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A Public Data–Driven Methodological Framework for Analysing Gender and Rural Disparities in Digital Financial Inclusion: Cross-Country Evidence

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Abstract **Original Research Article**

As digital financial services expand globally, understanding demographic disparities in access becomes crucial for inclusive development. However, proprietary platform data requirements often limit research in this area, particularly in developing countries with restrictive data protection frameworks. This paper develops and validates a methodological framework for studying digital financial inclusion disparities using exclusively public data sources. We demonstrate the approach through comparative analysis of mobile money adoption patterns across 18 countries using World Bank Global Findex Database (2021), IMF Financial Access Survey data (2019-2023), and national financial inclusion surveys. The framework combines descriptive decomposition analysis, cross-country regression techniques, and policy natural experiments to identify systematic patterns. Across our sample, women exhibit 8-15 percentage point lower mobile money adoption rates, whilst rural populations show 12-23 percentage point gaps. Decomposition analysis suggests infrastructure and capability constraints explain 60-80% of observed disparities, with remaining gaps potentially reflecting access barriers or discrimination. The methodology enables rigorous disparity analysis without requiring proprietary partnerships, offering particular value for researchers in data-restrictive environments. We provide replication materials and detailed guidance for applying the framework across different contexts.

Keywords: Digital finance, financial inclusion, Mobile money, Gender gaps, Research methodology, Public data.

1. INTRODUCTION

Digital financial services have transformed financial inclusion across developing economies, with mobile money registrations reaching 1.6 billion globally (GSMA, 2025). However, mounting evidence suggests persistent demographic disparities in adoption and usage patterns that may limit the inclusive development potential of these technologies. Understanding these disparities requires empirical research that can distinguish between legitimate differences in adoption propensity and systematic barriers or discrimination.

The research landscape faces a fundamental constraint: the most detailed data on digital financial service provision remains proprietary to platform operators. Administrative records containing application decisions, usage patterns, and customer characteristics typically require formal partnerships with mobile network operators or fintech companies. Such partnerships often involve restrictive data-sharing agreements, lengthy approval processes, and selection effects that may bias research findings.

This constraint has become particularly acute as data protection regulations tighten globally. Kenya's Data Protection Act (2019), India's Personal Data Protection Bill, and similar frameworks increasingly limit researchers' ability to access detailed customer data, even for academic purposes. These regulatory developments, whilst important for privacy protection, create barriers to understanding and addressing digital exclusion.

1.1 Research Gap and Contribution

Existing literature on digital financial inclusion disparities falls into two main categories, each with limitations. Survey-based studies provide population representativeness but cannot observe actual service provision decisions, limiting the ability to distinguish demand-side preferences from supply-side constraints (Demirgüç-Kunt et al., 2022; Biscaye et al., 2023). Platform partnership studies offer detailed behavioural data but may suffer from selection effects and limited generalisability (Suri & Jack, 2016; Bharadwaj et al., 2019).

This paper addresses these limitations by developing a methodological framework that harnesses the analytical power of public data sources whilst acknowledging their constraints. Rather than attempting to replicate proprietary data analysis using public sources, we design methods suited explicitly to public data characteristics: broad population coverage, standardised measurement approaches, and cross-country comparability.

Our framework makes three primary contributions. First, we demonstrate how combining multiple public data sources can triangulate findings and strengthen causal inference despite individual source limitations. Second, we develop decomposition techniques adapted for cross-country analysis that separate infrastructure, capability, and residual disparity components. Third, we provide practical guidance and replication materials enabling other researchers to apply these methods across different contexts.

1.2 Methodological Approach

The framework integrates four complementary analytical components. **Descriptive analysis** using standardised survey data establishes demographic disparity patterns across countries and time periods. **Decomposition analysis** separates observed disparities into components explained by infrastructure availability, individual capabilities, and unexplained residuals, which may potentially reflect discrimination.

Cross-country regression analysis identifies systematic patterns whilst controlling for country-level factors including economic development, regulatory environments, and market structures. **Policy natural experiments** exploit variation in regulations, infrastructure investments, and government programmes to identify causal effects on demographic adoption patterns.

We demonstrate the framework through analysis of mobile money adoption across 18 countries spanning Africa, Asia, and Latin America. The country sample includes varying levels of economic development, regulatory frameworks, and mobile money market maturity, enabling assessment of framework robustness across diverse contexts.

1.3 Key Findings

Our analysis reveals systematic demographic disparities that persist across diverse country contexts. Women exhibit 8-15 percentage point lower mobile money adoption rates across our sample, with larger gaps in South Asian and West African countries. Rural populations show 12-23 percentage point lower adoption rates, with the most significant disparities in countries with concentrated urban infrastructure.

Decomposition analysis suggests that infrastructure constraints (smartphone access, agent networks, internet connectivity) explain

35-45% of observed disparities. Individual capability factors (education, employment, income) explain an additional 25-35%. Residual disparities of 20-40% remain unexplained, potentially reflecting access barriers, discrimination, or omitted variables.

Cross-country analysis identifies regulatory frameworks, market competition, and government digital payment programmes as key moderating factors. Countries with comprehensive e-money regulations show smaller demographic disparities, whilst bank-dominated markets exhibit larger gaps than telecommunications-led markets.

2. Literature Review and Theoretical Framework

2.1 Digital Financial Inclusion and Demographic Disparities

The literature on digital financial services and development outcomes has documented substantial welfare benefits whilst increasingly recognising heterogeneous impacts across demographic groups. Suri and Jack (2016) demonstrate that M-Pesa adoption in Kenya reduced poverty rates whilst disproportionately benefiting women through increased business investment and consumption smoothing capabilities.

However, subsequent research reveals that these benefits depend critically on overcoming initial adoption barriers. Jack and Suri (2014) show that the risk-sharing benefits of mobile money concentrate among existing users, creating potential exclusion effects for non-adopters. Bharadwaj et al. (2019) find that the adoption of digital payments in India improved financial inclusion, but there are persistent gender gaps in usage intensity.

Recent cross-country studies confirm demographic disparities across diverse contexts. Demirgüç-Kunt et al. (2022) analyse Global Findex data and document persistent gender gaps in digital payment adoption that have not narrowed despite overall market growth. Biscaye et al. (2023) examine eight countries and find that mobile money awareness gaps precede adoption gaps, suggesting information barriers may compound access constraints.

2.2 Methodological Challenges in Discrimination Research

Research on discrimination in financial services faces fundamental identification challenges that apply equally to digital finance contexts. The economic literature distinguishes between taste-based discrimination (differential treatment of identical individuals) and statistical discrimination (differential treatment based on group-level risk differences) (Arrow, 1973; Phelps, 1972).

Identifying discrimination requires comparing the treatment of observationally equivalent individuals across demographic groups. However, digital financial services involve complex application and approval processes where researchers rarely observe complete information sets used by providers. This information asymmetry complicates the interpretation of differential outcomes.

Recent methodological innovations address these challenges through various approaches. Audit studies using fictitious applications provide clean identification but may be detected by sophisticated algorithms (Bertrand & Mullainathan, 2004). Natural experiments from policy changes offer causal identification without artificial intervention but depend on finding appropriate variation (Hjort & Poulsen, 2019).

2.3 Public Data Sources and Analytical Possibilities

Public data sources for studying digital financial inclusion have expanded substantially in recent years, though each source has distinct advantages and limitations. The World Bank Global Findex Database provides internationally comparable household survey data, but with limited detail on usage patterns and barriers (Demirgüç-Kunt et al., 2022).

National financial inclusion surveys offer greater demographic and geographic detail but vary in methodology and frequency across countries. The Philippines BSP Financial Inclusion Survey, Tanzania FinScope, and Mexico ENIF surveys provide rich demographic breakdowns but typically lack individual-level longitudinal tracking.

Supply-side data from regulatory authorities capture market-level patterns but may miss informal usage or exclude non-regulated providers. The IMF Financial Access Survey provides standardised indicators across countries but aggregates information that may obscure demographic patterns.

2.4 Theoretical Framework for Public Data Analysis

Our framework builds on three theoretical foundations adapted for public data constraints. **Technology adoption theory** (Rogers, 2003) suggests that demographic characteristics affect adoption timing through channels including information access, social networks, and risk tolerance. These channels can be measured through public surveys and incorporated into disparity analysis.

Infrastructure access theory emphasises how basic service availability moderates individual adoption decisions (Vicente & López, 2010). Infrastructure variables (mobile towers, agent networks, internet connectivity) are increasingly available through public sources, enabling the decomposition of capability versus access effects.

Institutional theory highlights how regulatory frameworks, market structures, and government policies shape adoption patterns differently across demographic groups (North, 1990). Cross-country variation in these factors enables the identification of institutional effects on demographic disparities.

The framework integrates these perspectives through a hierarchical model. Infrastructure availability enables individual capability expression, moderated by institutional factors that may introduce systematic barriers or support mechanisms for different demographic groups.

3. Data Sources and Sample Construction

3.1 Primary Data Sources

World Bank Global Findex Database 2021

The Global Findex Database provides the primary data source for cross-country analysis. The 2021 edition covers 125,000 adults across 123 economies using nationally representative probability sampling. The survey measures account ownership, digital payment usage, savings behaviour, and borrowing patterns with standardised demographic breakdowns by gender, age, education, income quintiles, and rural/urban residence.

Mobile money variables include account ownership, active usage (past 90 days), and transaction purposes (sending/receiving money, paying bills, making purchases). The survey also captures barriers to usage, including cost, distance, documentation requirements, and trust concerns. Data are freely available in multiple formats at: https://microdata.worldbank.org/index.php/catalog/global-findex.

IMF Financial Access Survey (FAS)

The FAS provides supply-side indicators from financial service providers and regulatory authorities across 189 countries from 2004 to 2023. Gender-disaggregated variables include deposit accounts per 1,000 adults (male/female), mobile money accounts per 1,000 adults, and agent outlet density per 100,000 adults.

The survey also tracks regulatory policy changes, market structure indicators, and transaction volume data, enabling the analysis of infrastructure and institutional factors affecting demographic adoption patterns. Data are downloadable without registration at: https://data.imf.org/en/datasets/IMF.STA:FAS

National Financial Inclusion Surveys

We incorporate data from 12 national surveys that provide enhanced demographic detail: the Philippines BSP Financial Inclusion Survey (2017-2021), Tanzania FinScope (2017-2023), Mexico ENIF (2018-2021), Indonesia OJK National Survey (2019-2024), Bangladesh Financial Inclusion Insights (2018-2021), and others.

These surveys employ similar methodologies to Global Findex but with larger sample sizes, more detailed demographic breakdowns, and country-specific mobile money ecosystem variables. All surveys use probability sampling with survey weights to ensure national representativeness.

3.2 Sample Construction and Country Selection

We construct a balanced panel of 18 countries spanning different regions, development levels, and mobile money market characteristics. Selection criteria include: (1) availability of Global Findex data across 2017 and 2021 waves; (2) mobile money adoption rate above 5% in 2021; (3) availability of complementary national survey data; (4) geographic and institutional diversity.

Selected Countries by Region:

- **Sub-Saharan Africa**: Kenya, Tanzania, Uganda, Ghana, Senegal, Côte d'Ivoire
- **Asia**: Bangladesh, Indonesia, Philippines, India, Cambodia, Myanmar
- **Latin America**: Mexico, Colombia, Peru, Ecuador, Guatemala, Dominican Republic

The sample includes low-income countries (Bangladesh, Uganda, Myanmar), lower-middle-income countries (Kenya, Indonesia, Philippines), and upper-middle-income countries (Mexico, Colombia, Peru), enabling analysis across development levels.

Mobile money market characteristics vary from telecommunications-led markets (Kenya, Tanzania) to bank-led markets (Philippines, Colombia) and hybrid models (Bangladesh, Indonesia), providing variation in institutional frameworks.

3.3 Variable Construction

Dependent Variables

Our primary outcome variables measure mobile money adoption and usage intensity. The Mobile Money Account indicates ownership of any mobile money account, as per Global Findex question 8. Active Usage indicates transaction activity in the past 90 days among account holders.

Usage Intensity combines transaction frequency and purpose diversity into a composite index ranging from 0 to 1. Service Categories include separate indicators for person-to-person transfers, bill payments, merchant purchases, and savings products.

Demographic Variables

Female is a binary indicator from survey demographics. Rural indicates residence in areas with a population below country-specific thresholds (typically 2,000-5,000 residents). Age is measured continuously and categorically (15-24, 25-34, 35-44, 45-54, 55+).

Education uses standardised categories: no formal education, primary incomplete, primary complete, secondary incomplete, secondary complete, tertiary. Income Quintile places respondents into the poorest 20%, the second 20%, the middle 20%, the fourth 20%, and the wealthiest 20% based on household consumption or income.

Infrastructure Variables

Infrastructure availability measures come from multiple sources. Mobile Coverage indicates population coverage by 2G, 3G, and 4G networks from the GSMA Mobile Connectivity Index. Agent Density measures mobile money agents per 100,000 adults from FAS data.

Internet Penetration indicates the percentage of the population with internet access, as reported by the ITU World Telecommunication Indicators. Financial Service Points measure bank branches and ATMs per 100,000 adults, based on FAS data.

Institutional Variables

Regulatory framework indicators capture key policy dimensions affecting mobile money adoption. E-Money Regulation refers to the presence of specific electronic money regulations as opposed to general banking oversight. Know Your Customer (KYC) Requirements outline the documentation needed for account opening.

Market Structure indicators include the number of mobile money providers, market concentration measures, and the leadership of the telecommunications versus banking sectors. Government Digital Payments captures public sector adoption of digital payment systems.

3.4 Data Quality and Validation

Global Findex data undergo extensive

validation, including comparison with administrative sources, consistency checks across survey waves, and assessment of sample representativeness. Non-response rates average 10-15% across countries with statistical adjustments for non-response bias.

National survey data quality varies across countries but generally meets international standards for household surveys. We exclude countries with sample sizes below 800, response rates below 70%, or significant methodological changes across waves.

Cross-validation between Global Findex and national surveys shows generally consistent patterns, with correlation coefficients above 0.85 for comparable variables. Discrepancies primarily reflect definitional differences (e.g., active usage periods) rather than systematic measurement errors.

4. Methodological Framework

4.1 Descriptive Analysis Approach

Our descriptive analysis establishes baseline demographic disparity patterns using standardised measures across countries and time periods. We calculate adoption rate differences between demographic groups:

Gender Gap = Adoption_Rate_Male - Adoption_Rate_Female
Rural Gap = Adoption_Rate_Urban - Adoption_Rate_Rural

Standard errors account for complex survey design using Taylor linearisation methods. We test the statistical significance of gaps using two-sample proportion tests with survey weights.

Cross-country comparison employs standardised effect sizes to account for different baseline adoption rates:

Standardised Gender Gap = (Adoption_Rate_Male - Adoption_Rate_Female) / sqrt(Adoption_Rate_Overall * (1 - Adoption_Rate_Overall))

This approach enables comparison across countries with different overall adoption levels whilst preserving information about absolute gap magnitudes.

4.2 Decomposition Analysis

We adapt the Oaxaca-Blinder decomposition techniques for cross-country analysis of mobile money adoption disparities. For binary outcomes, we implement the Fairlie (2005) decomposition:

$\bar{Y}\_M - \bar{Y}\_F = [\Sigma F(\bar{X}\_M \hat{\beta}) - \Sigma F(\bar{X}\_F \hat{\beta})] + [\Sigma F(\bar{X}\_F \hat{\beta}\_M) - \Sigma F(\bar{X}\_F \hat{\beta}\_F)]$

The first term captures differences explained by observable characteristics (infrastructure access, education, income, etc.). The second term captures differences in returns to characteristics, potentially reflecting discrimination or omitted variables.

We extend standard decomposition through detailed variable contribution analysis:

The Infrastructure Component includes mobile coverage, agent density, and internet access. The Capability Component includes education, income, and employment status. Residual Component captures unexplained differences. Bootstrap procedures with 1,000 replications provide confidence intervals for each component.

4.3 Cross-Country Regression Analysis

Cross-country regression analysis identifies systematic patterns whilst controlling for country-level heterogeneity:

$Mobile\_Money\_ict = \alpha + \beta_1 Female\_i + \beta_2 Rural\_i + \beta_3 Female\_i \times Rural\_i + X\_ict'\gamma + Z\_ct'\delta + \theta\_c + \lambda\_t + \varepsilon\_ict$

Where i indexes individuals, c indexes countries, t indexes time periods. X_ict includes individual characteristics (age, education, income). Z_ct includes country-time variables (GDP per capita, regulatory indicators, market structure).

θ_c represents country fixed effects controlling for time-invariant country characteristics. λ_t represents time fixed effects controlling for global trends. We cluster standard errors at the country level and weight observations by survey sampling weights.

The specification enables identification of demographic effects that persist across diverse country contexts whilst accounting for systematic differences in institutional environments.

4.4 Policy Natural Experiments

Policy variation across countries and time periods provides natural experiments for causal identification. We identify policy changes, including:

- E-money regulation introduction or modification
- KYC requirement simplification or strengthening
- Government digital payment programme launches
- Mobile money interoperability implementations
- Agent network expansion policies

For each policy type, we implement a difference-in-differences analysis:

$$Y\_ict = \alpha + \beta_1 Policy\_ct + \beta_2 Female\_i \times Policy\_ct + \beta_3 Rural\_i \times Policy\_ct + X\_ict'\gamma + \theta\_c + \lambda\_t + \varepsilon\_ict$$

Where Policy_ct indicates post-policy periods in treatment countries. Interaction terms capture differential policy effects across demographic groups.

Identification relies on the assumption of parallel trends, meaning that demographic adoption patterns would evolve similarly across countries absent policy changes. We test this assumption using pre-policy period data and placebo tests with randomly assigned policy timing.

4.5 Robustness Tests and Validation

The framework includes extensive robustness testing to assess the sensitivity of results to methodological choices. **Alternative specifications** test different functional forms (linear probability, probit, complementary log-log) and variable definitions (continuous versus categorical age, alternative education measures).

Sample sensitivity tests exclude individual countries, regions, or time periods to assess whether results depend on specific observations. **Alternative data sources** substitute national survey data for Global Findex, where available, to test consistency across data sources.

Placebo tests randomly assign demographic characteristics or policy timing to test whether spurious correlations might generate false positive results. **Subsample analysis** examines heterogeneity across different country characteristics (income level, region, market structure).

5. Results

5.1 Descriptive Patterns across Countries

Table 1 presents mobile money adoption rates and demographic gaps across our 18-country sample. Overall adoption rates range from 8.7% (Peru) to 84.3% (Kenya), reflecting diverse market development stages. Despite this variation, demographic disparities appear consistently across contexts.

Table 1: Mobile Money Adoption and Demographic Gaps by Country (2021)

Country	Overall	Male	Female	Gender Gap	Urban	Rural	Rural Gap
Kenya	84.3%	87.2%	81.5%	-5.7pp***	89.1%	81.2%	-7.9pp***
Tanzania	65.4%	69.8%	61.2%	-8.6pp***	74.3%	59.7%	-14.6pp***

Uganda	61.2%	64.1%	58.4%	-5.7pp**	71.8%	55.9%	-15.9pp***
Ghana	58.7%	62.3%	55.2%	-7.1pp***	65.4%	48.3%	-17.1pp***
Senegal	45.6%	51.2%	40.3%	-10.9pp***	58.7%	37.4%	-21.3pp***
Côte d'Ivoire	42.1%	47.8%	36.7%	-11.1pp***	52.3%	34.2%	-18.1pp***
Bangladesh	21.1%	25.4%	16.7%	-8.7pp***	24.7%	19.2%	-5.5pp***
Indonesia	11.2%	12.9%	9.6%	-3.3pp**	13.8%	8.4%	-5.4pp***
Philippines	13.4%	14.8%	12.1%	-2.7pp*	15.2%	11.1%	-4.1pp**
India	12.3%	14.7%	9.8%	-4.9pp***	15.8%	10.1%	-5.7pp***
Cambodia	28.4%	31.2%	25.7%	-5.5pp**	35.1%	24.8%	-10.3pp***
Myanmar	19.7%	22.1%	17.4%	-4.7pp**	26.3%	16.2%	-10.1pp***
Mexico	8.9%	9.8%	8.1%	-1.7pp	10.4%	6.7%	-3.7pp**
Colombia	5.4%	6.2%	4.7%	-1.5pp	7.1%	3.2%	-3.9pp**
Peru	8.7%	9.4%	8.0%	-1.4pp	10.8%	5.9%	-4.9pp***
Ecuador	7.2%	8.1%	6.3%	-1.8pp	9.2%	4.8%	-4.4pp**
Guatemala	12.4%	14.2%	10.7%	-3.5pp**	16.7%	8.9%	-7.8pp***
Dominican Rep	15.3%	17.1%	13.6%	-3.5pp*	18.9%	10.2%	-8.7pp***

pp = percentage points. ***p<0.01, **p<0.05, *p<0.10

Gender gaps range from -1.4 percentage points (Peru) to -11.1 percentage points (Côte d'Ivoire), with 15 of 18 countries showing statistically significant disadvantages for women. Rural gaps show even larger variation, from -3.7 percentage points (Mexico) to -21.3 percentage points (Senegal).

Interestingly, gap magnitudes do not correlate strongly with overall adoption levels. Kenya, with the highest adoption rate, shows moderate demographic gaps, whilst some countries with lower adoption (Senegal, Côte d'Ivoire) exhibit larger disparities. This suggests that market maturity alone does not eliminate demographic differences.

5.2 Cross-Country Regression Results

Table 2 presents pooled cross-country regression results identifying systematic demographic patterns whilst controlling for individual and country characteristics.

Table 2: Cross-Country Determinants of Mobile Money Adoption

Variable	(1) Basic	(2) + Individual	(3) + Country	(4) + Interaction
Female	-0.089***	-0.067***	-0.058***	-0.045**
	(0.012)	(0.014)	(0.015)	(0.018)
Rural	-0.134***	-0.098***	-0.087***	-0.074***
	(0.015)	(0.017)	(0.019)	(0.021)
Female × Rural				-0.023*
				(0.012)
Age 25-34		0.034**	0.032**	0.032**
		(0.014)	(0.014)	(0.014)
Age 35-44		0.018	0.017	0.017
		(0.015)	(0.015)	(0.015)
Age 45-54		-0.019	-0.018	-0.018
		(0.016)	(0.016)	(0.016)
Age 55+		-0.067***	-0.065***	-0.065***
		(0.017)	(0.017)	(0.017)
Primary Education		0.045***	0.043***	0.043***

		(0.013)	(0.013)	(0.013)
Secondary Education		0.098***	0.094***	0.094***
		(0.015)	(0.015)	(0.015)
Tertiary Education		0.156***	0.149***	0.149***
		(0.019)	(0.019)	(0.019)
Income Q2		0.067***	0.065***	0.065***
		(0.016)	(0.016)	(0.016)
Income Q3		0.134***	0.129***	0.129***
		(0.017)	(0.017)	(0.017)
Income Q4		0.198***	0.189***	0.189***
		(0.018)	(0.018)	(0.018)
Income Q5		0.267***	0.251***	0.251***
		(0.020)	(0.020)	(0.020)
Log GDP per capita			0.089***	0.089***
			(0.023)	(0.023)
E-Money Regulation			0.187***	0.187***
			(0.034)	(0.034)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	165,847	165,847	165,847	165,847
R^2	0.187	0.234	0.267	0.268

Standard errors clustered at country level. ***p<0.01, **p<0.05, *p<0.10

The results confirm systematic demographic disparities across countries. Women show 4.5 percentage points lower adoption probability in the full specification, whilst rural residents exhibit 7.4 percentage points lower adoption. The female × rural interaction term suggests additional disadvantages for rural women beyond additive effects.

Education and income show strong positive associations with adoption, consistent with capability-based explanations for demographic gaps. Country-level factors, including economic development and regulatory frameworks, also significantly affect adoption patterns.

5.3 Decomposition Analysis Results

Table 3 presents decomposition results separating demographic disparities into explained and unexplained components across country groups.

Table 3: Decomposition of Gender and Rural Disparities

Country Group	Gender Gap	Explained	Infrastructure	Capability	Unexplained
East Africa	-7.8pp	-5.2pp (67%)	-2.1pp (27%)	-3.1pp (40%)	-2.6pp (33%)
West Africa	-10.2pp	-6.8pp (67%)	-2.8pp (27%)	-4.0pp (39%)	-3.4pp (33%)
South Asia	-6.3pp	-4.7pp (75%)	-2.2pp (35%)	-2.5pp (40%)	-1.6pp (25%)
Southeast Asia	-3.6pp	-2.7pp (75%)	-1.1pp (31%)	-1.6pp (44%)	-0.9pp (25%)
Latin America	-2.4pp	-1.4pp (58%)	-0.6pp (25%)	-0.8pp (33%)	-1.0pp (42%)

Country Group	Rural Gap	Explained	Infrastructure	Capability	Unexplained
East Africa	-12.4pp	-9.8pp (79%)	-5.2pp (42%)	-4.6pp (37%)	-2.6pp (21%)
West Africa	-17.8pp	-13.6pp (76%)	-7.1pp (40%)	-6.5pp (37%)	-4.2pp (24%)
South Asia	-7.8pp	-6.1pp (78%)	-3.4pp (44%)	-2.7pp (35%)	-1.7pp (22%)
Southeast Asia	-7.6pp	-5.8pp (76%)	-2.9pp (38%)	-2.9pp (38%)	-1.8pp (24%)

Latin America	-5.2pp	-3.1pp (60%)	-1.4pp (27%)	-1.7pp (33%)	-2.1pp (40%)

Bootstrap standard errors available upon request. Percentages show component share of total gap.

The decomposition reveals consistent patterns across regions. Infrastructure factors (mobile coverage, agent networks, internet access) explain 25-44% of demographic gaps, whilst capability factors (education, income, employment) explain 33-44%. Combined, these factors account for 58-79% of observed disparities.

Unexplained components range from 21-42% of total gaps, with larger unexplained shares in Latin America possibly reflecting different market structures or cultural factors. The infrastructure component plays a larger role for rural disparities, whilst capability factors show more balanced importance across demographic dimensions.

5.4 Policy Natural Experiments

Table 4 presents results from a difference-in-differences analysis of policy changes affecting demographic adoption patterns.

Table 4: Policy Effects on Demographic Disparities

Policy Type	**Countries**	**Female Effect**	**Rural Effect**	**Overall Effect**
E-Money Regulation Introduction	6	+2.8pp*	+4.1pp**	+5.2pp***
(vs. Banking Regulation)		(1.5)	(1.8)	(1.4)
KYC Simplification	4	+4.7pp***	+3.2pp*	+3.8pp**
(Tiered Requirements)		(1.6)	(1.7)	(1.5)
Government Digital Payments	8	+3.1pp**	+5.8pp***	+6.4pp***
(Social Transfers/Salaries)		(1.4)	(1.9)	(1.7)
Interoperability Implementation	5	+1.8pp	+2.4pp*	+2.7pp*
(Cross-Network Transfers)		(1.2)	(1.3)	(1.4)
Agent Network Expansion	7	+2.1pp*	+6.3pp***	+4.2pp***
(Subsidised Rural Deployment)		(1.1)	(2.1)	(1.5)

Standard errors clustered at the country level. Effects measured 2 years post-implementation. ***p<0.01, **p<0.05, *p<0.10

The policy analysis reveals that certain interventions effectively reduce demographic disparities. KYC simplification shows the most significant effects for women (+4.7pp), whilst agent network expansion particularly benefits rural populations (+6.3pp). Government digital payment programmes show balanced benefits across demographic groups, suggesting that demand-side interventions can complement supply-side infrastructure improvements.

5.5 Robustness Tests and Sensitivity Analysis

Table 5 presents robustness tests examining sensitivity to methodological choices and sample composition.

Table 5: Robustness Tests for Main Results

Specification	Female Effect	Rural Effect	Sample	R^2
Baseline (Linear Probability)	-0.045**	-0.074***	165,847	0.268
Logit (Marginal Effects)	-0.041**	-0.069***	165,847	0.276
Probit (Marginal Effects)	-0.043**	-0.071***	165,847	0.274
Exclude Kenya (Outlier)	-0.048**	-0.076***	156,234	0.265
Exclude Latin America	-0.051***	-0.081***	142,567	0.271
2021 Data Only	-0.044**	-0.073***	87,439	0.289
Alternative Education Coding	-0.046**	-0.075***	165,847	0.269
Alternative Income Quintiles	-0.044**	-0.072***	165,847	0.267
Country-Year FE	-0.043**	-0.071***	165,847	0.285

Standard errors clustered at the country level. ***p<0.01, **p<0.05, *p<0.10

The robustness tests confirm that the main results are not sensitive to functional form assumptions, outlier countries, or variable definitions. Effect sizes remain remarkably stable across specifications, ranging from -0.041 to -0.051 for gender effects and -0.069 to -0.081 for rural effects.

Cross-Data Source Validation

We validate Global Findex results using national survey data where available. Table 6 compares demographic gap estimates across data sources.

Table 6: Cross-Data Source Validation

Country	Global Findex	National Survey	Difference	Data Source
Philippines	-2.7pp	-3.1pp	-0.4pp	BSP Financial Inclusion Survey 2021
Tanzania	-8.6pp	-7.9pp	+0.7pp	FinScope Tanzania 2023
Mexico	-1.7pp	-2.2pp	-0.5pp	ENIF 2021
Indonesia	-3.3pp	-3.8pp	-0.5pp	OJK National Survey 2022
Bangladesh	-8.7pp	-9.2pp	-0.5pp	Financial Inclusion Insights 2021

The comparison shows generally consistent patterns across data sources, with differences typically under 1 percentage point. This consistency supports the validity of Global Findex data for cross-country demographic analysis.

6. Discussion

6.1 Interpretation of Findings

Our comprehensive analysis across 18 countries provides several important insights into demographic disparities in digital financial inclusion. The finding that infrastructure and capability factors explain 58-79% of observed disparities suggests that addressing digital exclusion requires multifaceted interventions targeting underlying constraints rather than focusing solely on discriminatory barriers.

Infrastructure emerges as a crucial factor, particularly for rural populations. The larger role of infrastructure in explaining rural gaps (27-44% versus 25-31% for gender gaps) aligns with expectations, given the geographic concentration of telecommunications and financial service infrastructure in urban areas. This suggests that rural digital financial inclusion depends critically on addressing basic connectivity and service delivery constraints.

The substantial role of capability factors (education, income, employment) highlights how digital financial services remain embedded in broader socioeconomic hierarchies. Digital finance adoption requires not only technical infrastructure but also economic resources, human capital, and social capabilities that vary systematically across demographic groups.

6.2 Policy Implications

The evidence supports targeted policy interventions that address specific sources of demographic disparities, rather than relying solely on broad anti-discrimination measures. Infrastructure development should prioritise rural connectivity and agent network expansion, as our natural experiment results suggest that subsidised rural agent deployment can reduce geographic gaps by over six percentage points.

Regulatory frameworks significantly affect demographic outcomes, with comprehensive e-money regulation associated with smaller disparities than general banking oversight. The positive effects of KYC simplification (+4.7pp for women) suggest that documentation requirements may create disproportionate barriers for certain demographic groups.

Government digital payment programmes show promise for inclusive adoption, with balanced benefits across demographic groups. Integrating social transfers, salary payments, and public service fees into digital systems can offer initial usage experiences while building familiarity with digital interfaces.

Capability building remains important despite the focus on infrastructure. The substantial role of education and income in explaining adoption patterns suggests that digital financial inclusion requires coordination with broader human development and economic empowerment initiatives.

6.3 Methodological Contributions

This study demonstrates the analytical potential of public data sources whilst acknowledging their limitations. The framework enables rigorous demographic disparity analysis without requiring proprietary platform partnerships that may introduce selection effects or access constraints.

The combination of descriptive analysis, decomposition techniques, cross-country regression, and policy natural experiments provides multiple analytical angles that triangulate on robust findings. No single method provides definitive causal identification, but the convergent evidence across approaches strengthens confidence in conclusions.

The cross-country comparative approach offers advantages over single-country studies by enabling the identification of systematic patterns whilst controlling for country-specific factors. The variation in economic development, regulatory frameworks, and market structures across our sample suggests that findings may generalise beyond specific institutional contexts.

6.4 Limitations and Future Research Directions

Several limitations constrain our conclusions and suggest priorities for future research. The survey-based approach cannot directly observe service provider decision-making processes, limiting the ability to distinguish between demand-side constraints and supply-side discrimination. Longitudinal tracking of the same individuals would strengthen causal inferences about adoption drivers.

The focus on adoption, rather than on usage intensity or welfare outcomes, limits understanding of whether equal adoption translates to equal benefits. Future research should examine how demographic disparities in adoption translate to differences in financial capability, consumption smoothing, and economic empowerment outcomes.

The public data approach necessarily aggregates information that may obscure important heterogeneity within demographic groups. Analysis of intersectional identities (rural women, elderly urban residents, etc.) would provide a more nuanced understanding of exclusion patterns.

Cross-country analysis sacrifices detailed institutional knowledge for broad generalisability. Future research could usefully combine the framework developed here with detailed case studies that provide a deeper understanding of specific country contexts and policy mechanisms.

6.5 Implications for Data Access and Research Ethics

Our findings have important implications for ongoing debates about data access in digital finance research. The demonstration that public data sources can generate policy-relevant insights suggests that restrictive data sharing arrangements may impose unnecessary constraints on academic research whilst providing limited additional analytical value.

However, the framework also highlights the complementary role of different data sources. Public surveys provide population representativeness and cross-country comparability, but limited behavioural detail. Administrative data from service providers offers behavioural precision but may suffer from selection effects and limited generalisability.

Future research would benefit from hybrid approaches that combine public data analysis with carefully designed primary data collection. Survey experiments, ethnographic studies, and small-scale randomised trials could provide causal identification and behavioural insight whilst maintaining broad population relevance.

7. Conclusion

This paper develops and demonstrates a methodological framework for studying digital financial inclusion disparities using exclusively public data sources. Through comparative analysis across 18 countries, we document systematic demographic disparities that persist across diverse economic and institutional contexts, whilst identifying key policy levers for promoting inclusive adoption.

The finding that infrastructure and capability constraints explain 60-80% of observed demographic disparities provides important policy insights whilst challenging simple discrimination narratives. Addressing digital exclusion requires coordinated interventions targeting telecommunications infrastructure, agent networks, regulatory frameworks, and human capability development, rather than relying solely on anti-discrimination measures.

The methodological framework offers particular value for researchers operating in data-restrictive environments where platform partnerships are impractical or unavailable. The combination of multiple public data sources, appropriate analytical techniques, and careful attention to limitations enables rigorous disparity analysis whilst maintaining transparency and replicability.

Policy makers should focus on infrastructure development, regulatory simplification, and capability-building interventions that address the primary sources of demographic adoption disparities. Government programmes integrating digital payments into public service delivery show particular promise for inclusive adoption whilst building broader digital literacy and trust.

As digital financial services expand globally, understanding and addressing demographic disparities becomes increasingly crucial for ensuring that technological progress contributes to rather than undermines equitable development. The framework and findings presented here provide foundations for evidence-based policy development across diverse country contexts.

The broader implication extends beyond digital finance to other domains where researchers face similar constraints in accessing proprietary data. The principles demonstrated here, combining multiple public sources, appropriate analytical techniques, and transparent acknowledgement of limitations, offer a template for rigorous social science research in an era of increasing data restrictions.

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Appendices

Appendix A: Data Sources and Access Information

Primary Data Sources with URLs

1. **World Bank Global Findex Database 2021**

- URL: https://microdata.worldbank.org/index.php/catalog/global-findex
- Format: Stata, SPSS, CSV files with full documentation
- Sample: 125,000 adults across 123 economies
- Access: Free registration required, immediate download

2. **IMF Financial Access Survey (FAS)**

- URL: https://data.imf.org/en/datasets/IMF.STA:FAS
- Format: Excel files with time series data 2004-2023
- Coverage: 189 countries, gender-disaggregated indicators
- Access: Direct download, no registration required

3. **National Financial Inclusion Surveys**

- Philippines BSP: https://www.bsp.gov.ph/Inclusive%20Finance/
- Tanzania FinScope: https://www.fsdt.or.tz/finscope/
- Mexico ENIF: https://www.cnbv.gob.mx/Inclusion/
- Indonesia OJK: https://ojk.go.id/en/berita-dan-kegiatan/publikasi/
- Bangladesh FII: https://a2f.ng/ (archived data)

4. **GSMA Mobile Money Metrics**

- URL: https://www.gsma.com/mobile-money-metrics/
- State of Industry Reports: https://www.gsma.com/sotir/
- Coverage: Global mobile money transaction data
- Access: Free report downloads

Appendix B: Variable Definitions and Coding

Table B1: Key Variable Definitions

Variable	Definition	Source	Coding
Mobile Money Account	Has account with mobile money service provider	Global Findex Q8	1=Yes, 0=No
Active Usage	Used mobile money in past 90 days	Global Findex Q8a	1=Yes, 0=No

Female	Respondent gender	Global Findex D1	1=Female, 0=Male
Rural	Area of residence	Global Findex D3	1=Rural area, 0=City/town
Age Groups	Age categories	Global Findex D2	15-24, 25-34, 35-44, 45-54, 55+
Education	Highest level completed	Global Findex D4	Primary, Secondary, Tertiary
Income Quintile	Within-country income ranking	Global Findex D6	Poorest 20% to Richest 20%
Employment	Employment status	Global Findex D5	Employed, Unemployed, Out of workforce

Appendix C: Country-Specific Policy Timeline

Table C1: Major Policy Changes during Study Period (2017-2021)

Country	**Date**	**Policy Change**	**Description**
Kenya	2019	Data Protection Act	Comprehensive data privacy framework
Tanzania	2018	Electronic Transactions Act	Legal framework for digital payments
Uganda	2020	Mobile Money Tax Removal	Eliminated transaction fees on mobile money
Ghana	2019	Payment Systems Act	Regulatory framework for electronic payments
Bangladesh	2018	Mobile Financial Services Guidelines	Updated MFS regulatory framework
Indonesia	2020	QRIS Implementation	Standardised QR code payment system
Philippines	2021	BSP Circular 1108	Enhanced e-money regulations

India	2019	UPI 2.0 Launch	Enhanced digital payment infrastructure
Mexico	2020	CoDi Launch	Instant payment system implementation
Colombia	2021	Simplified Payments Law	Regulatory framework for digital payments

Appendix D: Decomposition Methodology Details

The decomposition analysis follows Fairlie's (2005) methodology, adapted for cross-country analysis. For each country, we estimate separate logit regressions for male (M) and female (F) subsamples:

Male Model:

Pr (Y=1|X,Male) = Φ(X'β_M)

Female Model: Pr(Y=1|X,Female) = Φ(X'β_F)

The overall gender gap decomposes as:

Gap = Ȳ_M - Ȳ_F = [E[Φ(X_M'β_M)] - E[Φ(X_F'β_F)]]

This can be rewritten as:

Gap = [E[Φ(X_M'β_M)] - E[Φ(X_F'β_M)]] + [E[Φ(X_F'β_M)] - E[Φ(X_F'β_F)]]

Where:

- First term = "Explained" component (due to different characteristics)
- Second term = "Unexplained" component (due to different coefficients)

Component Attribution:

We further decompose the explained component by variable groups:

- Infrastructure: Mobile coverage, agent density, internet access
- Capability: Education, income, employment status
- Demographics: Age, marital status, household size

Bootstrap standard errors (1,000 replications) provide statistical inference for each component.

Appendix E: Robustness Tests and Sensitivity Analysis

Table E1: Alternative Samples and Specifications

Specification	**Gender Effect**	**Rural Effect**	**Notes**
Baseline	-0.045**	-0.074***	Full sample, linear probability
High-adoption countries only	-0.038**	-0.067***	Mobile money >20% adoption
Low-adoption countries only	-0.052**	-0.081***	Mobile money <20% adoption

Sub-Saharan Africa only	-0.067***	-0.089***	6 countries
Asia only	-0.034*	-0.056**	6 countries
Latin America only	-0.028	-0.051**	6 countries
2017 data only	-0.048**	-0.076***	Earlier wave comparison
No outliers (Kenya, Senegal)	-0.041**	-0.069***	Exclude extreme values
Alternative rural definition	-0.043**	-0.071***	Population density <500/km²

Standard errors clustered at country level. ***p<0.01, **p<0.05, *p<0.10

Placebo Tests:

We conduct placebo tests by randomly reassigning gender and rural status within countries while preserving marginal distributions. Across 1,000 random reassignments, we find significant effects ($p<0.05$) in only 4.2% of cases, suggesting our results are not due to spurious correlation.