What Drives Digital Financial Inclusion? A Comparison of the Drivers of Mobile Banking Adoption Across Non-High Income Regions

[redacted]

Abstract

This paper performs a comparative analysis of the drivers of mobile money account adoption across regions covering non-High income countries, utilizing data from the World Bank's 2021 Global Findex. Recognizing the pivotal role of digital finance in fostering financial inclusion in developing countries, this study employs a country fixed effects probit model to explore the explanatory power of different individual-level drivers including gender, age, age squared, urbanicity, employment, income, and education in explaining mobile money account ownership. A separate regression is run for each region to allow for cross-regional comparisons of significant drivers. The results show variation in the explanatory power of gender, age, urbanicity, and employment status across regions. Education and income exhibit consistent positive associations with mobile money adoption across the regions considered. The implications of these findings underscore the necessity for nuanced policy interventions to address regional barriers to digital financial inclusion. Despite the inherent limitations of this study, including the exclusion of country-wide policy and cultural indicators from the analysis and the narrow scope used to define mobile money service providers, it contributes to the literature to support policymakers in addressing the barriers to digital financial inclusion.

1 Introduction

Financial inclusion (FI) is defined as the concept whereby "individuals and businesses have access to useful and affordable financial products and services that meet their needs" (*Overview*, n.d.). The benefits of FI, both in terms of individual as well as macro-level economy-wide contributions, have been well documented in the literature. From an individual perspective, empirical evidence suggests that FI fosters financial stability to low-income individuals through deposits and savings, which increases "economic activities and employment opportunities" and has multiplier effects on the economy as a whole ("H R Khan: Financial inclusion and financial stability: are they two sides of the same coin?", n.d.).

Despite these documented benefits, there are clear barriers to FI. By using the Findex database to analyse FI, Demirguc et al. (2018) found that such barriers include the cost of opening an account, distance from financial institutions, and documentation requirements (Demirguc-Kunt, Klapper, Singer, Ansar, & Hess, 2018). From an individual perspective, gender, age, education, and employment were found to have a notable impact on whether an individual has a formal financial account. In light of these barriers, mobile banking, more broadly known as digital finance, has been improving access to financial services to the under-served population. It is also attributed to improving women's empowerment, risk sharing, labour market outcomes, and reductions in poverty (Islam, Basher, & Enamul Haque, 2022).

The key contribution of this paper is that it analyses the drivers of mobile money account adoption by taking a holistic approach and makes direct comparisons across regions. The research question that this paper aims to address is whether the individual-level drivers of mobile money adoption vary across geographic regions in non-High income countries where mobile money adoption is most needed. This is possible using the 2021 Global Findex survey which collects individual-level survey responses of 1,000 randomly selected nationally representative respondents per country, as information on mobile money account ownership is available for a wide range of countries (*Global Financial Inclusion (Global Findex) Database*, n.d.).

To answer this question, the research design employed is a modified version of that used in Coulibaly (2021) who explored the factors affecting mobile money penetration rates in the West African Economic and Monetary Union (WAEMU) compared with East Africa (*A study of the factors affecting mobile money penetration rates in the West African Economic and Monetary Union (WAEMU) compared with East Africa | Financial Innovation | Full Text*, n.d.). I applied a country fixed effects probit regression model to each non-High income region covered by the Findex database, regressing mobile money account ownership on individual characteristics including gender, age, age squared, whether the individual lives in an urban area, employment status, education level, and income level. The main goal of this analysis is to compare the explanatory power of features in each region based on coefficient significance and sign, where I hypothesize that there are notable differences in the significant drivers across regions that can lead to identifying regional clusters for policy development.

The analysis shows significant variation in the importance of gender, age, urbanicity, and employment in driving mobile money account adoption. On the other hand, mobile money account ownership has a consistent positive association with higher education and income levels. As such, there is a clear role for policy in addressing the significant drivers per region by encouraging demand-side attainment of education, employment, and financial literacy. From a supply-side, it is also important to bridge urbanization and infrastructure gaps within countries. The analysis has certain limitations that warrant further exploration in future research. These include the exclusion of contextual country policy and cultural indicators in understanding mobile money adoption, and the narrow definition used for what constitutes a mobile money service provider.

This paper is divided into 6 sections. Section 2 describes the dataset and sample used. Section 3 explains the research design. Section 4 describes the results. Section 5 contains a discussion of the results. Section 6 concludes the study. Section 7 includes an appendix of supplementary material.

2 Data Description

The data used in this empirical analysis comes from the World Bank's 2021 Findex database. It provides individual-level survey responses for 1,000 randomly selected nationally representative respondents per country, covering 144 countries. The target audience of this survey is the non-institutionalized population of individuals aged 15 and above. The database was first published in 2011, and is published every 3 years since then.

Data cleaning constituted the process of dummy variable generation from the categorical questions asked to respondents. The main target variable used to respond to the research question is mobile money account ownership, which takes the value 1 if the respondent used mobile money services to pay bills, send or receive money, receive wages, government transfers, public sector pensions, or payments for agricultural products in the last year, and 0 otherwise. Mobile money accounts in this context are defined by the mobile money service providers included in the GSM Association's Mobile Money for the Unbanked Database (GSMA MMU) (*Global Financial Inclusion (Global Findex) Database*, n.d.). The data cleaning process also involved fixing errors in the data. For example, data points from Taiwan did not have a "region" label, which was manually inputted to place respondents from Taiwan under the East Asia & the Pacific region, as per UN classification.

Rows with missing values in the target variable of mobile money ownership were removed from the data before performing the regressions, as not all country surveys covered mobile money accounts. High income countries were excluded from the analysis as they do not have information on mobile money accounts and do not help answer the research question focused on developing countries. After removing rows with missing values for the target variable, as evident in Table 1, South Asia (SA) included 7,003 respondents covering 5 countries, Europe & Central Asia (ECA) included 3,994 respondents covering 4 countries, the Middle East & North Africa (MENA) included 4,014 respondents covering 4 countries, Latin America & the Caribbean (LAC) included 8,502 respondents covering 9 countries, Sub-Saharan Africa (SSA) included 34,011 respondents covering 34 countries, and East Asia & the Pacific (EAP) included 6,061 respondents covering 6 countries. Table 11 (see appendix Section 7.3) notes the set of countries analysed under each region.

The explanatory variables included in each regional regression were gender, age, age squared, urbanicity, employment status, education level, and income level. Gender, employment status, and urbanicity are dummy variables that take the value 1 if true. Age and age squared are continuous variables recorded quantitatively. Education level and income level are categorical variables representing 3 and 5 categories, respectively. Each level is included in the regression as a dummy variable using one-hot encoding (variables detailed in Section 3.2).

Table 1: Regional Descriptive Statistics

region	Male	Age	Education	Income	Employment	Urbanicity	Mob Acc	Economies	N
SA	0.0-1.0	15-93	1.0-3.0	1.0-5.0	0.0-1.0	0.0-1.0	0.0-1.0	5	7003
ECA	0.0-1.0	15-97	1.0-3.0	1.0-5.0	0.0-1.0	0.0-1.0	0.0-1.0	4	3994
MENA	0.0-1.0	15-96	1.0-3.0	1.0-5.0	0.0-1.0	0.0-1.0	0.0-1.0	4	4014
LAC	0.0-1.0	15-99	1.0-3.0	1.0-5.0	0.0-1.0	0.0-1.0	0.0-1.0	9	8502
SSA	0.0-1.0	15-99	1.0-3.0	1.0-5.0	0.0-1.0	0.0-1.0	0.0-1.0	34	34011
EAP	0.0-1.0	15-99	1.0-3.0	1.0-5.0	0.0-1.0	0.0-1.0	0.0-1.0	6	6061

Note: Descriptive statistics for the variables of interest, showing the range of outcomes for each variable and the number of countries and observations per region.

3 Research Design

3.1 Summary Statistics

Primarily, descriptive statistics were performed to gain a better understanding of the sample and the respondents included per region. The distribution of respondents across gender, age, urbanicity, employment status, education level, income level, mobile ownership, internet access, and mobile money account ownership were analysed to get an understanding of the underlying patterns in the data.

Given that the Findex database asks respondents about the barriers they face to owning an account, both in terms of formal financial institutions and mobile money accounts, the reported barriers were also analysed.

3.2 Empirical Design

The methodology of this paper focuses on exploring and comparing the drivers of mobile money account adoption across regions. As such, the target variable, of mobile money account ownership, is a binary variable that either takes the value 1 or 0.

Based on Gujarati's (2011) book "Economics By Example", probit models are most appropriate when the target variable is binary. The error term in a probit model follows a normal distribution with narrower tails compared to logit estimations. Most papers conducting a similar analysis using the Findex database with a binary target variable use probit models. For example, Coulibaly (2021) used a probit model to explore determinants of mobile money account adoption, Asuming et al. (2018) used probit models to explore the determinants of FI at large in Sub-Saharan Africa (Asuming, Osei-Agyei, & Mohammed, 2019), and Sanderson et al. (2018) used a probit model to explore determinants of financial integration in Zimbabwe (*A Review of Determinants of Financial Inclusion - ProQuest*, n.d.).

The model applied in my paper is a modified version of that defined in Coulibaly (2021), who used a probit model to understand the predictors of mobile money account ownership and use in WAEMU compared to East African countries. Individual-level data from the Global Findex Database was used to regress mobile money ownership on gender, age, age squared, income level, education level, and employment status. My paper employed a similar probit model approach but included additional individual-level regressors and country fixed effects.

Country fixed effects were added as controls to ensure that the explanatory variable coefficient estimates are accurate and are not skewed by macro-level country variations. This method is often applied when data is taken from multiple groups, such that these groups can be characteristically different from one another (Schmelzer, n.d.-a). For example, Ansar et al. (2023) included country fixed effects in their probit regression when exploring the role of education in driving formal FI using the Global Findex (Ansar, Klapper, & Singer, 2023). I added country fixed effects into this analysis to account for unobserved country-specific factors that may influence the dependent variable, adjusting for increased similarities among observations from the same country and segmenting overall variation into individual and country variation. As such, a variance components model was used to control for country effects, whereby each group is controlled for as a dummy variable.

A probit regression is applied to each region separately to explore determinants of mobile money adoption. The regressions employed across regions used the following specification:

$$
\begin{aligned}
y_{ij} = {} & \beta_0 + \beta_1(\text{male}_{ij}) + \beta_2(\text{age}_{ij}) + \beta_3(\text{age}^2_{ij}) + \beta_4(\text{urbanicity}_{ij}) + \beta_5(\text{employed}_{ij}) \\
& + \beta_6(\text{education\_level\_2}_{ij}) + \beta_7(\text{education\_level\_3}_{ij}) + \beta_8(\text{income\_level \_2}_{ij}) \\
& + \beta_9(\text{income\_level\_3}_{ij}) + \beta_{10}(\text{income\_level\_4}_{ij}) + \beta_{11}(\text{income\_level\_5}_{ij}) + Z'_j + \epsilon_{ij}
\end{aligned} \tag{1}
$$

where, for the n countries in the sample:

$$Z'_j = \gamma_2 D_{2i} + \gamma_3 D_{3i} + \ldots + \gamma_n D_{ni} \tag{2}$$

Male is a dummy variable taking the value 1 if the individual i in country j is male, age is a continuous variable recording individual i in country j's age, age squared is a computed square of the age numerical value of individual i in country j, urbanicity is a dummy variable taking the value 1 if individual i in country j lives in an urban area, employed is a dummy variable taking the value 1 if individual i in country j is employed, education_level_2 is a dummy variable that takes the value 1 if the individual i in country j has completed secondary schooling, education_level_3 is a dummy variable that takes the value 1 if the individual i in country j has completed tertiary schooling or more, income_level_2 takes the value 1 if the individual i in country j is in the second lowest 20% income bracket, income_level_3 takes the value 1 if the individual i in country j is in the third 20% income bracket, income_level_4 takes the value 1 if the individual i in country j is in the fourth 20% income bracket, income_level_5 takes the value 1 if the individual i in country j is in the richest 20% income bracket, and Z'_j is a vector of country fixed effect dummy variables that take the value 1 if individual i is from country j and 0 otherwise, such that the model has n different intercepts for each of the countries. ϵ_{ij} is the random error term.

Probit models use maximum likelihood as the optimization to compute coefficients. The density of y_i given x_i can be expressed as:

$$f(y_i \mid x_i; \beta) = [G(x_i\beta)]^y [1 - G(x_i\beta)]^{1-y}, \quad y = 0, 1 \tag{3}$$

The log-likelihood function can be obtained by taking the log of equation (3), such that:

$$l_i(\beta) = y_i \log[G(x_i\beta)] + (1 - y_i) \log[1 - G(x_i\beta)] \tag{4}$$

Where the log-likelihood for a sample size of n maximizes the function:

$$\mathcal{L}(\beta) = \sum_{i=1}^{n} (l_i(\beta)) \tag{5}$$

The estimation differs from that of logit models in that the cumulative standard normal distribution function $\Phi(.)$ is used to compute probabilities, such that:

$$(Y \mid X) = P(Y = 1 \mid X) = \Phi(\beta_0 + \beta_1 X) \tag{6}$$

In this case, $\beta_0 + \beta_1 X$ represents the z value where: $\Phi(z) = P(Z \leq z), \quad Z \sim N(0,1)$

To interpret the results of a Probit model, it is important to mirror the Z-value onto the normal distribution. Based on the equations above, the Probit coefficient β_1 is the "change in z associated with a one-unit change in X" (Schmelzer, n.d.-b). From the Probit model's normal distribution, the effect of X on z is linear, but the effect of z on Y is non-linear given that Φ is a non-linear function of X. Therefore, the interpretation of coefficients from a Probit model is not directly associated with its impact on the Y outcome variable, but is rather related to the impact on the z value that non-linearly relates to the probability of Y.

As such, the regression function could also be written as:

$$\begin{aligned}
\Pr(y_{ij}) &= \Phi(Z) \\
&= \Phi(\beta_0 + \beta_1(\text{male}_{ij}) + \beta_2(\text{age}_{ij}) + \beta_3(\text{age}^2_{ij}) + \beta_4(\text{urbanicity}_{ij}) + \beta_5(\text{employed}_{ij}) \\
&\quad + \beta_6(\text{education level } 2_{ij}) + \beta_7(\text{education level } 3_{ij}) + \beta_8(\text{income level } 2_{ij}) \\
&\quad + \beta_9(\text{income level } 3_{ij}) + \beta_{10}(\text{income level } 4_{ij}) + \beta_{11}(\text{income level } 5_{ij}) + Z'_j + \epsilon_{ij})
\end{aligned} \tag{7}$$

where Pr denotes the probability of the target variable and Φ is the standard normal cumulative distribution function underlying the probit model (expressed as an integral).

Given that mobile money account ownership and usage are relatively new developments, and that this paper looks at this phenomenon in developing countries where penetration is still low, class imbalance may occur. Class imbalance takes place when the occurrence of one class of the target variable is very high compared to the other. If this imbalance is present in the data, where mobile money account ownership is a rare occurrence making it a minority class, it must be corrected for to avoid model non-convergence errors. Non-convergence of the probit model may make the estimated coefficients inaccurate. For regions with class imbalance, the classes were re-weighted to penalize the misclassification into the minority class and reduce the weight assigned to the majority class (Singh, 2020). Balanced weights, automatically computed by inversing the classes' proportional frequencies, were used.

4 Results

4.1 Summary Statistics

The summary statistics below analyse the cleaned data that was used in the regressions. Figure 1 shows the summary statistics of the variables of interest. The gender split is slightly skewed towards females, with 60% females in the data. Age range goes from 15 to 100, with most respondents in the bracket of 15-40 years. In terms of education, most respondents have completed secondary schooling, followed by a large proportion of respondents who have only completed primary schooling, and a very small proportion of respondents who have completed tertiary schooling or more. Respondents are relatively equally distributed across income brackets, with the data being slightly skewed to the right towards higher incomes. Around one third of the sample is unemployed, with 55% of respondents reporting living in an urban area. The majority of respondents (85%) report having a mobile phone, but only 45% report having internet access. A small fraction of respondents (25%) report having a mobile money account. Mobile ownership and internet access are analysed in descriptive statistics but excluded from the regressions to avoid multicollinearity.

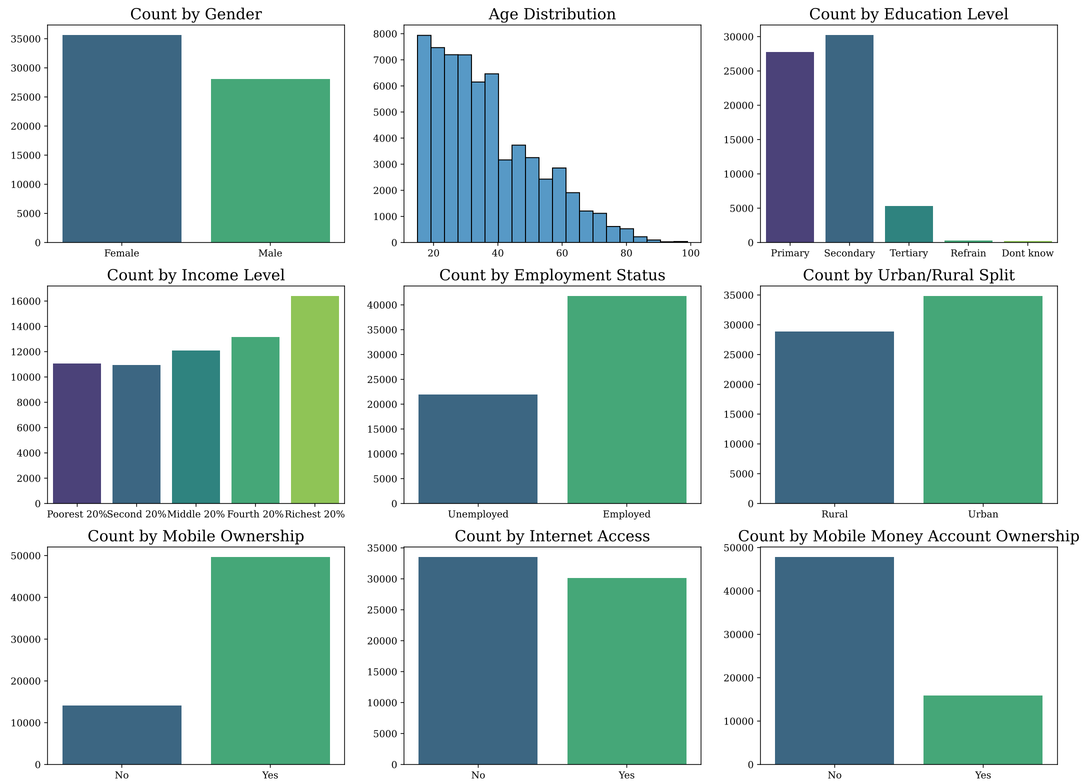

Figure 1: Sample Summary Statistics

Note: Figure 1 shows the frequency distribution of outcomes per variable for the variables of interest in the global sample of 63,585 observations.

Given this general understanding of the data, it is important to take a closer look at variation across regions, as evident on Table 2. The gender split is close to 40% across regions, ranging between 32% to 50% males. Average age across regions ranges between 34 to 45 years, with the highest average age being in ECA and the lowest being in SSA. Average education ranges around 1.51 and 2.12 (considering the 3 categories of education levels), with the highest education recorded in ECA and the lowest in SA. Average income levels across regions are more homogeneous, ranging between 3.07 and 3.24. Average employment ranges between 49% and 71%, with highest employment rates recorded in EAP and the lowest employment rates recorded in MENA. The proportion of urban population ranges between 47% and 85%, with the highest proportion recorded in MENA and the lowest proportion recorded in SA. On average, the proportions of mobile money account ownership are generally low across regions. SA, ECA, MENA, and LAC all have mobile money penetration figures below 15%. This suggests the potential need to apply class weighting for the minority class of mobile money account ownership in those regions. A correlation matrix (phi-coefficient) was performed on these variables of interest (see Figure 5 in appendix) to check that there is no collinearity between the variables that may result in model fitting issues.

Table 2: Regional Summary Statistics

Region	Male Avg.	Male SD	Age Avg.	Age SD	Educ Avg.	Educ SD	Inc. Avg.	Inc. SD	Emp. Avg.	Emp. SD	Urban Avg.	Urban SD	Mob Acc Avg	Mob Acc SD
SA	0.50	0.50	35.63	14.49	1.51	0.63	3.15	1.42	0.54	0.50	0.47	0.50	0.11	0.32
ECA	0.32	0.47	45.21	18.48	2.12	0.62	3.19	1.42	0.50	0.50	0.69	0.46	0.09	0.29
MENA	0.50	0.50	37.73	16.23	1.81	0.67	3.24	1.42	0.49	0.50	0.85	0.35	0.04	0.20
LAC	0.38	0.48	41.14	17.68	1.70	0.65	3.17	1.43	0.70	0.46	0.64	0.48	0.13	0.33
SSA	0.46	0.50	33.74	14.68	1.58	0.58	3.24	1.44	0.70	0.46	0.49	0.50	0.36	0.48
EAP	0.41	0.49	39.72	15.78	1.70	0.66	3.07	1.43	0.71	0.45	0.53	0.50	0.19	0.39

Note: Table 2 displays the average outcome and standard deviation of the variables of interest per region.

Further, given that the study focuses on the determinants of digital finance, the barriers to formal and digital FI reported by unbanked respondents were analysed to understand the broader context. In terms of reasons reported for not having a formal financial account displayed on Figure 2, more than 90% of participants without a formal financial account reported lack of money as a key reason for not having an account. 45-55% of respondents reported expensiveness, banks being too far, lack of a need for a financial account, and lack of documentation as reasons for not having formal accounts. Lack of trust (35%) and another family member already having an account (26%) are also reported with less frequency. For digital finance, lack of money was the main reason reported by respondents without a mobile money account (80%), followed by not having a mobile phone (46%), lack of documentation (41%), expensiveness (39%), and that banking institutions are too far (37%).

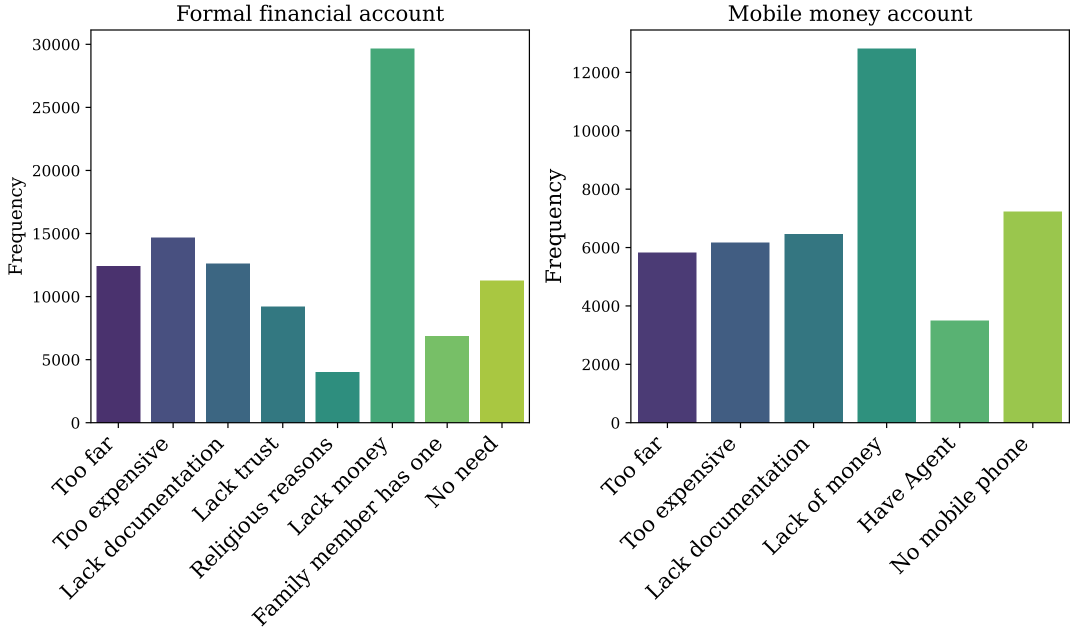

Figure 2: Financial Exclusion Reasons Reported

Note: The Findex survey asks respondents to report reasons for not having an account at a formal financial institution and/or a mobile money account, where more than one reason can be selected from the list of options provided by the survey.

4.2 Regression Results

Data from SA, ECA, and MENA had to be re-weighted using balanced weights for the minority class to allow for model convergence.

As evident on Table 3 there are key differences in the explanatory power of the variables across regions when comparing coefficient significance at the 95% level. Gender is a statistically significant determinant of mobile money account ownership in SA, MENA, LAC, and SSA but not in ECA or EAP. Age is only statistically significant in SSA where the average age was lowest, positively associated with mobile money account ownership. Age squared, on the other hand, is statistically significant at the 95% level in LAC, SSA, and EAP, confirming the expected non-linearity associated with age and financial integration. Urbanicity is statistically significant in LAC, SSA, and EAP, suggesting individual-level variation based on urbanization in those regions. Employment status is statistically significant in all regions except MENA, where there could be a high level of informal work.

Across regions, there is a clear and statistically significant positive association between education and mobile money account ownership, where higher levels of education (compared to the dropped level of primary schooling) are associated with increased likelihood of mobile money account ownership. Similarly, while lower income levels do not seem to be significantly positively associated with mobile money ownership (relative to the poorest 20% level), higher income levels (fourth 20% and richest 20%) show a more consistent statistically significantly positive association across all regions.

The pseudo R-squared scores, calculated as $(1 - \frac{\mathcal{L}_{\text{ur}}}{\ell_{\text{o}}})$, where $\mathcal{L}_{\text{ur}}$ is the log-likelihood function for the estimated model and ℓ_{o} is the log-likelihood function in the model with only an intercept, were analyzed to understand the overall regression explanatory power. It is evident that the individual features included in these regressions have highest explanatory power in EAP, explaining around 32.5% of the variation in the target variable. On the other hand, explanatory power is lowest in MENA, explaining only 10% of the variation in the target variable.

Table 3: **Main Regression Results**

	Dependent variable: mobile_ account_ ownership					
	SA	ECA	MENA	LAC	SSA	EAP
	(1)	(2)	(3)	(4)	(5)	(6)
const	-80.723	-1.291***	-2.522***	-1.951***	-1.750***	-2.090***
	(834.866)	(0.243)	(0.334)	(0.152)	(0.066)	(0.184)
male	0.467***	-0.054	0.244***	0.131***	0.101***	0.029
	(0.051)	(0.068)	(0.085)	(0.040)	(0.016)	(0.047)
age	0.010	-0.004	0.010	0.003	0.030***	0.011
	(0.008)	(0.011)	(0.016)	(0.006)	(0.003)	(0.009)
age_squared	-0.000	-0.000*	-0.000	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
urban	0.053	0.102	0.140	0.124***	0.177***	0.262***
	(0.049)	(0.073)	(0.117)	(0.043)	(0.017)	(0.053)
employed	0.219***	0.331***	0.121	0.210***	0.386***	0.262***
	(0.051)	(0.071)	(0.090)	(0.049)	(0.018)	(0.058)
educ_2.0	0.466***	0.201	0.327***	0.219***	0.521***	0.596***
	(0.053)	(0.126)	(0.106)	(0.050)	(0.018)	(0.068)
educ_3.0	1.130***	0.704***	0.638***	0.546***	0.899***	1.144***
	(0.077)	(0.133)	(0.123)	(0.066)	(0.039)	(0.083)
income_2.0	0.114	0.119	-0.128	0.112	0.158***	0.067
	(0.086)	(0.125)	(0.153)	(0.071)	(0.028)	(0.083)
income_3.0	0.162*	0.207*	-0.133	0.106	0.289***	0.244***
	(0.083)	(0.118)	(0.143)	(0.070)	(0.027)	(0.080)
income_4.0	0.264***	0.301***	0.027	0.255***	0.368***	0.310***
	(0.080)	(0.115)	(0.135)	(0.067)	(0.026)	(0.078)
income_5.0	0.487***	0.490***	0.308**	0.450***	0.531***	0.494***
	(0.078)	(0.109)	(0.127)	(0.065)	(0.026)	(0.077)
Pseudo R-squared	0.225	0.198	0.098	0.155	0.217	0.325
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7003	3994	4014	8502	34011	6061
Note:			*p<0.1; **p<0.05; ***p<0.01			

4.3 Diagnostics and Robustness Checks

4.3.1 Model Diagnostics

The 5 key assumptions of probit models hold; of ensuring binary outcomes, linearity between regressors and the z-score of the coutcome variable, normally distributed errors, independent errors, and no multicollinearity. Primarily, the outcome variable of mobile money account ownership is binary.

Secondly, the linearity condition is fulfilled for the dummy variable features. For the continuous variable of age, as evident on Figure 3, a non-linear relationship to the predicted log-odds (z-score) of the outcome variable is identified, necessitating the inclusion of age squared to account for the non-linearity.

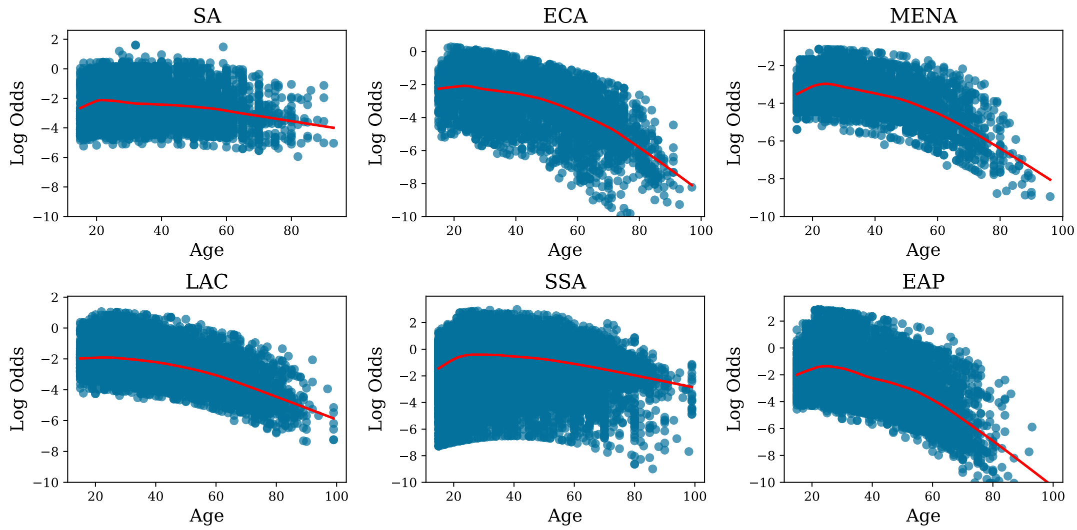

Figure 3: Continuous Variable Linearity Check

Note: Figure 3 shows a scatterplot between predicted probit outcomes and age (continuous variable) for each region, with a red line representing the lowess curve.

Thirdly, as evident on the Q-Q plots on Figure 4 (see appendix Section 7.1) used to check for the normality of the errors, the errors terms for ECA, MENA, LAC, SSA, and EAP follow the theoretical normal distribution. Although the error terms for SA diverge from the normal distribution, the sample size of 7,003 observations is large enough to suggest this is not a modelling issue.

Fourthly, the independence of the error terms was catered to by controlling for country clusters using fixed effects to ensure that the remaining variation unaccounted for is random.

Fifthly, multicollinearity is tested by observing the variance inflator factor (VIF) and correlation matrix. The VIF captures how well each variable is explained by all other independent variables in the model. Table 4 shows a VIF below 10 for male, urban, employed, $income_2$, $income_3$, $income_4$, $income_5$, $educ_2$, and $educ_3$ across regional regressions. As expected, age and age squared have VIFs greater than 10 as they are powers of each other. Therefore, the multicollinearity here will not have negative impacts on the model

(*Variance Inflation Factor (VIF)*, n.d.). The results are confirmed by the correlation matrix obtained in Figure 5 (see appendix Section 7.1), showing no indications of strong correlation between the variables. An expanded validation of each of the assumptions can be found in Section 7.1.

Table 4: Variance Inflation Factors (VIF)

	Male	Urban	Emp	$Educ_2$	$Educ_3$	Inc_2	Inc_3	Inc_4	Inc_5	Age	Age^2
SA	2.5	2.1	2.7	1.9	1.3	1.9	2.0	2.2	2.5	47.6	22.1
ECA	1.6	3.3	2.4	5.8	3.4	1.9	2.1	2.2	2.5	86.5	42.1
MENA	2.4	6.6	2.7	2.9	1.7	2.0	2.2	2.3	2.7	62.9	31.4
LAC	1.8	3.1	3.9	2.8	1.5	1.9	2.0	2.2	2.6	69.4	34.6
SSA	2.0	2.3	3.7	2.6	1.3	1.9	2.0	2.2	2.8	81.1	30.8
EAP	1.8	3.0	4.3	3.4	1.7	1.9	2.0	2.0	2.3	63.3	32.2

4.3.2 Robustness Checks

Given that the probit models were brought to convergence by weighting the mobile money account ownership class to their balanced weights by using inverse proportional frequencies, it is important to check whether the coefficient estimations are robust to changing these weights. The same models were applied per region using the weights 1:10, 1:5, and 1:15 for the minority class. The three models were run and compared in terms of coefficient significance and magnitude for the three regions with convergence issues; SA, ECA, and the MENA. As evident on Tables 5, 6, and 7 (see appendix Section 7.2), the three models yield the same results in terms of coefficient significance, magnitude, and standard errors for the three regions, suggesting robustness of the results.

Considering the significance of gender and its inter-relations with other variables, especially concerning the challenges females may encounter in obtaining employment opportunities and traveling independently to urban areas, the robustness of model estimations was assessed. This involved the incorporation of interaction terms between gender and employment, as well as gender and urbanicity, into each of the regional regression models. As evident in Tables 5, 6, 7, 8, 9, and 10 (see appendix Section 7.2), the results remain consistent overall compared to the original model without the interaction variables. They only region with a notable difference in results is MENA, where gender alone is no longer statistically significant. This suggests that the gender gap was initially driven by underlying gender disparities in the ability to join the workforce, travel, and live in urban cities.

5 Discussion

5.1 Statement of Principal Findings

Gender, age squared, urbanicity, and employment have the biggest variation in terms of statistical significance in driving mobile money account ownership across regions. Since the male variable takes the value 1 for males, the positive association with mobile money account ownership suggests there is still a gender gap effect in digital finance. Urbanicity, being a statistically significant explanatory variable in only 3 of the 6 regions suggests that there are clear within-country divides affecting access to digital finance. Given that country fixed effects are controlled for in the regressions, the significance of urbanicity indicates that these regions have within-country infrastructure imbalances between urban and rural areas that are making it hard for individuals in rural areas to become digitally financially integrated. Considering the significance of employment in all countries except MENA, it is critical to investigate whether this is influenced by the prevalence of informal work. If so, identifying suitable proxies to capture such informalities becomes essential for quantifying the impact of labor force participation on digital FI in MENA. The significant negative quadratic relationship observed for age squared in LAC, SSA, and EAP suggests the importance of improving financial technology literacy and familiarity for the older population.

The consistent importance of education and income across regions is in line with expectations, such that those with higher education levels and household incomes have a greater need for mobile money accounts and the convenience they provide in usage.

The pseudo R-squared scores across the regressions suggest that while individual characteristics are important to understand individual variation in the adoption of mobile money accounts, it is critical to put these characteristics in the context of overall country policy and culture. The low pseudo R-squared scores are not alarming but rather serve as a reminder of the importance of overall context. The regressions are still informative in inferring which features represent barriers to digital FI and are important to address.

5.2 Discussion of Results in Relation to Other Research

While gender is a significant explanatory variable in SA, MENA, LAC, and SSA, even after controlling for other variables such as education and income, extensive literature has been dedicated to explaining the FI gender gap in these regions. For example, Agarwal et al. analysed the FI gender gap in SA and show its association with land property rights (Agarwal, 1994), Cicchiello (2021) associated the gender gap in FI in MENA to the higher likelihood of women to save semi-formally through a savings club or a person outside the family (Cicchiello, Kazemikhasragh, Fellegara, & Monferrà, 2021), Pailhe (2016) found that despite the narrowing FI gender gap in LAC it is still significantly impacted by legal discrimination, cultural norms, and adverse business climates for women (Pailhé, 2016), and Yeyouomo et al. (2023) observed that the gender gap in fintech usage in SSA is driven by disparities in access to electricity and information and communication technology (Yeyouomo, Asongu, & Agyemang-Mintah, 2023). This shows that the gender gap in digital FI is quite intertwined with other country-wide factors. It is also connected to gender disparities in other significant individual-level drivers including income, education, and employment ((Shafik, 2001), (Duryea, Galiani, Ñopo, & Piras, 2007), (Aterido, Beck,

& Iacovone, 2013)). It is interesting to note that while EAP generally has a higher gender gap than LAC, gender alone is not significant. This suggests that the gender gap in digital FI in EAP is likely explained by gender disparities in other variables, such as education and employment (Schwab et al., 2017).

In light of the benefits of mobile banking and digital finance, understanding the predictors of mobile money adoption and identifying potential barriers becomes critical. A number of studies have previously explored the predictors of mobile money adoption, but in case study contexts focusing on a particular country or region. For example, Ansar et al. (2023) explored determinants of mobile money account adoption in SSA and found that "women, the poor, the less educated, the young and those outside the labour market are less likely to be banked and are more likely to need assistance to use their mobile accounts even if they are banked" (Ansar et al., 2023). Similarly, Popov et al. (2010) performed an in-depth analysis on mobile money usage in Uganda utilizing data gathered through survey questionnaires gauging current use of mobile money accounts, and found that education, wealth, and overall need for financial services were important drivers for mobile money usage (Ndiwalana, Morawczynski, & Popov, n.d.). Centelleher et al. (2018) explored predictors to mobile money adoption and spending in the context of M-Pesa, finding the most explanatory features were those related to mobile phone activity, to the presence of other users in one's network, and to mobility (Centellegher et al., 2018).

The region-specific results of these studies, such that more educated, wealthier, older, urban, and employed males are more likely to have a mobile money account are in alignment with our analysis. However, since they are focused on analysing predictors in a single context, this paper serves as an effort to piece together cross-context comparisons and make larger clustering claims.

5.3 Practical Implications

From a regional standpoint, the comparative analysis of significant determinants across regions facilitates the identification of regional clusters, allowing for a specialized strategy for policy development and adjustment by cluster. In identifying regional clusters to comprehend the barriers to mobile money account adoption, I focus on the variables showing significance variations across regions—namely gender, age squared, urbanicity, and employment. LAC, SSA, and EAP show similar drivers in terms of the significance of age-squared, urbanicity, and employment. A key difference is in the significance of gender; while it holds statistical significance in LAC and SSA, it is not significant in EAP. This suggests an underlying difference in the appearance of the gender gap socio-demographically in EAP. Similarly, SA and the MENA show similar patterns in the significance and high magnitude of gender, but differ in the significance of employment such that it is significant in SA but not MENA. Cluster-based economic development policies have been growing in interest to attend to inter-regional competition and industrial hubs (Enright, 2003).

The results of this study serve as a clear indication that improving digital FI and access to financial services at large is strictly intertwined with education, employment, and overall socio-demographic equality. There is a clear role for policy in encouraging demand-side attainment of education, female employment, digital literacy, and improving awareness to the benefits of financial services and the ease of creating mobile money accounts.

Similarly, the importance of urbanicity relates to the reasons for not having a mobile money account reported, such that financial institutions are too far, too expensive, and that respondents have no mobile phones. This suggests a clear role for policy to adjust this imbalance by improving infrastructure and accessibility to urban areas, opening channels of connection between urban and rural areas, and enhancing individuals' ability to buy mobile phones in rural areas. For example, India introduced the concept of agent banking through bank kiosk networks to improve access to financial resources in rural areas (Shafi M.K & Reddy, 2022).

5.4 Limitations and Areas for Further Research

There are clear limitations to this study. Firstly, while it explores the role of individual-level characteristics, it is important to mirror these characteristics onto the broader country contexts they come from to be able to identify concrete action points. A key study that combines both individual and country-level drivers is that of Demirguc et al. (2013) (Demirguc-Kunt, Klapper, & Singer, 2013). Demirguc et al. (2013) looked at the individual, cultural, and political drivers of the gender gap in FI. The study focused on formal financial accounts, and pieced together individual-level data from the Findex survey with country-level cultural and policy indicators. The cultural and country policy indicators analyzed included policies for obtaining a job, females' ability to choose where to live, equality in property inheritance, and asset rights. Having conducted a thorough exploration of individual characteristics in the context of digital finance, a similar approach to that used in Demirguc et al. (2013), incorporating country-level policy and cultural indicators, could be employed in future studies. This approach would shed light on whether similar contextual factors, encompassing individual, cultural, and political aspects, come into play for mobile banking adoption.

Also, the Findex database defines mobile money service providers as those in the GSMA MMU. Given the context of emerging and developing countries, it is critical to understand whether the findings change when other more informal digital financial service providers such as fintech companies and start-ups are counted as mobile money players. For example, a growing fintech company named "Fawry" in Egypt is extending wallets, term loans, and bill payment overdraft services to Egyptian citizens (*Microfinance*, n.d.). Access to financial services through providers such as Fawry are not included in this analysis, and could be critical to understanding the overall landscape of digital FI in developing countries.

6 Conclusion

This study shows clear differences in the drivers of mobile money adoption across regions, specifically in terms of the role of gender, age squared, urbanicity, and employment. The results of this study contribute to the literature and help provide direction for further research to get a more holistic understanding of how to improve the penetration of digital banking. This paves the way to cater policy according to the regional clusters identified to address the individual disparities and barriers to digital financial adoption identified.

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7 Appendix

7.1 Validation of Probit Model Assumptions

The probit model makes 5 key assumptions that should hold in our data. This section goes through the assumption validation for our data and model.

I. **The outcomes are binary:** The outcome variable, mobile money account ownership, is binary. The "success" class is characterized by owning a mobile money account, and the "failure" class is characterized by not owning a mobile money account.

II. **The probit of the outcome (the z-score) and the independent variables have a linear relationship:** This assumption is always met for dummy/categorical variables. I test it only for the continuous variable "age" across the 6 regional regressions performed. As suggested by Werth (2022), this is done by computing the z-scores of the predicted outcome variable and plotting it against the values of age (Werth, n.d.). Figure 3 shows a quadratic relationship between age and the predicted probit outcomes, confirming the necessity to include age_squared into the regressions to maintain linearity.

III. **The errors are normally distributed:** I test the normality of errors using a Q-Q plot. As evident on Figure 4, the residuals from the regional regressions exhibit normality as indicated by their alignment with the theoretical red line, except for SA. The residuals in SA diverge from a normal distribution, however this divergence does not pose a concern for the inference task of this study given the large sample size of 7,003 observations. Usually, normality of errors should not affect inference results if the sample size is large enough (i.e. more than 20 observations). Therefore, I assume that normality of the errors is not an issue in model fitting due to the substantial sample size.

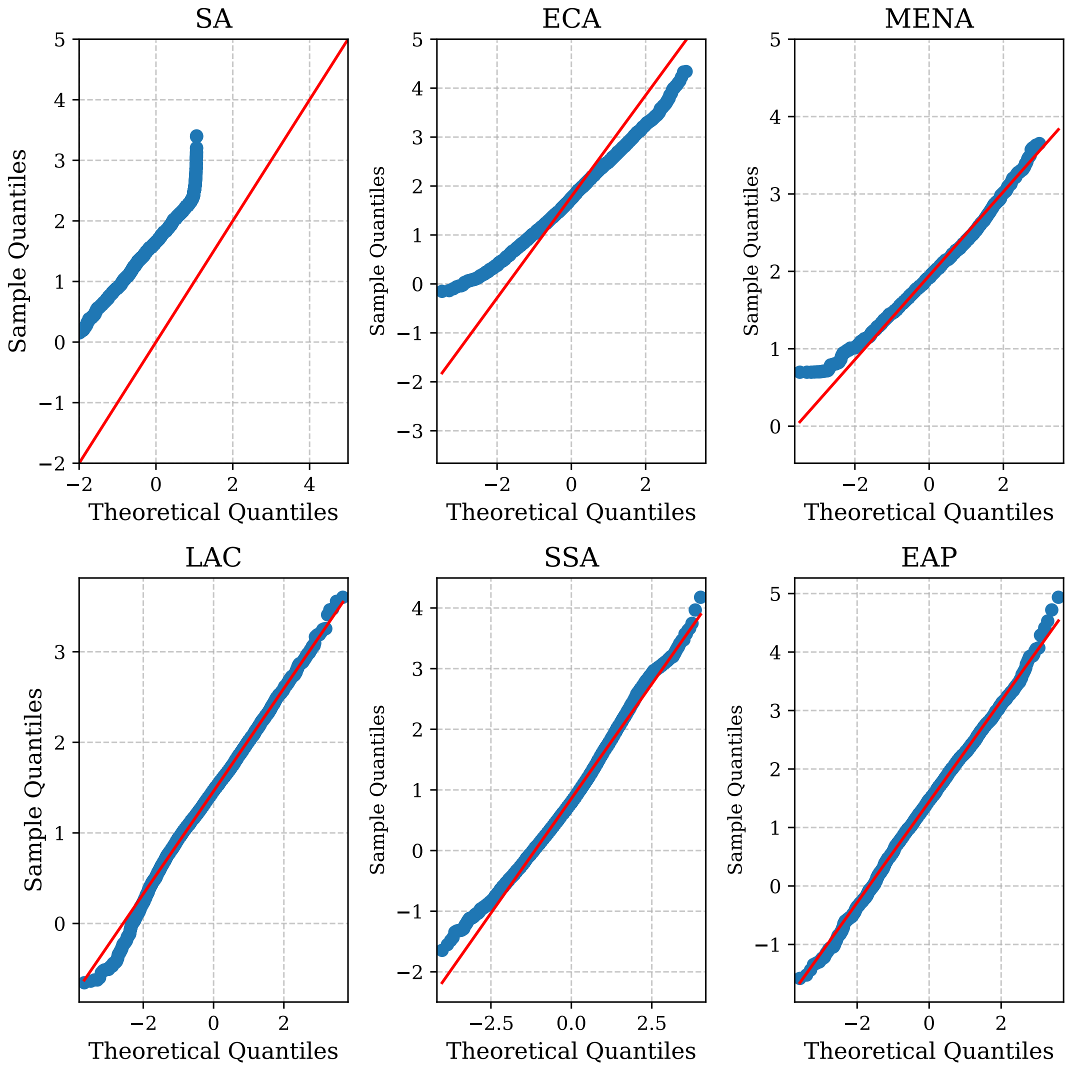

Figure 4: Residual Normal Q-Q Plots

Note: Q-Q plots are used to test the normality of errors assumption. The x-axis represents the quantiles of the theoretical distribution and the y-axis represents the quantiles of the residuals of the fitted model.

IV. **The errors are independent:**

Clusters in the data could make groups of observations more similar compared to others because of contextual factors regarding their grouping. In the Findex data used, observations within a region are clustered by country, where individuals in a given country may appear more similar compared to individuals in other countries due to factors that are not attributed to the individual. I account for clusters in the data by using country fixed-effects for each regional regression to ensure that the error terms in the regression are random and independent.

V. **There is no strong multicollinearity between the variables of interest:**

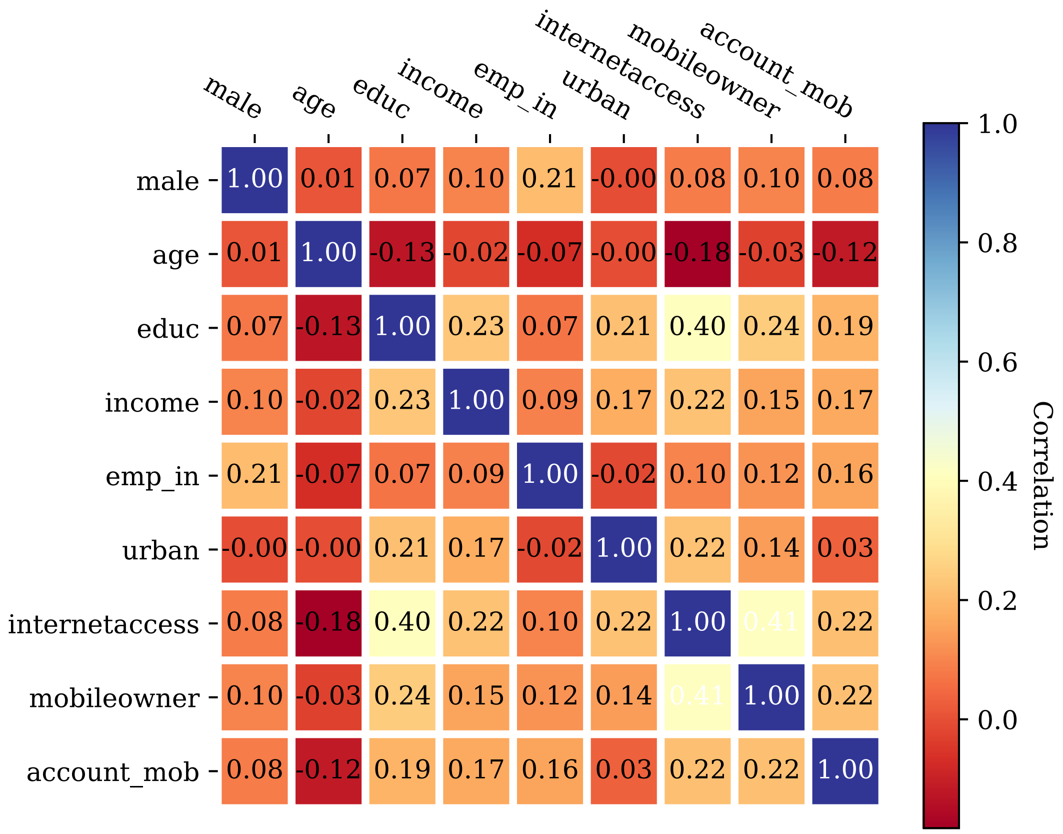

Figure 5: Correlation Matrix

Figure 5 shows that there is no strong correlation between any of the variables, with the highest absolute magnitude being 0.41 between internet access and mobile ownership, and 0.4 between education and internet access. Both variables, mobile ownership and internet access, are excluded from the regressions to avoid any multicollinearity with mobile money account ownership, given that having a mobile money account by definition requires having a mobile phone and internet access.

Given that multi-collinearity can exist between three or more variables even if no pair-wise significant correlation is observed, the variance inflation factors (VIF) are also computed for each covariate, found in Table 4.

7.2 Robustness Checks

Table 5: South Asia Robustness Checks

	Dependent variable: account_mob				
	Balanced weights	1:10 weighting	1:5 weighting	1:15 weighting	Interactions
	(1)	(2)	(3)	(4)	(5)
const	-80.723	-80.723	-80.723	-80.723	-51.074
	(834.866)	(834.866)	(834.866)	(834.866)	(750.415)
male	0.467***	0.467***	0.467***	0.467***	0.395***
	(0.051)	(0.051)	(0.051)	(0.051)	(0.094)
age	0.010	0.010	0.010	0.010	0.010
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
age_squared	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
urban	0.053	0.053	0.053	0.053	0.007
	(0.049)	(0.049)	(0.049)	(0.049)	(0.078)
employed	0.219***	0.219***	0.219***	0.219***	0.181**
	(0.051)	(0.051)	(0.051)	(0.051)	(0.079)
educ_2.0	0.466***	0.466***	0.466***	0.466***	0.466***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
educ_3.0	1.130***	1.130***	1.130***	1.130***	1.131***
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
income_2.0	0.114	0.114	0.114	0.114	0.112
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
income_3.0	0.162*	0.162*	0.162*	0.162*	0.161*
	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)
income_4.0	0.264***	0.264***	0.264***	0.264***	0.264***
	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)
income_5.0	0.487***	0.487***	0.487***	0.487***	0.487***
	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)
male*urban					0.070
					(0.095)
male*emp					0.061
					(0.102)
Pseudo R-squared	0.225	0.225	0.225	0.225	0.225
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	7003	7003	7003	7003	7003
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6: Europe & Central Asia Robustness Checks

	Dependent variable: account_mob				
	Balanced weights	1:10 weighting	1:5 weighting	1:15 weighting	Interactions
	(1)	(2)	(3)	(4)	(5)
const	-1.291***	-1.291***	-1.291***	-1.291***	-1.258***
	(0.243)	(0.243)	(0.243)	(0.243)	(0.247)
male	-0.054	-0.054	-0.054	-0.054	-0.137
	(0.068)	(0.068)	(0.068)	(0.068)	(0.165)
age	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
age_squared	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
urban	0.102	0.102	0.102	0.102	0.026
	(0.073)	(0.073)	(0.073)	(0.073)	(0.088)
employed	0.331***	0.331***	0.331***	0.331***	0.360***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.082)
educ_2.0	0.201	0.201	0.201	0.201	0.199
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
educ_3.0	0.704***	0.704***	0.704***	0.704***	0.701***
	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)
income_2.0	0.119	0.119	0.119	0.119	0.122
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
income_3.0	0.207*	0.207*	0.207*	0.207*	0.208*
	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)
income_4.0	0.301***	0.301***	0.301***	0.301***	0.302***
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
income_5.0	0.490***	0.490***	0.490***	0.490***	0.494***
	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
male*urban					0.232
					(0.153)
male*emp					-0.119
					(0.153)
Pseudo R-squared	0.198	0.198	0.198	0.198	0.199
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	3994	3994	3994	3994	3994
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 7: Middle East & North Africa Robustness Checks

	Dependent variable: account_mob				
	Balanced weights	1:10 weighting	1:5 weighting	1:15 weighting	Interactions
	(1)	(2)	(3)	(4)	(5)
const	-2.522***	-2.522***	-2.522***	-2.522***	-2.422***
	(0.334)	(0.334)	(0.334)	(0.334)	(0.358)
male	0.244***	0.244***	0.244***	0.244***	0.047
	(0.085)	(0.085)	(0.085)	(0.085)	(0.242)
age	0.010	0.010	0.010	0.010	0.014
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
age_squared	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
urban	0.140	0.140	0.140	0.140	-0.073
	(0.117)	(0.117)	(0.117)	(0.117)	(0.175)
employed	0.121	0.121	0.121	0.121	0.224*
	(0.090)	(0.090)	(0.090)	(0.090)	(0.126)
educ_2.0	0.327***	0.327***	0.327***	0.327***	0.323***
	(0.106)	(0.106)	(0.106)	(0.106)	(0.107)
educ_3.0	0.638***	0.638***	0.638***	0.638***	0.624***
	(0.123)	(0.123)	(0.123)	(0.123)	(0.124)
income_2.0	-0.128	-0.128	-0.128	-0.128	-0.127
	(0.153)	(0.153)	(0.153)	(0.153)	(0.154)
income_3.0	-0.133	-0.133	-0.133	-0.133	-0.131
	(0.143)	(0.143)	(0.143)	(0.143)	(0.144)
income_4.0	0.027	0.027	0.027	0.027	0.025
	(0.135)	(0.135)	(0.135)	(0.135)	(0.136)
income_5.0	0.308**	0.308**	0.308**	0.308**	0.312**
	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)
male*urban					0.354
					(0.233)
male*emp					-0.195
					(0.168)
Pseudo R-squared	0.098	0.098	0.098	0.098	0.100
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	4014	4014	4014	4014	4014
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 8: Latin America & the Caribbean Robustness Checks

	Dependent variable: account_mob	
	Balanced weights	Interactions
	(1)	(2)
const	-1.951***	-1.972***
	(0.152)	(0.158)
male	0.131***	0.188*
	(0.040)	(0.109)
age	0.003	0.004
	(0.006)	(0.006)
age_squared	-0.000***	-0.000***
	(0.000)	(0.000)
urban	0.124***	0.102*
	(0.043)	(0.055)
employed	0.210***	0.241***
	(0.049)	(0.056)
educ_2.0	0.219***	0.218***
	(0.050)	(0.050)
educ_3.0	0.546***	0.543***
	(0.066)	(0.066)
income_2.0	0.112	0.112
	(0.071)	(0.071)
income_3.0	0.106	0.107
	(0.070)	(0.070)
income_4.0	0.255***	0.254***
	(0.067)	(0.067)
income_5.0	0.450***	0.451***
	(0.065)	(0.066)
male*urban		0.049
		(0.082)
male*emp		-0.109
		(0.104)
Pseudo R-squared	0.155	0.155
Country Fixed Effects	Yes	Yes
Observations	8502	8502
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 9: Sub-Saharan Africa Robustness Checks

	Dependent variable: account_mob	
	Balanced weights	Interactions
	(1)	(2)
const	-1.750***	-1.736***
	(0.066)	(0.068)
male	0.101***	0.067*
	(0.016)	(0.035)
age	0.030***	0.029***
	(0.003)	(0.003)
age_squared	-0.000***	-0.000***
	(0.000)	(0.000)
urban	0.177***	0.187***
	(0.017)	(0.022)
employed	0.386***	0.362***
	(0.018)	(0.023)
educ_2.0	0.521***	0.521***
	(0.018)	(0.018)
educ_3.0	0.899***	0.900***
	(0.039)	(0.039)
income_2.0	0.158***	0.158***
	(0.028)	(0.028)
income_3.0	0.289***	0.289***
	(0.027)	(0.027)
income_4.0	0.368***	0.367***
	(0.026)	(0.026)
income_5.0	0.531***	0.530***
	(0.026)	(0.026)
male*urban		-0.021
		(0.031)
male*emp		0.059
		(0.036)
Pseudo R-squared	0.217	0.217
Country Fixed Effects	Yes	Yes
Observations	34011	34011
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 10: East Asia & the Pacific Robustness Checks

	Dependent variable: account_mob		
	Balanced weights	Interactions	
	(1)	(2)	
const	-2.090***	-2.124***	
	(0.184)	(0.191)	
male	0.029	0.090	
	(0.047)	(0.116)	
age	0.011	0.012	
	(0.009)	(0.009)	
age_squared	-0.000***	-0.000***	
	(0.000)	(0.000)	
urban	0.262***	0.244***	
	(0.053)	(0.067)	
employed	0.262***	0.299***	
	(0.058)	(0.068)	
educ_2.0	0.596***	0.596***	
	(0.068)	(0.068)	
educ_3.0	1.144***	1.144***	
	(0.083)	(0.083)	
income_2.0	0.067	0.070	
	(0.083)	(0.083)	
income_3.0	0.244***	0.244***	
	(0.080)	(0.080)	
income_4.0	0.310***	0.310***	
	(0.078)	(0.078)	
income_5.0	0.494***	0.497***	
	(0.077)	(0.077)	
male*urban		0.038	
		(0.095)	
male*emp		-0.111	
		(0.111)	
Pseudo R-squared		0.325	0.325
Country Fixed Effects	Yes	Yes	
Observations	6061	6061	
Note:		*p<0.1; **p<0.05; ***p<0.01	

7.3 Country Mapping

Table 11: List of Countries Included in Each Region

South Asia (SA)	Europe & Central Asia (ECA)	Middle East & North Africa (MENA)	Latin America & the Caribbean (LAC)	Sub-Saharan Africa (SSA)	East Asia & the Pacific (EAP)
Afghanistan	Armenia	Egypt, Arab Rep.	Dominican Republic	Benin	Cambodia
Bangladesh	Georgia	Iraq	El Salvador	Botswana	Indonesia
India	Kyrgyz Republic	Tunisia	Guatemala	Burkina Faso	Lao PDR
Nepal	Tajikistan	West Bank and Gaza	Honduras	Cameroon	Malaysia
Pakistan		Iraq	Jamaica	Chad	Mongolia
		Tunisia	Mexico	Comoros	Vietnam
		West Bank and Gaza	Nicaragua	Congo, Dem. Rep.	
			Paraguay	Congo, Rep.	
			Peru	Côte d'Ivoire	
				Eswatini	
				Ethiopia	
				Gambia, The	
				Ghana	
				Guinea	
				Kenya	
				Lesotho	
				Liberia	
				Madagascar	
				Malawi	
				Mali	
				Mauritania	
				Mozambique	
				Namibia	
				Niger	
				Nigeria	
				Senegal	
				Sierra Leone	
				South Africa	
				South Sudan	
				Tanzania	
				Togo	
				Uganda	
				Zambia	
				Zimbabwe	