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What Drives the Global Diffusion of Digital Finance? Socioeconomic and Demographic Determinants

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Abstract

This study investigates the global drivers for the adoption and usage of digital financial services (DFS) using three waves of repeated cross-sectional data from 160 countries, exploiting a pooled logit regression and the Heckman selection model. We predict the impact of proxies of digital financial services, including mobile money account ownership, mobile or internet transactions, as well as the ownership and usage of credit and debit cards, into the adoption and usage of digital financial services. While confirming findings from existing literature, our findings highlight several original insights. We find that the diffusion of informal digital financial services begins in countries with negative net migration, whereas the diffusion of formal digital financial services begins in countries with positive net migration. Population density is an adverse driver of adoption and usage of informal digital financial services, and of the transition from adopting to using debit cards. The historical level of digital infrastructure has a strong legacy effect on the usage of digital financial services, at both extensive and intensive margins. Population density is an adverse driver of adoption and usage of informal digital financial services and debit cards, as well as the transition from adopting to using debit cards. This study offers guidance to policymakers and other stakeholders by identifying the global determinants of both adoption and usage of formal and informal digital financial services, independent of market-specific contexts, and the key determinants influencing the transition from adoption to effective usage of specific digital financial services tools.

JEL Classification: C35; G21; O33.

Keywords: Digital finance; Financial inclusion; Technological diffusion; ROC.

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1 Introduction

1.1 Definition and Study Motivation

Regarded among the important enablers of the United Nations' Sustainable Development Goals, financial inclusion has been enjoying growing attention from various entities. The World Bank defines financial inclusion as the ability of individuals and businesses to access "useful and affordable financial products and services that meet their needs – transactions, payments, savings, credit and insurance – delivered in a responsible and sustainable way"(World Bank, 2018). Over the years, the range of institutions and services contributing to financial inclusion has expanded beyond cooperatives and microfinance institutions to include more mainstream financial entities such as commercial banks (Mushtaq & Bruneau, 2019). This expansion has been significantly favoured by the rapid development of information and communication technology, including big data, artificial intelligence, and cloud computing, resulting in the emergence of digital financial services (DFS). In 2016, the World Bank's G20 High-Level Principles of Digital Financial Inclusion stated that digital financial services, coupled with effective supervision, are essential to close the remaining gaps in financial inclusion. In 2023, the World Bank published G20 Policy Recommendations for Financial Inclusion through Digital Public Infrastructure (DPI) and acknowledged the contribution of digital financial services models to financial inclusion across developing countries.

The definition of digital finance is still under debate, in both academia and industrial practice. Organisations and institutions such as the World Bank and McKinsey define digital finance as financial services - such as payment, savings, and credit - delivered through mobile phones, computers, or other devices with access to the internet (Manyika et al., 2016; Pazarbasioglu et al., 2020). While we adopt this definition in our study, we would like to investigate at a more granular level by differentiating between digital financial services (DFS) that require an account at a formal financial institution and those that do not. We name the first type of DFS "formal DFS" and measure them with variables *debit holding*, *debit usage*, *credit holding*, and *credit usage*; we name the latter type "informal DFS" and measure them with variables *mobile money account* and *transaction_mobile_bi*. We also differentiate between the holding and usage of various DFS tools to assess whether there are heterogeneities.

A substantial body of literature highlights the positive effects of DFS on financial inclusion through reducing information asymmetry (Demir et al., 2022), lowering the cost of receiving and providing financial services (Makina, 2019; Morgan, 2022), and increasing the access to financial services for customers, especially to the poor. Other argued benefits of DFS include the promotion of sustainable economic development (Yang & Masron, 2022) and enhancing corporate resilience (Xia et al., 2022).

The benefits of DFS have prompted economies worldwide to adopt FinTech and digital finance in the hope of enhancing the financial sector's inclusion and efficiency. However, the level of development and popularization of DFS vary across countries, even within regions and at national income levels. To understand the sources of such differences, it is vital to examine the factors determining the adoption and popularization of DFS.

1.2 Literature Review

Several research works explored the factors determining the development of DFS in the context of specific economies and regions. Kandari et al. (Kandari et al., 2021), in the context of India, revealed the comparative vulnerability of females in terms of mobile usage and a significant correlation between financial literacy and the probability of DFS usage. Financial literacy appears to be another one of the relevant determinants of DFS (Liu et al., 2021). Besides Asia, similar factors were found applicable to cases of Saudi Arabia (Alnemer, 2022), Tunisia (Amari & Anis, 2021), and moreover, in MENA (Middle East and North Africa) region. Studies were conducted in the context of other countries, country groups, and regions, such as the OECD and Sub-Saharan Africa. (Chikalipah, 2017; Lo Prete, 2022).

Some macro and institutional factors are found to be determinants of DFS as well. The nexus between migrants' remittance and the development of digital finance has been gaining increasing attention in recent years. By conducting an experiment study using data collected from migrants in Dhaka, Bangladesh, Lee et al. (2021) examined the impact of net migration towards the adoption of DFS. Studies suggest an increased adoption and usage of DFS after migrating. Another study examined the effects of international net migration on the development of DFS in the migrants' home country. The results suggest that digital remittances of migrants have a positive effect on DFS adoption and usage in the destination of migrants' remittances (Jemiluyi & Jeke, 2023). Legitimisation (Kingiri & Fu, 2020), financial market efficiency and financial institution credibility (Ozili, 2023) are also described as relevant determinants of DFS in studies conducted in various countries and regions. Some studies stress that religion can also be a determinant of DFS (Aziz & Naima, 2021).

This study seeks to contribute to the existing literature by exploring the determinants of DFS development on a global scale and examining the universality of these factors. Moreover, we would like to address the scarcely attended perspective of the diffusion of DFS on a global scale and the potential clustering of DFS adoption within certain regions. By examining these factors and exploring the effects of international activities and interactions, such as net migration, on DFS development, we aim to shed light on the potential distribution of DFS. This understanding is crucial not only for identifying universal determinants across countries but also for gaining insights into how globalization influences the development of DFS within the borders of economies. Working towards a deeper understanding of the above-mentioned issue is essential for various practices, including policy-making, especially in the context of globalization.

We use the repeated cross-section data from the World Bank's Findex microdata, encompassing 160 countries and 3 waves, for our analysis. We conduct pooled logit regression followed by a probit regression with sample selection. A seminal contribution has been provided by Ghosh and Chaudhury (2022), which examines the demographic determinants of digital finance in the context of India, adopting 2014 and 2017 data of India from the same database. Our research extends the literature by including 2021 data and 160 countries in our analysis. In the first part, we identify a series of socioeconomic demographic determinants of DFS on a global scale, including individual income, gender, age, and education, which is consistent with the findings of the current literature within the local context. In the second part, we investigate the factors determining the adoption/usage of DFS in different stages with a bivariate model.

The results suggest that population density has a negative effect on the adoption and usage of informal DFS tools and that net migration negatively determines the adoption and usage of informal DFS tools - observations that have not been reported in the existing literature. Additionally, our results confirm that the adoption and usage of DFS have increased over time, particularly for informal tools like mobile money, with stronger growth in transitioning from adoption to usage compared to formal DFS. Gender disparities are less pronounced in informal DFS, where women face barriers mainly during the adoption phase, unlike in formal DFS, where discrimination persists across all stages. A reverse U-shaped age pattern is observed, with younger users more inclined toward informal DFS. Education and income positively influence DFS adoption and usage, though informal tools show less discrimination by socioeconomic status. Over time, gender and income-related disparities have diminished. Policy recommendations include increasing female literacy and education levels, and prioritising digital infrastructure investments.

The rest of the article is structured as follows: this section is followed by a literature review examining current studies of determinant factors of DFS and other related issues. The third section presents the data and methodology, followed by a section showcasing and discussing the results. The final section concludes.

2 Data

2.1 Data Source and Variables

The main data source, the World Bank's Findex database, contains over 100 indicators reflecting various dimensions of financial inclusion from the demand side. This large, granular set of data allows us to conduct robust analyses across countries and various demographic groups. Such characteristics of the dataset have attracted various studies with similar topics to rely on for their analysis, benefiting both within-country and cross-country analyses (Ghosh & Hom Chaudhury, 2022; Sabbaghi, 2024; Tripathi & Rajeev, 2023). Moreover, despite irregularity between 2021-2023, the dataset regularly updates its data, enabling us to track the changes in determinant factors of adoption and usage of DFS over time, potentially benefiting our future analyses based on this study. Since 2011, the Findex database has been releasing integrated individual-level cross-country data typically in 3-year intervals, with the exception of the 2020 and 2021 datasets. Due to the obstacles created by the COVID-19 pandemic, instead of releasing 2020 data following the 2017 data, 2021 data was released by the World Bank. The indicators included in the database slightly differ across editions. Used in our analysis are 9 out of over 100 indicators, specifically, "has a mobile money account", "has a debit card", "used a debit card in the past 12 months", "has a credit card", "used a credit card in the past 12 months", "respondent gender", "respondent age", "respondent education level", and "respondent income quintile".

2014, 2017, and 2021 data are adopted for our analysis. Survey data from 160 countries are included in our dataset, with a total of 424,355 rows of individual-level and country-level data included. The dataset has no identical individual identification codes, meaning that different individuals were surveyed each year. Thus, our data is a repeated cross section, not panel data.

Table 2 summarises the definition of the variables used in our analysis. As shown in the table, most of the variables are binary dummy variables taking values 0 and 1, including the main dependent variables and the majority of the independent variables denoting socioeconomic demographic factors of individuals. There are also continuous variables, such as age, population density, and net migration.

It is worth noting that variables *debit card holding* and *debit card usage* account for all respondents who hold/use a debit card, regardless of whether the debit card they are holding/using is registered under their own names. Variables *credit card holding* and *credit card usage* do not suffer from the same ambiguity, with all the respondents reporting holding and having used their credit cards under their own names.

The variables *income level* and *income group* denote the levels of personal and national income, respectively. *Income level* consists of individual-level observations of within-economy income quintiles of each respondent, ranging from the poorest 20% to the richest 20%. *Income group* is a categorical variable denoting the national income classification of each economy. The variable takes values from 1 to 4, assigned to low-income, lower-middle income, upper-middle income, and high-income, respectively.

The variable *income level* may not capture well the purchasing power of individual income, as it does not account for the differences in income level across countries. To tackle this key aspect, we estimate the amount of dollar income at each quintile for each economy with a commonly assumed functional specification, using GINI coefficient and GDP per capita[1,2] . Table 1 summarizes the two indicators' descriptive statistics by time and national income group. Over time, the GINI coefficient tends to remain stable across income groups. GDP per head experiences notable increases over time across all income groups, with the Upper-Middle income country group's GDP per head increasing the fastest.

Note that the number of observations is not balanced across national income groups, with the low-income group having the least observations and the high-income group having the most income, almost four times that of the low-income group. A sizeable drop in the number of observations in 2021 for the low-income group is also observed.

[1]The data source is the World Bank's World Development Database, and Poverty and Inequality Platform.

[2]Details of the estimation of the new income variable are shown in Appendix A.1.

Table 1: Descriptve Statistics of GINI Index and GDP per head

	(1) GINI					(2) GDP per head				
	Num. of Obs.	Mean	St. Dev.	Min	Max	Num. of Obs.	Mean	St. Dev.	Min	Max
Low Inc.										
2014	18,086	0.39	0.05	0.33	0.46	21,590	736.02	268.14	307.77	1,412.20
2017	22,000	0.40	0.06	0.33	0.54	23,504	786.75	278.62	371.60	1,426.63
2021	11,002	0.40	0.07	0.30	0.56	11,003	755.82	229.81	407.62	1,277.61
2024	13,020	0.39	0.04	0.33	0.50	13,020	754.24	197.36	453.38	1,134.09
Total	64,108	0.40	0.05	0.30	0.56	69,117	759.85	255.01	307.77	1,426.63
Low.-Mid. Inc.										
2014	32,083	0.38	0.08	0.24	0.52	37,103	2,289.60	897.70	937.00	3,903.05
2017	32,307	0.38	0.07	0.26	0.56	36,907	2,442.99	1,023.56	1,090.99	4,427.54
2021	34,090	0.37	0.06	0.26	0.50	38,112	2,560.46	1,260.56	1,041.75	6,107.46
2024	38,237	0.38	0.08	0.26	0.59	38,227	2,354.22	1,015.63	990.18	4,186.50
Total	136,717	0.38	0.07	0.24	0.59	150,349	2,412.35	1063.70	937.00	6,107.46
Up.-Mid. Inc.										
2014	32,307	0.41	0.09	0.27	0.63	39,325	6,755.20	2,280.30	3,304.68	13,155.45
2017	35,717	0.40	0.08	0.25	0.63	40,727	7,294.42	2,318.38	3,947.97	12,267.16
2021	33,100	0.39	0.09	0.26	0.63	33,100	7,715.06	2,954.45	3,688.65	13,449.93
2024	37,662	0.37	0.08	0.26	0.63	38,662	7,573.00	3,004.73	2,219.04	13,121.68
Total	140,794	0.40	0.09	0.25	0.63	151,814	7,317.40	2,669.12	2219.04	13,449.93
High Inc.										
2014	40,127	0.33	0.05	0.26	0.47	46,670	33,516.20	20,235.56	9,520.95	105,583.90
2017	39,095	0.33	0.05	0.23	0.50	45,675	35,972.19	20,853.09	13,203.82	107,142.10
2021	38,114	0.32	0.06	0.24	0.51	42,638	37,134.08	20,094.56	11,607.40	90,589.20
2024	43,128	0.33	0.06	0.24	0.50	49,167	34,641.30	20,881.14	4,017.75	91,514.33
Total	160,464	0.33	0.05	0.23	0.51	184,150	35,263.44	20,575.39	4,017.75	107,142.10
Total										
2014	123,603	0.37	0.08	0.24	0.63	144,688	13,343.82	18,215.89	307.77	105,583.90
2017	130,127	0.37	0.08	0.23	0.63	146,813	13,954.93	19,006.54	371.60	107,142.10
2021	116,306	0.36	0.07	0.24	0.63	124,853	15,575.05	19,668.9	407.62	90,589.20
2024	134,048	0.36	0.08	0.24	0.63	140,077	14,968.4	19,245.11	453.38	91,514.33
Total	504,084	0.37	0.08	0.23	0.63	556,431	14,414.68	19,036.09	307.77	107,142.10

Note: Columns (1)-(5) are the descriptive statistics of the GINI index by country income for each year in our dataset, and columns (6)-(10) are the descriptive statistics of GDP per capita by country income for each year in our dataset.

Table 2: Description of Variables

Variable	Description	Data Source
DEPENDENT VARIABLES		
transaction using mobile/internet_bi	Has made a transaction using a mobile phone or internet, binary	World Bank, Findex database
mobile money account	Has a mobile money account	World Bank, Findex database
debit card holding	Has a debit card	World Bank, Findex database
debit card usage	If has debit card: used card in past 12 months	World Bank, Findex database
credit card holding	Has a credit card	World Bank, Findex database
credit card usage	If has credit card: used card in past 12 months	World Bank, Findex database
INDEPENDENT VARIABLES		
female	Respondent is female	World Bank, Findex database
age	Respondent age	World Bank, Findex database
education	Respondent education level	World Bank, Findex database
income level	Within-economy income quintile	World Bank, Findex database
individual income	Natural logarithm of estimated absolute personal income	generated by author
income group	Level of the economy's national income	World Bank, World Development Indicators
banked	Euqals to 1 if respondent formally banked, 0 if otherwise	generated by author
population density	Natural logarithm of the density of adult population per sq. km	Food and Agriculture Organization
net migration	Net migration (the number of immigrants minus the number of emigrants) as a ratio of total population. Lagged variable	United Nations, Population Division
financial development index (FD)	Aggregate of financial institution index and financial market index	IMF
branch	Number of commercial bank branches per 100,000 adults	IMF
fixed-telephone subscription	Historical data: the number of fixed telephone subscription per person in years 2004, 2007 and 2011	International Telecommunication Union

Note: Description of all dependent and independent variables, including measurement and source of data.

2.2 Descriptive Statistics

Descriptive statistics are summarized in Table 3. In 2014, 60,325 out of 146,688 respondents reported having a debit card, of which over 95% reported the card to be under their own name. The percentage remains similar in 2017 when 68,242 out of 148,155 respondents reported having a debit card. The variable *mobile money account* denotes the ownership of mobile money accounts, while the variable *transaction using mobile/Internet* denotes the usage of DFS tools, including mobile money accounts. While the means of both variables remain relatively low, they have increased by approximately 4 times in size over the years. Meanwhile, the means of debit and credit holding and usage have been increasing at a relatively low speed over the years. Nevertheless, the overall means of debit and credit holding and ownership are considerably higher than those of mobile money accounts and transactions using mobile or the internet.

Table 12 in the Appendix provides a further breakdown of the above-mentioned descriptive statistics by income groups. As shown in the table, for each income group, the gender ratio of the respondents all fall into a similar percentage of around 50%. The age and educational level are representative of the characteristics of each income class and the ownership of financial accounts, and the income quintile of respondents belonging to all income classes falls between the 3.0 and 3.5 intervals. This indicates that the World Bank's data effectively reflects the characteristics of the average population conditional to the country. However, the income quintile does not account for the differences in national income levels and is thus not comparable across countries. We take this matter into account by introducing the estimated variable *individual income* and country fixed-effects.

The correlation matrix of all dependent and independent variables is shown in Tables 10 and 11 in the Appendix, suggesting that potential problems due to collinearity or multicollinearity are not relevant.

Table 3: Descriptive Statistics

	(1) 2014					(2) 2017					(3) 2021				
	N. of Obs.	Mean	St. Dev.	Min	Max	N. of Obs.	Mean	St. Dev.	Min	Max	N. of Obs.	Mean	St. Dev.	Min	Max
DEPENDENT VARIABLES															
mobile money account	74 298	0.07	0.26	0.00	1.00	79 475	0.15	0.36	0.00	1.00	68 681	0.27	0.44	0.00	1.00
mobile/internet transaction_bi	109 199	0.05	0.21	0.00	1.00	109 493	0.13	0.33	0.00	1.00	86 728	0.29	0.45	0.00	1.00
debit holding	145 329	0.42	0.49	0.00	1.00	148 155	0.46	0.50	0.00	1.00	126 942	0.55	0.50	0.00	1.00
debit usage	144 622	0.29	0.45	0.00	1.00	147 487	0.31	0.46	0.00	1.00	57 125	0.00	0.00	0.00	0.00
credit holding	145 109	0.20	0.40	0.00	1.00	147 504	0.20	0.40	0.00	1.00	83 651	0.38	0.49	0.00	1.00
credit usage	145 109	0.17	0.37	0.00	1.00	147 504	0.17	0.38	0.00	1.00	83 651	0.32	0.47	0.00	1.00
INDEPENDENT VARIABLES															
female	146 688	0.53	0.50	0.00	1.00	149 813	0.54	0.50	0.00	1.00	127 854	0.47	0.50	0.00	1.00
age	146 364	41.62	17.69	15.00	99.00	149 362	41.90	17.97	15.00	99.00	127 399	41.71	17.44	15.00	99.00
education	146 033	1.83	0.68	1.00	3.00	148 902	1.83	0.69	1.00	3.00	127 182	2.00	0.70	1.00	3.00
income quintile	146 672	3.19	1.42	1.00	5.00	149 813	3.19	1.42	1.00	5.00	127 854	3.24	1.42	1.00	5.00
individual income	123 599	7.89	2.21	1.63	12.66	129 127	7.89	2.20	1.30	12.65	115 305	8.11	2.13	1.50	12.61
income classification	146 688	2.22	1.06	1.00	4.00	149 813	2.26	1.07	1.00	4.00	126 854	2.15	1.00	1.00	4.00
banked	145 914	0.44	0.50	0.00	1.00	148 766	0.48	0.50	0.00	1.00	127 144	0.57	0.50	0.00	1.00
population density	144 687	4.34	1.40	0.62	8.95	147 813	4.33	1.41	0.69	8.98	125 854	4.41	1.36	0.77	8.95
fixed telephone subscription	142 687	20.26	19.26	0.02	71.09	145 813	19.96	18.02	0.01	65.25	125 854	20.72	18.06	0.02	64.03
net migration	145 688	0.00	0.02	−0.03	0.13	148 813	0.00	0.01	−0.06	0.02	126 854	0.00	0.00	−0.03	0.02
FD	138 180	0.37	0.24	0.04	0.95	142 813	0.37	0.24	0.04	0.96	121 840	0.40	0.23	0.05	0.94
branch	138 163	17.77	15.24	0.77	79.57	139 753	16.39	13.81	0.45	71.72	111 789	15.65	12.46	0.39	72.07

Note: Descriptive statistics for all variables by year, including number of observations, mean, standard deviation, minimum and maximum values.

3 Methodology

In this section, the methodology is presented. We use the logit model in the main part of our analysis and the Heckman selection model for further analysis.

The above-mentioned methodologies have been adopted by papers with similar topics or with similar study objectives. Birdat and Kalra (2025) adopted logit model to analyse the determinants of digital financial inclusion in South Asia using the Findex database 2021 data; Heckman selection model is frequently utilised for the purpose of analysing the transitioning decisions accross literature (Chen et al., 2020; Dorfleitner et al., 2022).

Both models fit the objective of our study on different stages, where the logit model helps us identify the key factors affecting the propensity to adopt and use the DFS tools overall, and the Heckman selection model allows us to examine the factors determining the transition from non-adoption to adoption, as well as that from adoption to usage, while tackling the potential selection bias, i.e. only a subset of the population completes the process of transitioning from non-adoption to adoption, and/or from adoption to usage.

3.1 Logit Model

3.1.1 Fixed Effects Logit Model

The following equation is adopted to examine the effects of the above-mentioned factors on the adoption and usage of various DFS tools. We adopt the logit model in our analysis.

$$P(Y = 1) = P(Y^* > 0) = \Lambda(W_i'\beta) = \frac{1}{1 + e^{-W_i'\beta}} \tag{1}$$

where P(Y=1) is the probability that the dependent variable Y equals 1; $P(Y^* > 0)$ is the probability that the latent variable Y^* exceeds 0; $\Lambda(W_i'\beta)$ is the logistic function, which transforms the linear prediction into a probability, and $W_i'\beta$ is a linear combination of the independent variables W_i and the coefficient vector β.

The propensity of respondent i in country j in Year t to adopt digital financial services is:

$$
\begin{aligned}
Y_{ijt}^{*} = f(W_{ijt}) + u_{ijt} = f(&Age_{ijt}, IndividualIncome_{ijt}, Education_{ijt}, \\
&Gender_{ijt}, Migration_{jt}, Telephone\ Subscription_{jt}, \\
&Income\ Group_{jt}, Population\ Density_{jt}, FD_{jt}, Year_{t}, \\
&Country_{j}) + u_{ijt}
\end{aligned} \tag{2}
$$

where $f(W_{ijt})$ includes quadratic and interaction terms: age squared, female × age, female × individual income, female × education, time × female, time × age, time × individual income, time × education. u_{ijt} is logistically distributed.

3.1.2 Weighted Fixed Effects Logit Model

In consideration of controlling for the difference in the size, power of influence, and other factors of different countries in our sample, we assign weights to each observation by country and compare the results with the unweighted results. We adopt sampling weights by country GDP for this purpose.

3.1.3 Average Marginal Effects

The scale of impact of dependent variables on the probability of adoption and usage of DFS tools cannot be observed from the estimates of logit regressions. In order to understand the magnitude of the impact, average marginal effects are required. We obtain average marginal effects after each regression in order to better understand the impact of each factor considered in the analysis.

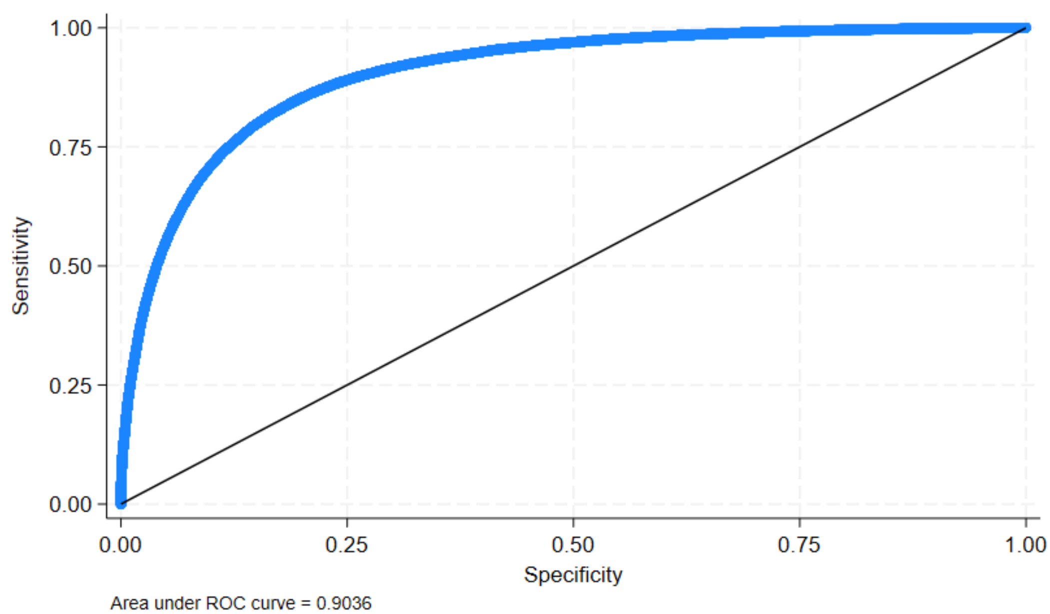
For the same purposes, we estimate the marginal effects after the two-step Heckman regression. For each column in Table 9, we estimate the marginal effects on the probability of selection, the probability of success, and the probability of success conditional on selection, respectively.

3.2 Area Under the ROC Curve

We use the area under the ROC curve (AUC_{ROC}) to examine the fit of our model. In our case, the AUC_{ROC} measures the model's ability to separate positives from negatives, an ability also referred to as discrimination (Kim et al., 2022). To assess the discriminatory performance of a model, the predicted probability of adopting/using a certain type of DFS for each individual is obtained and compared to the actual probability of the individual's using/adopting the DFS. The usage/adoption is predicted whenever the predicted probability exceeds a certain threshold. The curve of the true positive rate (sensitivity) against the false positive rate (specificity) on various thresholds is called the ROC curve. A larger area under the ROC curve indicates a better fit of the given model. According to Hosmer et al. (2013), that an AUC_{ROC} over 0.7 indicates an acceptable discrimination, an AUC_{ROC} between 0.8 and 0.9 indicates excellent discrimination, and an AUC_{ROC} above 0.9 indicates outstanding discrimination.

For example, Figure 1 shows the ROC curve of regression of our logit model with income and country fixed effects with one of the dependent variables used in our study - debit usage. The area under the ROC curve (AUC_{ROC}), as shown at the bottom left of the figure, is 0.9036, indicates an outstanding fit of the model.

Figure 1: ROC curve of fixed-effects logit regression against debit usage. An AUC_{ROC} above 0.9 indicates an outstanding fit.



Note: an example of ROC curve. Source: generated by the author.

3.3 Heckman Selection Model

In our analysis, we also use the Heckman selection model (Heckman, 1979) to capture the factors affecting one's transition from one stage of DFS adoption or usage to another[1]. Specifically, our aim is to examine the factors affecting the transition from not holding any DFS to holding at least one of them, as well as the transition from holding DFS to using them. While a large proportion of the sample does not hold any of the DFS tools, this feature has shrunk over time. Therefore, we are interested in examining the determinants of these transitions: which factors are the most significant for the decision to transition to the next stage of the ones on the edge of transitioning? Are the determinant factors different across stages?

We use all the previously mentioned variables in this part of our analysis and examine how these variables affect the individual's probability of advancing to the next stage. Two main equations are used in the analysis:

$$Z^*_{ijt} = W'_{ijt}\gamma + u_{ijt} \tag{3}$$

$$Y^*_{ijt} = W'_{ijt}\beta + \epsilon_{ijt} \tag{4}$$

where:

Z^*_{ijt} is an unobserved latent variable, indicating the propensity of individual i in country j adopting DFS tools at time t.

W_{ijt} is a vector of explanatory variables.

γ and β are vectors of coefficients.

Y^*_{ijt} is the unobserved latent variable underlying the outcome of interest, indicating the propensity of individual i in country j using DFS tools at time t, given that they have adopted the DFS tools.

[1]See Greene (2008) for more details related to our model choice

u_{ijt} and ϵ_{ijt} are error terms that follow normal distribution.

Quadratic and interaction terms: age squared, female $\times$ age, female $\times$ individual income, female $\times$ education, time $\times$ female, time $\times$ age, time $\times$ individual income, time $\times$ education are included.

In the first stage, the observed selection indicator Z_{ijt} is:

$$Z_{ijt} = \begin{cases} 1 & \text{if} \quad Z^*_{ijt} > 0 \\ 0 & \text{if} \quad otherwise \end{cases} \tag{5}$$

In the second stage, the observed outcome Y_{ijt} is:

$$Y_{ijt} = \begin{cases} 1 & \text{if} \quad Z^*_{ijt} = 1 \, and \, Y^*_{ijt} > 0 \\ 0 & \text{if} \quad otherwise \end{cases} \tag{6}$$

4 Results

This section reports the regression results of the simple logit model, the weighted logit model, and the Heckman selection model, as well as their average marginal effects.

4.1 Logit Regression Results

4.1.1 Simple Logit Regression Results

The estimates of the logit regression results of the independent variables against various dependent variables representing different DFS tools are reported in Table 4. From the results reported in the table, the time variable positively affects the adoption and usage of all DFS tools. Being female negatively determines the propensity to adopt and use DFS tools. However, positive coefficients of the interaction term *time = 2021* $\times$ *female* indicate that over time, the propensity of females to use and adopt DFS tools has not only been increasing but also reverted. Significantly positive coefficients of *age* and significantly negative coefficients of *age squared* indicate a reverse U shape for the correlation between age and the possibility of adopting and using DFS tools. This set of results is consistent with the theory of diffusion of innovations: the early adoption of an innovation is lower at younger and older ages, and peaks at middle-aged demographic groups. Education and individual income also determined the propensity to adopt and use DFS tools positively. The results are consistent with literature of country- and region-specific contexts, as discussed in previous sections. $PseudoR^2$ and AUC_{ROC} are at an acceptable level, indicating that the model fits well. However, considering the variety of countries of different income levels included in our sample, it is worth conducting a country-weighted analysis to control for potential bias in the representation of countries.

Table 4: Logit Regression with Country and Income Group Fixed Effects

	(1) mobile money account	(2) transaction mobile_bi	(3) debit holding	(4) debit usage	(5) credit holding	(6) credit usage
time=2017	2.411***	1.977***	0.860***	0.508***	0.665***	0.316*
	(0.187)	(0.187)	(0.090)	(0.106)	(0.120)	(0.131)
time=2021	2.393***	2.923***	1.125***	1.569***	2.389***	2.106***
	(0.211)	(0.195)	(0.097)	(0.109)	(0.128)	(0.138)
female	−0.128	−0.274*	−0.057	−0.265**	−0.254*	−0.424***
	(0.124)	(0.119)	(0.075)	(0.087)	(0.100)	(0.109)
age	0.063***	0.013	0.104***	0.084***	0.118***	0.116***
	(0.008)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
age square	−0.001***	0.000***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
secondary edu	0.596***	0.408***	1.010***	1.074***	0.963***	1.019***
	(0.051)	(0.061)	(0.024)	(0.030)	(0.035)	(0.039)
tertiary edu	1.089***	0.759***	1.910***	1.933***	1.722***	1.795***
	(0.073)	(0.069)	(0.032)	(0.036)	(0.039)	(0.043)
individual income	0.172***	0.123***	0.228***	0.230***	0.239***	0.242***
	(0.011)	(0.012)	(0.005)	(0.006)	(0.007)	(0.008)
banked	1.010***	1.066***				
	(0.020)	(0.021)				
population density	−3.311***	−6.661***	−2.289***	−3.236***	0.264	0.245
	(0.445)	(0.304)	(0.179)	(0.203)	(0.226)	(0.245)
net migration	−11.278***	−5.228	−2.073*	−1.759	6.669***	6.226**
	(2.946)	(2.976)	(0.911)	(1.235)	(1.790)	(1.979)
FD	5.160***	4.297***	0.582*	−0.905***	−0.085	−0.393
	(0.486)	(0.404)	(0.269)	(0.267)	(0.279)	(0.293)
fixed telephone subscription	0.073***	0.023***	−0.003	0.002	−0.003	0.000
	(0.009)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
branch	−0.023***	0.001	0.007***	0.006***	0.014***	0.017***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
female× age	−0.004	−0.001	−0.012***	−0.002	0.002	0.005
	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)
female× secondary edu	0.027	0.070	0.055*	0.059*	0.114***	0.141***
	(0.038)	(0.042)	(0.023)	(0.029)	(0.034)	(0.038)
female× tertiary edu	0.010	0.003	0.004	0.022	0.050	0.058
	(0.054)	(0.047)	(0.031)	(0.034)	(0.037)	(0.041)
female× individual income	−0.009	0.005	−0.005	0.007	−0.015*	−0.004
	(0.008)	(0.008)	(0.005)	(0.006)	(0.006)	(0.007)
time=2017× female	−0.065	0.056	−0.023	−0.043	−0.020	−0.012
	(0.047)	(0.043)	(0.023)	(0.025)	(0.026)	(0.027)
time=2021× female	0.519***	0.359***	0.545***	0.301***	0.455***	0.462***
	(0.046)	(0.042)	(0.024)	(0.026)	(0.027)	(0.028)
time=2017×age	−0.031***	0.001	−0.004	0.000	−0.014**	−0.005
	(0.009)	(0.008)	(0.003)	(0.004)	(0.004)	(0.005)
time=2021×age	−0.004	0.020*	−0.019***	−0.018***	−0.032***	−0.023***
	(0.009)	(0.008)	(0.004)	(0.004)	(0.004)	(0.005)
time=2017×indiviudal income	−0.050***	−0.017	−0.036***	−0.006	−0.010	0.004
	(0.012)	(0.012)	(0.006)	(0.007)	(0.008)	(0.009)
time=2021×indiviudal income	−0.022	−0.029*	−0.040***	−0.050***	−0.105***	−0.102***
	(0.012)	(0.013)	(0.007)	(0.007)	(0.008)	(0.009)
time=2017 × secondary edu	−0.014	−0.075	−0.129***	−0.183***	−0.136***	−0.111*
	(0.056)	(0.065)	(0.027)	(0.035)	(0.040)	(0.045)
time=2017 × tertiary edu	0.085	−0.085	−0.067	−0.220***	−0.156***	−0.125*
	(0.081)	(0.075)	(0.038)	(0.042)	(0.045)	(0.049)
time=2021 × secondary edu	0.214***	0.190**	−0.076*	−0.132***	−0.606***	−0.607***
	(0.056)	(0.067)	(0.030)	(0.037)	(0.045)	(0.050)
time=2021 × tertiary edu	0.165*	0.163*	−0.160***	−0.258***	−0.755***	−0.761***
	(0.081)	(0.075)	(0.039)	(0.043)	(0.049)	(0.053)
cons	6.799***	22.592***	4.573***	7.809***	−8.965***	−9.555***
	(2.051)	(1.395)	(0.830)	(0.952)	(1.060)	(1.152)
N. of Obs.	174,096	241,348	328,565	328,565	296,833	294,233
$Pseudo-R^2$	0.3017	0.2675	0.3783	0.4247	0.3176	0.3128
AUC_{ROC}	0.8665	0.8523	0.8824	0.9036	0.8641	0.8653

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Base Groups: time=2014, primary education, Low Income, Afghanistan.

Table 5: Average Marginal Effects: Logit Regression with Country and Income Group Fixed Effects

	(1) mobile money account	(2) transaction_mobile_bi	(3) debit holding	(4) debit usage	(5) credit holding	(6) credit usage
time=2017	0.093***	0.091***	0.062***	0.033***	0.014***	0.013***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
time=2021	0.222***	0.291***	0.109***	0.104***	0.072***	0.054***
	(0.006)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
female	−0.007***	−0.004**	−0.017***	−0.011***	−0.013***	−0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age	0.000***	−0.002***	0.001***	−0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
secondary edu	0.062***	0.041***	0.146***	0.119***	0.086***	0.082***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
tertiary edu	0.117***	0.071***	0.282***	0.228***	0.181***	0.170***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
individual income	0.013***	0.009***	0.028***	0.025***	0.023***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
banked	0.101***	0.089***				
	(0.002)	(0.002)				
population density	−0.306***	−0.599***	−0.318***	−0.378***	0.032	0.027
	(0.041)	(0.027)	(0.025)	(0.024)	(0.027)	(0.027)
net migration	−1.044***	−0.471	−0.288*	−0.206	0.802***	0.684**
	(0.273)	(0.268)	(0.127)	(0.144)	(0.215)	(0.217)
FD	0.478***	0.387***	0.081*	−0.106***	−0.010	−0.043
	(0.045)	(0.036)	(0.037)	(0.031)	(0.034)	(0.032)
fixed telephone subscription	0.007***	0.002***	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
branch	−0.002***	0.000	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of Obs.	174,096	241,348	328,565	328,565	296,833	294,233

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Base Groups: time=2014, primary education, Low Income, Afghanistan.

4.1.2 Country-Weighted Logit Regression Results

Table 6 reports the estimates of the weighted logit regression. Comparing $PseudoR^2$ in Table 6 with those in Table 4, we confirm that no drastic differences are found in the weighted results. Similar to the results in Table 4, variables *time*, *individual income*, and *education* exhibit significantly positive effects on the adoption and usage of DFS tools. Similarly, the coefficients of variables *age* and *age squared* indicate a reversed U-shape for the correlation between age and propensity to adopt and use DFS tools. According to our calculation, the optimal ages for mobile money account adoption, mobile money transaction, debit card holding, debit card usage, credit card holding, and credit card usage are 36.67, 25.43, 43.76, 39.43, 48.52, and 47.72, respectively. The age of using and adopting credit cards and debit cards is significantly older than that of adopting and using mobile money and other online DFS tools. The age gap between adoption and usage of informal DFS appears to be larger than that between formal DFS tools, a cause of which could be the slight difference in sample selection for usage and adoption of informal DFS tools. Education variables are positively significant in all columns, indicating their substantial effect on the propensity to adopt and use all DFS tools. For informal DFS tools, the historical number of fixed telephone subscriptions in the country positively affects the propensity to adopt and use informal DFS tools, as this variable can be a proxy of a country's infrastructural preparedness for internet technology development. Coefficients of the interaction term between *time=2021* and *individual income* are significantly negative in all columns, indicating a declining determinant effect of income on the propensity to adopt and to use DFS tools, which suggests increasing inclusiveness of DFS tools in terms of less income discrimination. We have not found these results in the existing literature.

The average marginal effects, summarised in Table 5, indicate each variable's scale of impact. According to the significance and size of the coefficients, the main determinant factors of DFS are *population density*, *FD*, and *net migration*. *Education* appears to be another relevant determinant for the propensity to adopt and use formal DFS tools. Combining our findings with Rogers's (2003) relative advantage of innovation diffusion, the negative determinant effect of population density suggests that for less populated countries, the DFS tools have a significant relative advantage over traditional financial tools for their lower cost of access.

As shown in the table, between the two time variables *time=2017* and *time=2021*, *time=2021* has a more significant impact on the propensity of adoption and usage of each DFS tool. This indicates increasing diffusion of DFS tools over time, which is consistent with existing literature (Kingiri & Fu, 2020). Although for all DFS tools, being female seems to be associated with a lower propensity to adopt and use them, the negative effect is drastically smaller for informal DFS tools, suggesting that informal DFS tools, such as mobile money and online payment, have fewer characteristics of discrimination towards gender, compared to formal DFS tools. These results are consistent with the findings in existing literature (Chatterjee, 2024; Kusimba, 2018). Similar characteristics can be observed in the average marginal effects of *individual income*. While its effect on the propensity to adopt informal DFS is half of that for formal DFS tools, the effect on that to use informal DFS tools is drastically smaller than that of formal DFS tools, indicating a lower level of discrimination towards the income of informal DFS tools. The average marginal effects of education variables suggest a positive effect of years of education on the propensity of adoption and usage of all DFS tools. The above-mentioned results are consistent with those of the existing literature. In columns (1) and (2), net migration has a strong negative effect on the propensity of adoption and usage of informal DFS tools. When the percentage of net migration in the population increases by 1, the propensity of adopting a mobile money account decreases by 1.39 percentage points, and that of using a mobile money account decreases by 1.05 percentage points. A rationalisation of this result is that the attractiveness of a country as a destination of net migration is usually positively correlated with the socioeconomic development of the country, thus more popularising the ownership and usage of DFS tools of formal financial institutions (Blau et al., 2011). Moreover, countries that appear as sources of migrants are often lower-income countries with underdeveloped formal financial institutions, forming a pattern of participation in the financial market that is argued to persist for up to 28 years after immigration (Osili & Paulson, 2004). The results also indicate the different characteristics of diffusion for formal and informal DFS tools; for informal DFS tools, the diffusion happens from net migration home countries, whereas for formal DFS tools, the diffusion happens from net migration host countries.

Table 6: Weighted Logit Regression with Country and Income Group Fixed Effects

	(1) mobile money account	(2) transaction_mobile_bi	(3) debti holding	(4) debit usage	(5) credit holding	(6) credit usage
time=2017	1.786***	0.671*	1.468***	0.466*	0.0295	-0.178
	(0.419)	(0.317)	(0.392)	(0.209)	(0.194)	(0.202)
time=2021	1.963***	2.920***	2.202***	2.127***	0.817***	0.800***
	(0.388)	(0.310)	(0.417)	(0.213)	(0.196)	(0.203)
female	-0.022	-0.248	-0.257	-0.329	0.027	-0.032
	(0.271)	(0.209)	(0.332)	(0.174)	(0.159)	(0.165)
age	0.046**	0.006	0.012	0.018**	0.118***	0.113***
	(0.017)	(0.011)	(0.011)	(0.006)	(0.005)	(0.006)
age squared	-0.001***	-0.000**	-0.000**	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
secondary edu	0.487***	0.362*	0.217	0.621***	0.546***	0.560***
	(0.102)	(0.141)	(0.116)	(0.059)	(0.056)	(0.060)
tertiary edu	0.782***	0.548***	0.378**	1.128***	1.200***	1.234***
	(0.138)	(0.148)	(0.126)	(0.067)	(0.061)	(0.064)
individual income	0.146***	0.0900***	0.0658**	0.143***	0.160***	0.159***
	(0.022)	(0.020)	(0.021)	(0.012)	(0.011)	(0.011)
banked	1.098***	1.102***				
	(0.035)	(0.040)				
population density	-1.389*	-5.475***	-2.890***	-3.602***	-2.779***	-2.657***
	(0.604)	(0.487)	(0.788)	(0.388)	(0.363)	(0.372)
net migration	-5.852*	5.656	-2.614	1.137	-0.952	-3.793
	(2.424)	(4.358)	(9.397)	(2.459)	(3.573)	(3.972)
FD	7.150***	4.522***	3.001**	-1.242**	-0.380	-0.937*
	(0.606)	(0.546)	(0.916)	(0.425)	(0.371)	(0.380)
fixed telephone subscription	0.130***	0.005	-0.008	-0.003	-0.015***	-0.009***
	(0.012)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)
branch	-0.016**	-0.014***	0.034***	0.020***	0.005*	0.009***
	(0.005)	(0.004)	(0.007)	(0.003)	(0.003)	(0.003)
female$\times$ age	-0.013	0.003	-0.002	0.012*	-0.001	-0.003
	(0.014)	(0.008)	(0.011)	(0.006)	(0.005)	(0.005)
female$\times$ 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)
female$\times$ secondary edu	0.007	0.152	0.130	0.060	-0.019	-0.002
	(0.062)	(0.085)	(0.122)	(0.056)	(0.054)	(0.058)
female$\times$tertiary edu	0.054	0.063	0.132	0.007	-0.114*	-0.130*
	(0.087)	(0.089)	(0.131)	(0.063)	(0.058)	(0.061)
female$\times$individual income	-0.003	-0.016	0.009	0.010	-0.014	-0.004
	(0.014)	(0.013)	(0.022)	(0.011)	(0.010)	(0.011)
time=2017$\times$female	-0.128	0.068	-0.035	-0.142**	-0.003	0.011
	(0.096)	(0.063)	(0.083)	(0.044)	(0.038)	(0.038)
time=2021$\times$female	0.409***	0.259***	-0.031	-0.150***	0.388***	0.419***
	(0.090)	(0.062)	(0.087)	(0.046)	(0.038)	(0.039)
time=2017$\times$age	-0.018	0.025*	-0.006	0.005	-0.009	-0.0008
	(0.022)	(0.012)	(0.013)	(0.007)	(0.006)	(0.006)
time=2021$\times$age	0.014	0.012	-0.008	-0.003	-0.027***	-0.020**
	(0.017)	(0.012)	(0.014)	(0.007)	(0.006)	(0.007)
time=2017$\times$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)
time=2021$\times$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)
time=2017$\times$individual income	-0.024	0.017	-0.070**	-0.007	0.035**	0.046***
	(0.022)	(0.022)	(0.025)	(0.014)	(0.013)	(0.013)
time=2021$\times$individual income	-0.042	-0.043*	-0.121***	-0.119***	-0.012	-0.027*
	(0.022)	(0.021)	(0.029)	(0.014)	(0.013)	(0.013)
time=2017$\times$secondary edu	0.056	0.044	-0.335*	-0.133*	0.011	-0.038
	(0.108)	(0.148)	(0.138)	(0.066)	(0.064)	(0.069)
time=2017$\times$tertiary edu	0.603***	0.118	-0.757***	-0.425***	0.022	-0.014
	(0.147)	(0.155)	(0.149)	(0.076)	(0.070)	(0.074)
time=2021$\times$secondary edu	0.159	-0.083	-0.247	-0.105	-0.167*	-0.171*
	(0.103)	(0.150)	(0.164)	(0.072)	(0.070)	(0.075)
time=2021$\times$ tertiary edu	0.177	-0.223	-0.534**	-0.439***	-0.329***	-0.357***
	(0.141)	(0.157)	(0.176)	(0.080)	(0.075)	(0.080)
cons	-2.356	18.380***	14.640***	12.940***	7.638***	6.356***
	(2.777)	(2.271)	(3.665)	(1.814)	(1.696)	(1.741)
N. of Obs.	174096	241348	166013	167566	167055	166688
Pseudo - R^2	0.2634	0.1950	0.2568	0.1977	0.1598	0.1583
AUC_{ROC}	0.8652	0.8498	0.8017	0.8129	0.7685	0.7740

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Average Marginal Effects: Weighted Logit Regression with Country and Income Group Fixed Effects

	(1) mobile money account	(2) transaction_mobile_bi	(3) debit holding	(4) debit usage	(5) credit holding	(6) credit usage
time=2017	0.099***	0.096***	0.060***	0.036***	0.017***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
time=2021	0.255***	0.307***	0.108***	0.106***	0.069***	0.051***
	(0.008)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
female	−0.008***	−0.006***	−0.017***	−0.012***	−0.014***	−0.012***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
age	0.000***	−0.002***	0.001***	−0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
secondary edu	0.063***	0.044***	0.150***	0.119***	0.083***	0.076***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
tertiary edu	0.121***	0.076***	0.287***	0.229***	0.176***	0.164***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
individual income	0.014***	0.010***	0.028***	0.025***	0.024***	0.023***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
banked	0.103***	0.091***				
	(0.002)	(0.002)				
population density	−0.564***	−0.670***	−0.372***	−0.455***	0.076*	0.053
	(0.052)	(0.032)	(0.029)	(0.028)	(0.031)	(0.031)
net migration	−1.388***	−1.045***	−0.096	0.158	0.860***	0.808***
	(0.256)	(0.318)	(0.125)	(0.141)	(0.217)	(0.221)
FD	0.540***	0.423***	0.183***	−0.014	−0.044	−0.055
	(0.048)	(0.044)	(0.041)	(0.035)	(0.038)	(0.037)
fixed telephone subscription	0.010***	0.003***	0.001	0.001*	0.000	0.000*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
branch	0.000	0.001	0.001	0.001***	0.002***	0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of Obs.	174,096	241,348	328,565	328,565	296,833	294,233

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Base Groups: time=2014, primary education, Low Income, Afghanistan.

4.2 Heckman Selection Model Results

The regression results of the Heckman selection model with income group and country fixed effects are reported in Table 8. Column (1) reports the results for informal DFS, and column (2) reports the results for formal DFS, including debit card adoption/usage and credit card adoption/usage.

In column(1), the coefficient of *female* loses significance in the second stage, indicating that while having a negative effect on the holding of a mobile money account, being female is no longer a determinant of the usage of informal DFS tools once entering the second stage, indicating a comparatively higher level of inclusiveness of informal DFS tools. A similar phenomenon for time variables can be found in both columns. While time positively determines the propensity to adopt the DFS tools, once adopted, time does not determine the propensity to use the tools anymore. However, from Table 9, the average marginal effects of time variables appear to be overall positively significant, indicating time's importance in the propensity of adoption and usage of DFS tools.

Unlike the positive significant coefficient in both stages in column (2), in column (1), the coefficient of *branch* is negatively significant in the first stage and insignificant in the second stage. This indicates that the density of formal financial institution branches negatively affects the adoption of informal DFS, which is consistent with the implications in previous results. Moreover, net migration appears to be a determinant factor in the first stage of column (1), indicating that the attractiveness of a country has a negative impact on the adoption of informal DFS tools such as mobile money. Table 9 summarises the average marginal effects of the sequential probit regression. The coefficients of time variables indicate that over time, the adoption and usage of all DFS tools are increasing, especially informal DFS tools. The education level and individual income are positively correlated with the adoption and usage of all DFS tools. However, the size of the coefficients suggests that the importance of these factors is comparatively smaller in the adoption and usage of informal DFS tools.

Table 8: Heckman Selection Model Results: holding and usage of DFS tools, with Country and Income Group FE

	(1) Informal DFS		(2) Formal DFS			
	m. money acc.	trans. w mobile/intn.	debit holding	debit usage	credit holding	credit usage
time=2017	0.982***	0.322	0.512***	0.033	0.382***	−0.232
	(0.100)	(0.289)	(0.050)	(0.089)	(0.063)	(0.148)
time=2021	0.627***	−0.124	0.653***	0.631***	1.182***	0.232
	(0.114)	(0.302)	(0.055)	(0.089)	(0.070)	(0.221)
female	−0.114*	−0.100	−0.186***	−0.155***	−0.088*	−0.219***
	(0.045)	(0.096)	(0.027)	(0.044)	(0.035)	(0.066)
age	0.044***	−0.004	0.054***	0.024***	0.065***	0.040***
	(0.004)	(0.012)	(0.001)	(0.004)	(0.002)	(0.008)
age squared	−0.001***	0.000	−0.001***	0.000***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
secondary edu	0.374***	0.065	0.576***	0.462***	0.494***	0.429***
	(0.027)	(0.086)	(0.014)	(0.036)	(0.018)	(0.056)
tertiary edu	0.738***	0.269	1.094***	0.873***	0.937***	0.808***
	(0.039)	(0.139)	(0.018)	(0.055)	(0.021)	(0.086)
individual income	0.104***	0.040	0.130***	0.010***	0.128***	0.097***
	(0.006)	(0.021)	(0.003)	(0.008)	(0.004)	(0.014)
population density	−0.950***	0.095	−1.378***	−2.268***	0.0558	0.152
	(0.241)	(0.597)	(0.102)	(0.149)	(0.125)	(0.232)
migration	−2.910*	−5.396	−1.370*	−2.632**	2.721**	0.786
	(1.397)	(4.264)	(0.540)	(0.907)	(0.902)	(2.160)
branch	−0.013***	0.001	0.005***	0.003*	0.007***	0.010***
	(0.002)	(0.005)	(0.001)	(0.001)	(0.001)	(0.002)
FD	3.153***	0.818	0.370*	−1.039***	−0.097	−0.924**
	(0.287)	(0.713)	(0.155)	(0.200)	(0.162)	(0.296)
fixed tel. subscription	0.032***	0.039***	−0.001	0.001	−0.002	0.003
	(0.004)	(0.011)	(0.001)	(0.001)	(0.001)	(0.002)
female×age	−0.001	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)
female× secondary edu	0.024	0.023	0.040**	0.029	0.060***	0.071*
	(0.022)	(0.045)	(0.013)	(0.021)	(0.018)	(0.036)
female× tertiary edu	−0.016	−0.030	0.009	0.024	0.027	0.013
	(0.031)	(0.058)	(0.018)	(0.024)	(0.020)	(0.039)
time=2017×female	−0.057*	−0.082	−0.012	−0.040*	−0.012	0.0026
	(0.026)	(0.055)	(0.013)	(0.018)	(0.015)	(0.026)
time=2021×female	0.426***	0.265***	0.300***	0.066**	0.259***	0.224***
	(0.026)	(0.077)	(0.014)	(0.025)	(0.015)	(0.033)
female×indiv. inc.	−0.009	0.000	−0.001	0.008	−0.011**	0.004
	(0.005)	(0.009)	(0.003)	(0.004)	(0.004)	(0.007)
time=2017×age	−0.013**	0.004	−0.002	0.001	−0.008***	0.010*
	(0.005)	(0.011)	(0.002)	(0.003)	(0.002)	(0.005)
time=2021×age	0.006	0.018	−0.009***	−0.001	−0.016***	0.007
	(0.005)	(0.010)	(0.002)	(0.003)	(0.003)	(0.006)
time=2017×age square	0.000	0.000	0.000*	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
time=2021×age square	0.000*	0.000*	0.000***	0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
time=2017×indiv. inc.	−0.010	0.005	−0.022***	0.018**	−0.006	0.011
	(0.006)	(0.014)	(0.004)	(0.006)	(0.004)	(0.008)
time=2021×indiv. inc.	0.016*	0.035*	−0.025***	−0.017**	−0.049***	−0.031**
	(0.007)	(0.015)	(0.004)	(0.006)	(0.005)	(0.010)
time=2017× secondary edu	0.025	0.002	−0.074***	−0.078**	−0.071***	−0.051
	(0.030)	(0.066)	(0.016)	(0.026)	(0.021)	(0.043)
time=2017× tertiary edu	0.133**	−0.029	−0.056**	−0.112***	−0.078**	−0.053
	(0.044)	(0.096)	(0.022)	(0.030)	(0.024)	(0.048)
time=2021× secondary edu	0.130***	0.219***	−0.039*	−0.042	−0.298***	−0.204***
	(0.031)	(0.066)	(0.017)	(0.028)	(0.024)	(0.056)
time=2021× tertiary edu	0.181***	0.331***	−0.106***	−0.108***	−0.381***	−0.280***
	(0.044)	(0.092)	(0.022)	(0.032)	(0.027)	(0.062)
cons	−0.274	−2.670	3.000***	7.761***	−4.476***	−3.632**
	(1.117)	(2.376)	(0.473)	(0.703)	(0.585)	(1.242)
athrho	0.338		0.396***		0.634**	
	(0.225)		(0.117)		(0.213)	
N. of Obs.	169,254		328,565		296,833	

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Base Groups: time=2014, primary education, Low Income, Afghanistan.

Table 9: Heckman Selection Regression: Average Marginal Effects

	(1) Informal DFS			(2) formal DFS: debit card			(3) Formal DFS: credit card		
	mobile money account	transaction_bi	transaction—account	debit holding	debit usage	debit usage—holding	credit holding	credit usage	credit usage—holding
time=2017	0.071***	0.095***	0.073***	0.063***	0.023***	0.008*	0.014***	0.016**	0.001
	(0.002)	(0.012)	(0.019)	(0.002)	(0.004)	(0.004)	(0.002)	(0.005)	(0.007)
time=2021	0.165***	0.185***	0.130***	0.111***	0.119***	0.111***	0.074***	0.045***	−0.009
	(0.006)	(0.026)	(0.033)	(0.003)	(0.004)	(0.005)	(0.003)	(0.010)	(0.009)
female	−0.007***	−0.011	−0.007	−0.017***	−0.013***	−0.012***	−0.014***	−0.018***	−0.013*
	(0.001)	(0.006)	(0.009)	(0.001)	(0.002)	(0.003)	(0.001)	(0.004)	(0.005)
age	0.000***	−0.001**	−0.001***	0.001***	−0.002***	−0.002***	0.001***	0.000	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
secondary edu	0.063***	0.042***	0.008	0.147***	0.114***	0.095***	0.080***	0.119***	0.072***
	(0.002)	(0.012)	(0.010)	(0.002)	(0.003)	(0.004)	(0.002)	(0.007)	(0.007)
tertiary edu	0.143***	0.102***	0.043**	0.278***	0.217***	0.177***	0.179***	0.226***	0.120***
	(0.003)	(0.020)	(0.015)	(0.003)	(0.006)	(0.005)	(0.002)	(0.006)	(0.008)
individual income	0.015***	0.015***	0.009***	0.028***	0.026***	0.023***	0.022***	0.028***	0.016***
	(0.000)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
population density	−0.143***	0.027	0.132	−0.334***	−0.556***	−0.580***	0.012	0.045	0.043
	(0.036)	(0.170)	(0.192)	(0.025)	(0.040)	(0.044)	(0.027)	(0.068)	(0.077)
net migration	−0.439*	−1.507	−1.721	−0.332*	−0.645**	−0.689*	0.575**	0.232	−0.162
	(0.211)	(1.195)	(1.577)	(0.131)	(0.223)	(0.269)	(0.191)	(0.635)	(0.710)
FD	0.476***	0.229	−0.014	0.090*	−0.255***	−0.339***	−0.020	−0.273**	−0.301**
	(0.043)	(0.166)	(0.191)	(0.038)	(0.052)	(0.058)	(0.034)	(0.096)	(0.096)
fixedtelephone subscription	0.005***	0.011***	0.011**	0.000	0.000	0.000	0.000	0.001	0.001*
	(0.001)	(0.003)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
branch	−0.002***	0.000	0.002	0.001***	0.001*	0.001	0.002***	0.003***	0.002***
	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
N. of Obs.	169,254	169,254	169,254	328,565	328,565	328,565	296,833	296,833	296,833

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Base Groups: time=2014, primary education, Low Income, Afghanistan.

5 Conclusion

The study examines the determining factors of digital finance services (DFS) adoption and usage across a global context, using data consisting of 160 countries and three waves adopted from the World Bank's database. Our findings highlight several relevant socioeconomic and demographic factors influencing DFS adoption and usage.

A significant positive effect of individual income on the adoption and usage of DFS is confirmed in our study, aligning with existing literature. Similarly, gender appeared to be a significant factor, with females being less likely to adopt or use DFS tools. However, our interaction term analysis revealed a promising trend: over time, the probability of females adopting and using DFS has increased, indicating a gradual reduction in gender disparities in digital finance.

Education appears as another critical determinant, with higher educational attainment consistently associated with a greater likelihood of DFS adoption and usage. This underscores the importance of educational initiatives in promoting financial inclusion through digital means.

Moreover, age demonstrates a non-linear relationship with DFS adoption, characterized by a reversed U-shape, suggesting that middle-aged individuals are more likely to adopt DFS than younger or older cohorts. This finding highlights the need for targeted strategies to engage both younger and older populations in digital finance.

Our Heckman model further explores the transition dynamics within DFS adoption stages, revealing that historical fixed telephone subscriptions negatively impact initial DFS adoption but do not significantly influence subsequent usage. This nuanced understanding can inform policy and infrastructure development aimed at enhancing digital financial inclusion. These results have not been found in the current literature.

Our study contributes to the growing body of knowledge on digital finance by identifying and analyzing the key determinants of DFS adoption and usage on a global scale. These insights can inform policymakers, financial institutions, and other stakeholders aiming to foster inclusive digital financial ecosystems. For example, our findings suggest that, while gender remains a significant determinant of DFS adoption and usage, increasing literacy and level of education of the female population may be constructive for addressing gender disparity in the adoption and usage of DFS tools. As our estimation shows, the historical number of fixed telephone subscriptions is a relevant determinant of the adoption and usage of informal DFS tools, which indicates that the level of digital infrastructure development has a lengthy positive impact on the diffusion of digital financial products and services. Therefore, prioritizing investments in digital infrastructure is essential for policymakers aiming to increase financial inclusion through DFS tools. Future research should continue to explore these dynamics, particularly in the context of rapidly evolving technological landscapes and varying regional characteristics.

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A Appendix

A.1 Computation of Individual-Level Income

As mentioned in previous sections, the variable *income level* does not take differences of dollar income into account. To mitigate the potential bias created by this, we estimate the approximate dollar income of each individual with the help of GDP per capita data, GINI index, and variable *income level*, which denotes the income quintile in which the respondent lies on. GINI index, which reflects the level of income inequality in a country, is derived from the Lorenz curve (Gastwirth, 1972). With the help of Lorenz curve and GDP per head, we will be able to estimate the approximate dollar income at each quintile. We will assume that the Lorenz curve has the following form:

$$x(p) = p^{\alpha} \quad 0 < p < 1 \quad \alpha > 1 \tag{7}$$

where p is the proportion of the population earning at most x, and $\alpha > 1$ is a parameter. The area under (7) can be found easily to be:

$$\int_0^1 x(p)dp = \int_0^1 p^{\alpha} dp = \frac{1}{\alpha + 1} \tag{8}$$

Hence the area above the Lorenz curve and below the 45^o line is:

$$\frac{1}{2} - \frac{1}{\alpha + 1} = \frac{\alpha - 1}{2(\alpha + 1)} \tag{9}$$

Dividing (9) by 1/2, we obtain the Gini coefficient:

$$G = \frac{\alpha - 1}{\alpha + 1} \tag{10}$$

Rearranging (10), we obtain an equation for α in terms of G:

$$\alpha = \frac{1 + G}{1 - G} \tag{11}$$

Let mean income be $\bar{x}$ and assume that when $G = 0$ (minimal inequality), income varies with a uniform distribution between 0 and $2\bar{x}$.
Compute α using (11). When $G = 0$, the area under the Lorenz curve is $\frac{1}{2}$. When $G > 0$, the area under the Lorenz curve is clearly lower, and from (8), this area is $\frac{1}{\alpha+1}$.

To preserve the total income in the economy, we need to enhance the Lorenz Curve by the multiple $\frac{\alpha+1}{2}$.

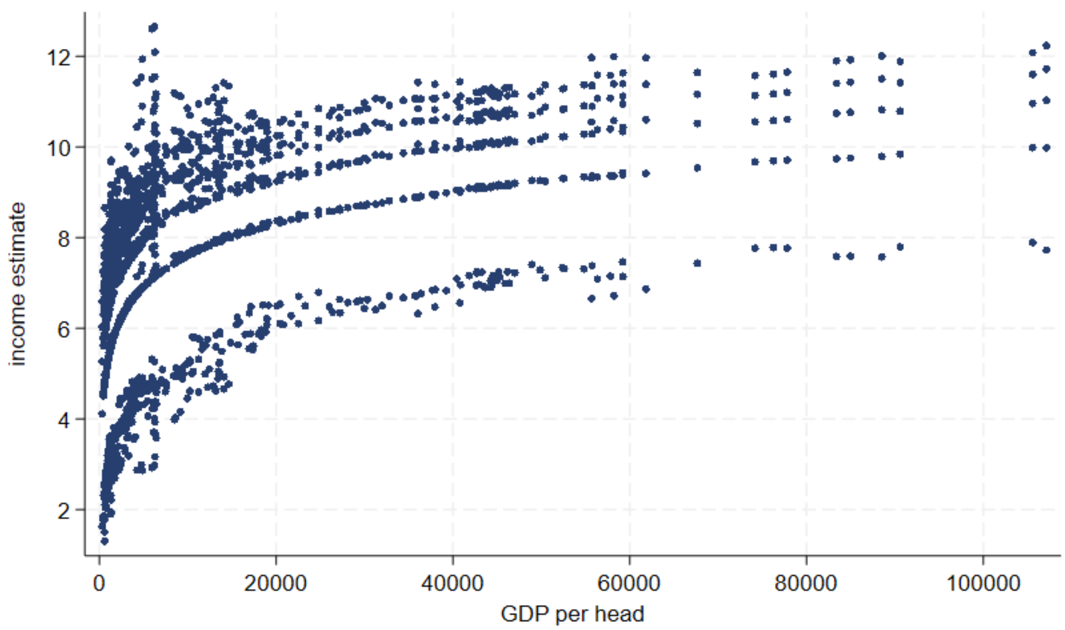
We will use the following equation for the calculation of individual-level income:

$$EI_{ijt} = \left[\left(\frac{\alpha+1}{2} \right) * QI_{jt} \right]^{\alpha} * GDP_{ijt} \tag{12}$$

where EI_{ijt} denotes the calculated income estimate for individual i from country j at time t, QI_{ijt} denotes the income quintile to which individual i from country j belongs at time t, and GDP_{jt} denotes the per capita GDP of country j at time t.

The scatter plot of the estimated income against GDP per head is shown below.

Figure 2: Scatter plot of Estimated Income and GDP per Head



Note: The shape of the plot is consistent with relative Theories of Growth and with the real world.

Table 10: Correlation Matrix of all Dependent Variables

	(1)					
	mobilemoneyaccount	*transaction_mobile_bi*	*debitholding*	*debitusage*	*creditholding*	*creditusage*
mobile money account	1.000					
transaction_mobile_bi	0.608	1.000				
debit holding	0.179	0.222	1.000			
debit usage	0.192	0.253	0.645	1.000		
credit holding	0.124	0.168	0.359	0.397	1.000	
credit usage	0.115	0.159	0.330	0.394	0.889	1.000

Note: all coefficients are significant at 1% significance level

Table 11: Correlation Matrix of All Independent Variables

	(1)												
	time	*female*	*age*	*education*	*individualincome*	*branch*	*banked*	*populationdensity*	*fixedtelephonesubscription*	*netmigration*	*FD*	*incomegroup*	*economy*
time	1.000												
female	−0.048	1.000											
age	−0.007	0.008	1.000										
education	0.100	−0.023	−0.031	1.000									
individual income	0.053	0.005	0.287	0.432	1.000								
branch	−0.076	0.020	0.178	0.208	0.466	1.000							
banked	0.100	−0.018	0.144	0.431	0.580	0.294	1.000						
population density	0.051	−0.004	0.009	−0.028	0.029	0.046	0.027	1.000					
fixed telephone subscription	−0.017	0.013	0.308	0.363	0.828	0.534	0.539	0.111	1.000				
net migration	0.003	−0.010	0.048	0.096	0.245	0.081	0.149	0.038	0.237	1.000			
FD	0.031	0.010	0.238	0.285	0.767	0.468	0.496	0.127	0.768	0.281	1.000		
income group	−0.024	−0.019	−0.293	−0.364	−0.887	−0.478	−0.534	0.008	−0.814	−0.228	−0.720	1.000	
economy	0.015	0.003	−0.032	0.026	−0.049	−0.027	−0.003	0.112	−0.045	−0.008	−0.012	0.074	1.000

Note: all coefficients are significant at at least 10% significance level

Table 12: Descriptive Statistics: by Income Groups

	(1) High Income					(2) Upper-Middle Income					(3) Lower-Middle Income					(4) Low Income				
	N.of Obs	*Mean*	*St.Dev.*	*Min*	*Max*	*N.of Obs*	*Mean*	*St.Dev.*	*Min*	*Max*	*N.of Obs*	*Mean*	*St.Dev.*	*Min*	*Max*	*N.of Obs*	*Mean*	*St.Dev.*	*Min*	*Max*
DEPENDENT VARIABLES																				
mobile money account	74,298	0.07	0.26	0.00	1.00	79,475	0.15	0.36	0.00	1.00	68,681	0.27	0.44	0.00	1.00	13,077	0.09	0.29	0.00	1.00
transation using mobile/internet_bi	146,688	0.04	0.21	0.00	3.00	149,813	0.11	0.36	0.00	3.00	127,854	0.22	0.46	0.00	3.00	138,983	0.14	0.37	0.00	3.00
debit holding	145,329	0.42	0.49	0.00	1.00	148,155	0.46	0.50	0.00	1.00	126,942	0.55	0.50	0.00	1.00	138,171	0.81	0.39	0.00	1.00
debit usage	145,329	0.30	0.46	0.00	1.00	148,155	0.31	0.46	0.00	1.00	126,942	0.42	0.49	0.00	1.00	138,171	0.70	0.46	0.00	1.00
credit holding	145,109	0.20	0.40	0.00	1.00	147,504	0.20	0.40	0.00	1.00	83,651	0.38	0.49	0.00	1.00	135,495	0.48	0.50	0.00	1.00
credit usage	145,109	0.17	0.37	0.00	1.00	147,504	0.17	0.38	0.00	1.00	83,651	0.32	0.47	0.00	1.00	135,495	0.41	0.49	0.00	1.00
INDEPENDENT VARIABLES																				
female	146,688	0.53	0.50	0.00	1.00	149,813	0.54	0.50	0.00	1.00	127,854	0.47	0.50	0.00	1.00	138,983	0.51	0.50	0.00	1.00
age	146,364	41.62	17.69	15.00	99.00	149,362	41.90	17.97	15.00	99.00	127,399	41.71	17.44	15.00	99.00	138,277	47.94	18.07	15.00	99.00
education	146,033	1.83	0.68	1.00	3.00	148,902	1.83	0.69	1.00	3.00	127,182	2.00	0.70	1.00	3.00	138,091	2.20	0.63	1.00	3.00
income quintile	146,672	3.19	1.42	1.00	5.00	149,813	3.19	1.42	1.00	5.00	127,854	3.24	1.42	1.00	5.00	138,967	3.20	1.41	1.00	5.00
individual income	123,599	7.89	2.21	1.63	12.66	129,127	7.89	2.20	1.30	12.65	115,305	8.11	2.13	1.50	12.61	117,332	9.48	1.60	4.66	12.23
income classification	146,688	2.22	1.06	1.00	4.00	149,813	2.26	1.07	1.00	4.00	126,854	2.15	1.00	1.00	4.00	138,983	1.00	0.00	1.00	1.00
banked	145,914	0.44	0.50	0.00	1.00	148,766	0.48	0.50	0.00	1.00	127,144	0.57	0.50	0.00	1.00	138,470	0.85	0.36	0.00	1.00
population density	144,687	4.34	1.40	0.62	8.95	147,813	4.33	1.41	0.69	8.98	125,854	4.41	1.36	0.77	8.95	135,983	4.60	1.63	1.12	8.98
fixed telephone subscription	142,687	20.26	19.26	0.02	71.09	145,813	19.96	18.02	0.01	65.25	125,854	20.72	18.06	0.02	64.03	135,983	40.58	14.06	12.76	71.09
lag_migration	135,983	0.003	0.01	−0.02	0.05	114,152	0.001	0.02	−0.04	0.12	112,112	−0.003	0.01	−0.03	0.01	58,098	−0.002	0.01	−0.06	0.004
FD	138,180	0.37	0.24	0.04	0.95	142,813	0.37	0.24	0.04	0.96	121,840	0.40	0.23	0.05	0.94	135,483	0.60	0.21	0.20	0.96
branch	138,163	17.77	15.24	0.77	79.57	139,753	16.39	13.81	0.45	71.72	111,789	15.65	12.46	0.39	72.07	127,405	23.57	13.67	5.45	79.57

Note: Descriptive statistics for all variables by income, including number of observations, mean, standard deviation, minimum and maximum values.