartest(fe)  # Wooldridge test

pcdtest(fe, test = "cd")   # Pesaran CD

bptest(fe)


#H1

# Hausman test
pdata <- pdata.frame(dataX, index = c("country", "year"))

fe <- plm(usage ~ mobile + democracy + GDP + broadband,
          data = pdata,
          model = "within")
fe

re <- plm(usage ~ mobile + democracy + GDP + broadband,
          data = pdata,
          model = "random")
re


pfff <- phtest(fe,re)
pfff



h1_1 <- feols(
  usage ~ mobile + democracy + GDP + broadband | country + year,
  data = dataX,
  vcov = ~country
)

h1_2 <- feols(
  usage ~ democracy + GDP + broadband | country + year,
  data = dataX,
  vcov = ~country
```

```
)

h1_3 <- feols(
  usage ~ mobile + democracy + GDP | country + year,
  data = dataX,
  vcov = ~country
)


etable(h1_1, h1_2, h1_3)

h1_4 <- feols(
  usage ~ mobile*broadband + democracy + GDP  | country + year,
  data = dataX,
  vcov = ~country
)

etable(h1_4)




library(ggplot2)

ggplot(dataX, aes(x = mobile, y = usage)) +
  geom_point() +
  geom_smooth(method = "lm") +
  labs(
    title = "Mobile Penetration and Financial Service Usage",
    x = "Mobile subscriptions (per 100 people)",
    y = "Usage of financial services (%)"
  )

ggplot(dataX, aes(x = broadband, y = usage)) +
  geom_point() +
  geom_smooth(method = "lm") +
  theme_minimal()+
  labs(
    title = "Broadband Penetration and Financial Service Usage",
    x = "Broadband penetration",
    y = "Usage of financial services (%)"
  )




#Hausman TEST
```

```
pdata <- pdata.frame(dataX, index = c("country", "year"))
fe <- plm(usage ~ mobile * gov_eff + democracy + GDP,
          data = pdata,
          model = "within")
fe

re <- plm(usage ~ mobile * gov_eff + democracy + GDP,
          data = pdata,
          model = "random")
re


phtest(fe,re)



# H2 v2

#
file_path <- "/Users/grigoriiegorov/Library/Mobile Documents/com~apple~CloudDocs/HS
#
write_xlsx(sheet_nd_summary, file_path)


usage ~ mobile * gov_eff + log_gdp + trust, data = data2)

h2_1 <- feols(
  usage ~ mobile * gov_eff + democracy + GDP + quality| country + year,
  data = dataX,
  vcov = ~country
)

h2_2 <- feols(
  usage ~ mobile * gov_eff + democracy + GDP + trust + quality| country + year,
  data = dataX,
  vcov = ~country
)
#
file_path <- "~/Library/Mobile Documents/com~apple~CloudDocs/HSE/Researches/Inclusi
#
```

```
write_xlsx(dataX, file_path)

etable(h2_1, h2_2)

h2_3 <- feols(
  usage ~ mobile * quality + democracy + GDP + trust + gov_eff| country + year,
  data = dataX,
  vcov = ~country)
etable(h2_3)

etable(h2_1, h2_2, h2_3)



ggplot(dataX, aes(x = mobile, y = usage, color = gov_eff)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(
    title = "Interaction between Mobile Penetration and Institutional Quality",
    x = "Mobile penetration",
    y = "Usage"
  )



#H3

dataX$trust_low <- ifelse(dataX$trust < median(dataX$trust, na.rm = TRUE), 1, 0)

h3_fix <- feols(
  usage ~ mobile * trust_low + democracy + GDP + broadband + gov_eff | country + ye
  data = dataX,
  vcov = ~country
)



etable(h3)


high_trust <- subset(dataX, trust >= median(dataX$trust))
low_trust  <- subset(dataX, trust < median(dataX$trust))

fe_high <- feols(usage ~ mobile + democracy + GDP + broadband + gov_eff | country +
fe_low  <- feols(usage ~ mobile + democracy + GDP + broadband + gov_eff | country +
etable(fe_high, fe_low)

ggplot(high_trust, aes(x = mobile, y = usage, color = trust)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(
```

```
    x = "Mobile penetration",
    y = "Usage"
  )

ggplot(low_trust, aes(x = mobile, y = usage, color = trust)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(
    x = "Mobile penetration",
    y = "Usage"
  )
```

10 Appendix B

Dataset

Table 10: Dataset

country	year	code	region	gov_eff	democracy	mobile	trust	usage	GDP	quality	broadband	trust_low
Argentina	2014.00	ARG	South America	-0.02	0.77	158.19	48.67	39.55	28200.81	14.42	15.15	0.00
Argentina	2017.00	ARG	South America	0.34	0.75	145.15	40.33	40.18	28334.90	43.81	17.71	0.00
Argentina	2021.00	ARG	South America	0.19	0.80	128.39	31.33	65.02	26300.27	30.00	23.15	1.00
Australia	2014.00	AUS	Oceania	1.62	0.86	107.33	47.00	97.36	55489.07	98.08	27.70	0.00
Australia	2017.00	AUS	Oceania	1.62	0.87	109.13	46.33	95.86	56881.86	98.10	32.03	0.00
Australia	2021.00	AUS	Oceania	1.72	0.84	109.61	47.67	98.95	58327.41	98.57	35.84	0.00
Austria	2014.00	AUT	Europe	1.57	0.88	156.48	40.33	93.63	60845.66	91.35	27.60	0.00
Austria	2017.00	AUT	Europe	1.66	0.85	126.80	43.00	96.12	62535.90	90.95	28.54	0.00
Austria	2021.00	AUT	Europe	1.75	0.85	120.97	52.33	99.30	62968.94	87.14	29.25	0.00
Belgium	2014.00	BEL	Europe	1.82	0.90	110.35	42.67	96.05	57002.91	84.13	35.78	0.00
Belgium	2017.00	BEL	Europe	1.35	0.90	110.75	45.00	97.06	58529.33	86.67	38.49	0.00
Belgium	2021.00	BEL	Europe	1.22	0.90	100.92	42.50	97.41	60669.21	86.67	43.02	0.00
Brazil	2014.00	BRA	South America	0.14	0.87	136.59	43.00	58.99	19183.17	50.96	11.98	0.00
Brazil	2017.00	BRA	South America	-0.10	0.78	120.10	27.33	57.86	17724.48	47.62	14.12	1.00
Brazil	2021.00	BRA	South America	-0.10	0.69	99.31	29.33	76.52	18075.71	47.14	19.84	1.00
Bulgaria	2014.00	BGR	Europe	-0.15	0.66	144.35	26.00	51.76	23455.58	70.19	20.50	1.00
Bulgaria	2017.00	BGR	Europe	-0.07	0.67	125.91	20.33	64.92	26691.87	73.33	25.39	1.00
Bulgaria	2021.00	BGR	Europe	-0.02	0.64	116.65	25.00	75.23	30959.11	66.67	32.77	1.00

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Continuation of Table 10

country	year	code	region	gov_eff	democracy	mobile	trust	usage	GDP	quality	broadband	trust_low
Canada	2014.00	CAN	North America	1.85	0.82	80.35	52.67	96.94	55723.48	97.60	35.27	0.00
Canada	2017.00	CAN	North America	1.87	0.83	84.59	59.33	97.85	56612.33	97.62	37.83	0.00
Canada	2021.00	CAN	North America	1.83	0.85	91.10	58.83	98.35	56995.12	94.29	41.69	0.00
Chile	2014.00	CHL	South America	1.23	0.89	133.78	32.33	54.65	27505.05	91.83	13.94	1.00
Chile	2017.00	CHL	South America	0.97	0.89	127.56	30.00	65.38	27892.99	89.05	16.50	1.00
Chile	2021.00	CHL	South America	0.96	0.83	132.80	24.00	84.29	29089.85	78.57	22.01	1.00
Colombia	2014.00	COL	South America	-0.05	0.67	108.98	36.67	32.64	16480.36	66.83	10.80	1.00
Colombia	2017.00	COL	South America	-0.12	0.68	123.71	27.67	37.33	16986.03	64.29	13.15	1.00
Colombia	2021.00	COL	South America	-0.04	0.67	144.50	29.67	52.11	17383.09	60.00	16.48	1.00
Costa Rica	2014.00	CRI	North America	0.34	0.91	150.80	28.67	52.53	20724.92	71.63	10.83	1.00
Costa Rica	2017.00	CRI	North America	0.32	0.90	171.17	31.33	59.18	22622.55	69.05	15.14	1.00
Costa Rica	2021.00	CRI	North America	0.21	0.88	150.60	39.83	59.16	23852.93	67.14	20.92	0.00
Croatia	2014.00	HRV	Europe	0.42	0.83	111.28	28.50	76.08	28456.74	62.50	23.33	1.00
Croatia	2017.00	HRV	Europe	0.27	0.77	106.72	27.33	83.13	32348.93	64.76	26.87	1.00
Croatia	2021.00	HRV	Europe	0.57	0.73	112.59	25.33	87.08	36930.28	68.10	26.72	1.00
Czechia	2014.00	CZE	Europe	0.69	0.86	130.52	20.67	80.05	40158.02	80.77	28.48	1.00
Czechia	2017.00	CZE	Europe	1.01	0.85	118.54	40.00	79.56	45177.52	86.19	29.85	0.00
Czechia	2021.00	CZE	Europe	1.08	0.83	126.12	34.67	94.11	47796.03	87.62	37.50	1.00
Denmark	2014.00	DNK	Europe	1.96	0.92	125.21	46.33	99.69	61552.80	93.75	41.49	0.00

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Continuation of Table 10

country	year	code	region	gov_eff	democracy	mobile	trust	usage	GDP	quality	broadband	trust_low
Denmark	2017.00	DNK	Europe	1.83	0.92	121.94	50.33	99.39	65352.40	92.38	43.57	0.00
Denmark	2021.00	DNK	Europe	2.02	0.92	125.53	64.00	100.00	69715.18	97.62	44.96	0.00
Estonia	2014.00	EST	Europe	1.06	0.88	146.25	31.67	96.14	35723.62	93.27	28.23	1.00
Estonia	2017.00	EST	Europe	1.06	0.91	144.24	36.33	96.76	39533.46	93.33	32.52	1.00
Estonia	2021.00	EST	Europe	1.28	0.90	149.66	45.33	98.65	44251.54	92.86	37.36	0.00
Finland	2014.00	FIN	Europe	2.23	0.89	136.26	53.00	98.52	52710.73	98.56	32.20	0.00
Finland	2017.00	FIN	Europe	1.94	0.87	131.38	50.67	98.30	55637.23	96.67	31.04	0.00
Finland	2021.00	FIN	Europe	2.02	0.88	128.76	68.33	98.47	56790.38	99.05	33.64	0.00
France	2014.00	FRA	Europe	1.47	0.89	98.35	40.67	92.53	50326.57	81.73	40.14	0.00
France	2017.00	FRA	Europe	1.42	0.88	103.82	29.00	92.19	51895.57	83.33	43.62	1.00
France	2021.00	FRA	Europe	1.47	0.87	112.78	40.50	98.45	52517.34	85.71	47.64	0.00
Germany	2014.00	DEU	Europe	1.81	0.89	123.44	50.00	95.80	59108.70	94.23	36.34	0.00
Germany	2017.00	DEU	Europe	1.91	0.89	125.02	59.33	97.76	61866.49	95.24	39.99	0.00
Germany	2021.00	DEU	Europe	1.83	0.87	126.22	60.67	99.48	62530.77	94.76	44.06	0.00
Greece	2014.00	GRC	Europe	0.40	0.89	114.14	15.00	60.99	31213.38	63.94	28.97	1.00
Greece	2017.00	GRC	Europe	0.08	0.87	116.36	25.33	73.74	31995.41	62.38	35.14	1.00
Greece	2021.00	GRC	Europe	0.51	0.81	109.94	29.33	91.40	33531.16	66.19	41.92	1.00
Hungary	2014.00	HUN	Europe	0.57	0.74	117.20	30.00	66.87	30264.95	75.00	26.16	1.00
Hungary	2017.00	HUN	Europe	0.56	0.61	101.44	29.67	71.46	33828.71	72.38	30.21	1.00

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Continuation of Table 10

country	year	code	region	gov_eff	democracy	mobile	trust	usage	GDP	quality	broadband	trust_low
Hungary	2021.00	HUN	Europe	0.59	0.46	105.47	42.33	86.37	38887.19	67.62	34.84	0.00
Iceland	2021.00	ISL	Europe	1.61	0.85	117.37	51.25	99.87	61610.21	91.90	38.41	0.00
Indonesia	2014.00	IDN	Asia	-0.16	0.67	122.42	69.67	23.31	10504.39	51.92	1.31	0.00
Indonesia	2017.00	IDN	Asia	0.12	0.64	145.70	70.00	34.61	11772.57	55.71	2.33	0.00
Indonesia	2021.00	IDN	Asia	0.27	0.58	124.06	81.50	37.19	12757.07	60.95	4.49	0.00
Ireland	2014.00	IRL	Europe	1.34	0.90	105.54	39.00	89.76	65575.81	95.19	27.02	1.00
Ireland	2017.00	IRL	Europe	1.42	0.89	102.56	53.33	93.53	87882.71	91.90	29.08	0.00
Ireland	2021.00	IRL	Europe	1.50	0.89	107.60	61.00	98.22	116903.61	93.33	31.36	0.00
Israel	2014.00	ISR	Asia	1.30	0.73	122.59	35.33	86.69	40872.58	86.54	26.98	1.00
Israel	2017.00	ISR	Asia	1.53	0.73	128.75	43.00	90.85	42947.06	87.14	28.01	0.00
Israel	2021.00	ISR	Asia	1.55	0.71	143.14	42.67	91.16	46162.08	84.76	29.71	0.00
Italy	2014.00	ITA	Europe	0.47	0.86	159.70	23.00	73.24	46825.65	71.15	23.71	1.00
Italy	2017.00	ITA	Europe	0.43	0.87	142.13	27.00	89.66	48849.22	74.76	27.47	1.00
Italy	2021.00	ITA	Europe	0.59	0.85	131.93	29.83	95.78	49825.39	68.57	31.29	1.00
Japan	2014.00	JPN	Asia	1.45	0.81	115.79	25.33	89.34	42674.70	83.65	29.64	1.00
Japan	2017.00	JPN	Asia	1.81	0.82	131.22	36.33	95.34	44505.28	90.00	31.90	1.00
Japan	2021.00	JPN	Asia	1.93	0.83	157.91	39.00	95.79	44355.35	90.00	35.94	1.00
Latvia	2014.00	LVA	Europe	0.71	0.83	127.07	17.67	87.16	29243.74	85.10	25.32	1.00
Latvia	2017.00	LVA	Europe	0.69	0.84	135.23	28.33	90.92	33036.39	82.38	27.09	1.00

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Continuation of Table 10

country	year	code	region	gov_eff	democracy	mobile	trust	usage	GDP	quality	broadband	trust_low
Latvia	2021.00	LVA	Europe	0.78	0.83	111.71	26.67	95.35	36912.01	85.24	25.98	1.00
Lithuania	2014.00	LTU	Europe	0.71	0.83	154.34	23.67	72.82	33975.09	85.58	27.34	1.00
Lithuania	2017.00	LTU	Europe	0.84	0.82	146.55	33.00	77.60	38774.49	82.86	28.23	1.00
Lithuania	2021.00	LTU	Europe	0.90	0.80	134.18	34.83	90.76	45873.53	86.19	28.71	1.00
Luxembourg	2014.00	LUX	Europe	1.83	0.87	145.09	75.00	93.41	130247.66	92.31	33.58	0.00
Luxembourg	2017.00	LUX	Europe	1.89	0.87	130.93	67.67	98.31	132169.83	93.81	35.98	0.00
Mexico	2014.00	MEX	North America	0.22	0.62	90.20	38.00	34.55	21069.77	65.38	10.88	1.00
Mexico	2017.00	MEX	North America	0.13	0.64	91.39	29.00	31.04	21777.52	61.43	13.78	1.00
Netherlands	2014.00	NLD	Europe	1.89	0.88	114.73	57.00	97.85	62045.86	95.67	40.23	0.00
Netherlands	2017.00	NLD	Europe	1.96	0.88	121.42	56.00	97.66	65666.00	98.57	42.10	0.00
Netherlands	2021.00	NLD	Europe	1.91	0.86	119.95	63.00	98.79	68573.56	96.19	42.95	0.00
New Zealand	2014.00	NZL	Oceania	1.94	0.89	107.01	59.67	97.95	44255.50	99.04	31.17	0.00
New Zealand	2017.00	NZL	Oceania	1.82	0.88	129.38	60.67	97.32	46193.29	99.05	32.89	0.00
New Zealand	2021.00	NZL	Oceania	1.67	0.88	118.23	61.67	97.60	48248.72	98.10	35.26	0.00
Norway	2014.00	NOR	Europe	1.93	0.90	112.05	66.00	99.30	84830.26	92.79	38.48	0.00
Norway	2017.00	NOR	Europe	1.96	0.89	109.43	65.00	99.09	87194.11	96.19	41.03	0.00
Norway	2021.00	NOR	Europe	1.88	0.89	109.83	70.67	99.48	88984.14	95.24	44.94	0.00
Peru	2014.00	PER	South America	-0.10	0.82	99.92	26.00	22.63	14244.57	67.31	5.87	1.00
Peru	2017.00	PER	South America	-0.17	0.79	119.66	23.33	33.90	15069.52	66.19	7.38	1.00

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country	year	code	region	gov_eff	democracy	mobile	trust	usage	GDP	quality	broadband	trust_low
Peru	2021.00	PER	South America	-0.02	0.77	123.45	22.83	49.14	15280.55	55.24	9.06	1.00
Poland	2014.00	POL	Europe	0.65	0.89	148.91	23.33	65.04	30334.88	81.25	18.90	1.00
Poland	2017.00	POL	Europe	0.75	0.73	138.52	28.00	81.88	34354.60	76.19	19.95	1.00
Poland	2021.00	POL	Europe	0.59	0.63	131.80	38.33	93.18	41059.59	75.71	22.82	1.00
Portugal	2014.00	PRT	Europe	0.91	0.89	114.66	20.67	75.24	35097.41	74.04	27.46	1.00
Portugal	2017.00	PRT	Europe	1.09	0.89	111.85	26.67	86.31	37943.11	79.05	34.60	1.00
Portugal	2021.00	PRT	Europe	1.02	0.87	118.97	54.00	90.64	38657.67	73.33	41.51	0.00
Romania	2014.00	ROU	Europe	-0.05	0.67	114.19	20.00	43.32	28156.25	70.67	20.11	1.00
Romania	2017.00	ROU	Europe	-0.12	0.73	115.79	22.33	47.23	32852.77	68.57	24.15	1.00
Romania	2021.00	ROU	Europe	0.03	0.72	118.70	21.83	63.51	37534.16	61.90	31.70	1.00
Slovenia	2014.00	SVN	Europe	0.83	0.85	111.05	19.33	87.67	37655.20	72.12	27.00	1.00
Slovenia	2017.00	SVN	Europe	1.20	0.86	115.74	21.00	95.73	41692.84	71.43	29.18	1.00
Slovenia	2021.00	SVN	Europe	1.27	0.81	123.51	35.33	97.02	45914.06	74.76	31.55	1.00
South Africa	2014.00	ZAF	Africa	0.33	0.77	140.58	52.33	65.77	14643.34	61.54	3.07	0.00
South Africa	2017.00	ZAF	Africa	0.20	0.75	143.93	51.67	60.11	14573.60	60.48	1.95	0.00
South Africa	2021.00	ZAF	Africa	0.09	0.72	161.73	48.00	80.81	13681.95	49.52	2.76	0.00
Spain	2014.00	ESP	Europe	1.02	0.88	107.04	27.67	94.20	41339.41	74.52	27.84	1.00
Spain	2017.00	ESP	Europe	1.05	0.85	110.25	26.33	90.49	45446.25	79.52	31.30	1.00
Spain	2021.00	ESP	Europe	1.13	0.87	120.05	34.00	97.53	44251.66	73.81	34.93	1.00

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Continuation of Table 10

country	year	code	region	gov_eff	democracy	mobile	trust	usage	GDP	quality	broadband	trust_low
Sweden	2014.00	SWE	Europe	1.94	0.92	125.14	61.67	99.21	57574.05	96.63	33.84	0.00
Sweden	2017.00	SWE	Europe	1.81	0.91	126.40	51.67	98.34	60288.80	95.71	38.33	0.00
Sweden	2021.00	SWE	Europe	1.90	0.90	133.12	59.17	99.06	62731.70	96.67	40.84	0.00
Switzerland	2014.00	CHE	Europe	1.89	0.91	136.55	77.00	92.79	76189.60	96.15	43.17	0.00
Switzerland	2017.00	CHE	Europe	2.09	0.90	134.24	78.00	96.45	77626.91	97.14	46.33	0.00
Switzerland	2021.00	CHE	Europe	2.04	0.90	125.45	83.17	98.22	81001.41	95.71	47.94	0.00
Thailand	2014.00	THA	Asia	0.15	0.45	134.37	58.33	36.77	18324.61	57.21	7.75	0.00
Thailand	2017.00	THA	Asia	0.09	0.16	168.88	67.67	62.27	20094.68	54.29	11.53	0.00
Thailand	2021.00	THA	Asia	0.18	0.21	178.72	43.67	92.03	20242.77	56.67	17.32	0.00
United Kingdom	2014.00	GBR	Europe	1.45	0.86	122.19	42.33	97.12	48964.28	97.12	36.58	0.00
United Kingdom	2017.00	GBR	Europe	1.65	0.85	119.79	43.00	95.61	51586.68	94.29	39.25	0.00
United Kingdom	2021.00	GBR	Europe	1.34	0.85	120.04	37.83	99.17	51004.43	90.95	41.11	1.00
United States	2014.00	USA	North America	1.55	0.91	97.06	34.00	92.01	63018.81	88.94	30.27	1.00
United States	2017.00	USA	North America	1.59	0.89	102.75	33.33	91.11	66155.56	92.86	32.57	1.00
United States	2021.00	USA	North America	1.51	0.83	107.05	37.17	92.97	71307.40	90.48	37.01	1.00

End of the table