Economic Inequality and Mobile Money Usage in Mozambique

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Abstract

The paper examines the impact of economic inequality on the Mobile Money services usage in Mozambique based on 2017 population census and 2020 household survey data. The study revealed two main findings. Firstly, it explores the influence of economic inequality on Mobile Money usage across 155 districts. Employing quantile regression analysis, the study shows that economic inequality, as measured by the Gini of the average asset ownership index and access to basic services, significantly affects the use of Mobile Money services. Higher levels of inequality are linked to reduced usage of Mobile Money services, with a 1% increase in the Gini index of the average asset ownership index corresponding to a 1.73% decrease in the district's Mobile Money usage rate. Secondly, at the individual level, the study employs probit and linear probability models to analyse the determinants of Mobile Money usage. The results indicate that factors such as asset ownership, access to basic services, gender, and residential location play significant roles in explaining the probability of individuals using Mobile Money services. The policy implications of the findings emphasize the need to addressing inequality beyond the financial sector to achieve successful financial inclusion efforts.

Keywords: Economic inequality, Mobile money, Financial inclusion

Introduction

Over the past decade, Mozambique has seen a significant increase in mobile phone adoption. The first mobile phone company was established in 1997, and mobile phone usage quickly surpassed that of traditional landlines. Currently, 86% of the urban population and 61% of the rural population own mobile phones (National Institute of

Statistics, 2021). Similar to other African nations such as Kenya, Tanzania, and South Africa, this digital transformation has also impacted the financial sector in Mozambique. In these countries, mobile network operators have been permitted to partner with financial institutions to provide mobile money services. For instance, M-Pesa, provided by Vodafone, is the leading mobile money transfer service in Kenya and Tanzania. It enables users to transfer, deposit, and withdraw funds, significantly benefiting the economies of these countries by facilitating transactions, increasing per capita income, and resolving temporary liquidity problems for households. However, existing research reveals that expanding financial inclusion does not always lead to reduced inequality, as the opposite scenario can also hold true (Ashenafi and Dong 2022; Park and Mercado 2018; Salazar-Cantú, Jaramillo-Garza, and Rosa 2015).

With the emergence of mobile money services and Mozambique grappling with high inequality rates and limited financial inclusion, the Mozambican government recognized an opportunity to address these challenges by promoting financial inclusion (Bank of Mozambique, 2013; 2016b). Statistics from the latest financial inclusion survey indicate that by 2019, only one fifth (3 million) of the adult population (aged 16 and older) in Mozambique had a bank account. The adoption of banking products is mainly driven by payments, where adults receive their income through a bank account. However, more than half, around 55%, owned a mobile phone, approximately 7.8 million people out of a total population of 14.19 million.

As part of its efforts to improve financial inclusion, the government of Mozambique also allowed mobile network operators to partner with financial institutions to provide mobile money services. For instance, in 2010, the government issued an operating license to mCel, a state-owned mobile phone company. Under this license, mCel established a new company called Carteira Móvel, which began offering mobile money services under the brand mKesh in 2011. In 2013, Vodacom, a subsidiary of a South-African multinational, introduced M-Pesa to Mozambique. Later, in 2017, a third mobile operator, Movitel (consortium majority-owned by Vietnamese mobile telecommunications group Viettel), launched mobile money services under the brand e-Mola, provided by its subsidiary m-Mola. Interoperability between the three mobile money services was established in 2022, when the Bank of Mozambique announced the interconnection of M-Pesa, mKesh, and e-Mola operations through the payment platform of the Mozambican Interbank Society, known as SIMO network. According to the Ministry of Transport and Communications, Movitel has been operating in the Mozambican market since 2012, serving approximately 4,008,157 subscribers, which represents about 27% of the market share, making it the second-largest provider. Vodacom holds the largest market share with 7,824,030 subscribers, representing 52%, while Tmcel accounts for the remaining 21% with 3,164,715 subscribers. Despite challenges related to transportation and electricity infrastructure, mobile network operators have made efforts to expand their coverage, currently reaching almost 80% of the national territory.

The potential of Mobile Money is vast, especially in rural areas of Mozambique, where bank branches do not extend beyond provincial capitals and a few district villages. The rural population often saves money by hiding it 'under the mattress,' burying it in cans, Before the introduction of Mobile Money services, or in areas beyond the coverage of these services, the rural population often saved money by hiding it 'under the mattress,' burying it in cans, keeping it with local traders or authorities, and participating in rotating savings and credit associations. These savings methods do not typically offer interest and carry significant risks. For money transfers, rural individuals often had to travel to urban bank branches or rely on third parties, leading to high costs and considerable risks.

Mobile Money services provide a safer, faster, and more economical alternative for saving and transferring money. These technological solutions allow users to conduct financial transactions more efficiently, overcoming the limitations and risks associated with traditional methods. However, in spatial terms, the primary limitation of Mobile Money is the expansion of the mobile network. Despite challenges related to transportation and electricity infrastructure, operators have made efforts to expand their coverage, currently reaching almost 80% of the national territory.

This article aims to assess the impact of economic inequality on the adoption of mobile money services in Mozambique from two perspectives. Firstly, it examines how economic inequality affects the usage of Mobile Money from a spatial standpoint, encompassing approximately 155 districts in Mozambique. Secondly, it identifies the determinants of Mobile Money usage among individuals and discusses how the findings reflect the influence of economic inequality on Mobile Money use. This analysis is of utmost importance for policymakers who seek to empower the most disadvantaged households and diminish income and wealth disparities in Mozambique.

This article is structured into five sections, commencing with this introduction. The second section provides a concise overview of the literature's approach to the impact of economic inequality on Mobile Money services. The third section outlines the methodology and the data employed. The fourth section presents the findings, while the fifth section delves into the discussion of the results and offers concluding remarks.

Economic Inequality and Mobile Money

Mobile money is a digital payment platform that enables money transfers between users of mobile devices using technology embedded in mobile phone service Subscribers Identification Module (SIM cards). This platform also grants users access to financial products and services, including deposits, credit, insurance, and savings, even if they are not formally registered with a banking or microfinance institution (Parekh and Hare 2020). The operation of these services involves a set of stakeholders. Firstly, mobile phone manufacturers (e.g., Nokia, Apple) produce compatible phones that facilitate financial transactions for individuals. Secondly, mobile phone network operators (e.g., Vodafone) develop and provide mobile payment software as part of their wireless services.

Subsequently, central banks, commercial banks, and other financial institutions (e.g., Bank of America, Visa, MasterCard) offer access to subscribers' financial accounts and the necessary financial licenses to authorize payments. In the case of mobile money, mobile phone operators offer access to financial transactions for users without conventional accounts (bank or microfinance accounts). In the fourth position, technology companies produce chips with software for managing financial accounts via mobile phones (e.g., E ewallet -wallets), allowing mobile phone users to store personal data and interact with mobile operators' data centres (Over the Air). Other companies may emerge to ensure the security and privacy of each transaction (e.g., Giesecke and Devrient). Finally, merchants (e.g., 7-Eleven, Macy's, McDonald's) enable their customers to make payments through mobile phone accounts in their stores (Ozcan and Santos 2015).

A review of the literature shows that the connections between economic inequality and mobile money services is generally framed in one direction in which the focus of several authors has been to analyse the impact of Mobile Money services on multidimensional economic and income inequality (Amoah, Korle, and Asiama 2020; Batista and Vicente 2013; Dahlberg 2015; Jack and Suri 2014; Nampewo et al. 2016). Nevertheless, this study seeks to examine the relationship in the opposite direction, aiming to find empirical evidence that illustrates how economic inequality can influence the usage of mobile money services. This analysis is significant primarily because some studies indicate that, although the concern for reducing inequality through increasing the use of financial services is substantial among policymakers, greater access to financial services has not always resulted in improved distribution of income and assets within a country's population (Ahnen 2017; Ashenafi and Dong 2022; Bateman 2017; Ghosh 2005; Turégano and Herrero 2018).

Despite the relative divergence in the aim of the analysis, the existing literature provides a foundation for analysing the impact of inequality on the usage of Mobile Money in two main areas. Firstly, the literature discusses and presents the determinants of Mobile Money usage. For example, Amoah et al. (2020), using a sample of 733 households in Ghana, concludes that the availability of services such as mobile phone credit top-ups, education, and income are among the key determinants of Mobile Money usage in Ghana. Furthermore, parametric and non-parametric tests of Mobile Money usage by gender show a statistically significant difference in Mobile Money usage by gender. Asongu (2018), studying the determinants of Mobile Money usage in 49 sub-Saharan African countries up to 2011, concludes that Mobile Money usage is positively correlated with education, domestic savings, regulatory quality, banking density, urban population density, and internet penetration. Secondly, the use of mobile phones for sending and receiving money is positively correlated with internet penetration and human development indicators. Ankinyemi and Mushunge (2020), using microdata from surveys in ten countries, namely Ghana, Kenya, Lesotho, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania, and Uganda, tested the determinants of Mobile Money service usage and concluded that age, bank account ownership, and net monthly income determine both the adoption of

Mobile Money and the amount of money received using these services. On the other hand, Meli et al. (2022) using estimates from three independent probit model, assuming the non-simultaneity of different uses of Mobile Money services in Cameroon to test the reliability and robustness of the results, concluded that socioeconomic factors such as age, education level, standard of living, and mobile phone ownership differentially influence the adoption and usage of Mobile Money services.

Secondly, the literature highlights obstacles to financial inclusion, which represent another approach of the analysing the distribution of essential goods, services, or opportunities among individuals necessary for the utilization of Mobile Money and other financial system products and services. For instance, Ulwodi and Muriu (2017) conducted an analysis of financial inclusion barriers across sub-Saharan Africa (SSA) using the 2014 Global Findex dataset, focusing on the demand-side perspective. Their findings indicated that literacy rates significantly influence the level of account ownership. Additionally, the estimation results revealed that as individuals age, they tend to transition from one account type to another. Another significant barrier to account ownership was the proximity to the nearest financial services. Similarly, Tiwari et al. (2019), based on microdata from the BOMA project in northern Kenya, observed that illiteracy, limited numeracy skills, and a lack of familiarity with technology acted as obstacles to the full adoption of Mobile Money services.

Methodology

Data

This study uses two data sources. The primary source is a sample of 10% of the 2017 population census. This dataset comprises approximately 2.68 million observations out of a total population of 26.8 million and is representative at the national, provincial, district, and rural-urban levels. It provides information on Mobile Money usage, as well as access to durable goods and basic services by households across the entire national territory. A complementary source is the 2019/20 household budget survey data. Unlike the population census, this database does not provide information on Mobile Money usage; however, it does include information on mobile phone ownership, one of the most critical factors in the expansion of Mobile Money services. The survey was conducted between August 2019 and August 2020. Both the population census and the household budget survey were organized and implemented by the National Institute of Statistics (Financial Sector deepening Mozambique and FinMark Trust 2020, 12,13; National Institute of Statistics 2019).

To examine the impact of economic inequality on the usage of Mobile Money services, this study employs the approach adapted by Demir et al (2022). In their article, the authors estimate the impact of digital innovation in financial services and financial inclusion on economic inequality. They use Gini indices for approximately 140 countries between 2011 and 2017 as a measure of inequality. Additionally, as a measure of financial inclusion, they employ the proportion of the adult population aged 16 and above who possess a bank account or use financial services for bill payments or bank loans by country.

In this study, the direction is reversed, with Mobile Money appearing as the dependent variable, while economic inequality is introduced as an explanatory variable. The impact of inequality on the usage of Mobile Money is assessed for Mozambique, employing a spatial approach at the district level encompassing 155 districts. This approach aims to investigate how economic inequality influences the utilization of Mobile Money services. Gini indices of the average asset index are estimated for each district in Mozambique to serve as a measure of inequality. This index is calculated using the Principal Component Analysis (PCA) methodology proposed by Wittenberg and Leibbrandt (2017)1. In addition to the spatial Gini index, control variables are included. These variables encompass access to basic services such as sanitation, electricity, improved water sources, as well as individual characteristics like education and literacy skills.

The selection of these variables aligns with two prevailing approaches: firstly, the broader range of variables presented in the empirical literature such as income, education, literacy, numeracy location urban/rural and gender (Batista and Vicente 2013; Dahlberg 2015; Jack and Suri 2014; Nampewo et al. 2016; Parekh and Hare 2020; Yunus et al. 2016). These variables also represent factors that may explain what motivates individuals to use Mobile Money services for financial transactions. To account for this, in this paper we tested for the variables may be considered as the determinants of Mobile Money usage in Mozambique using Equation number 2. Identifying the determinants of Mobile Money usage in Mozambique is pertinent to pinpoint variables whose averages could be established at the district level in equation 1.

Econometric Approach

In sum, the econometric approach in this paper seeks to: a) To examine how economic inequality impacts the usage of Mobile Money from a spatial perspective, considering approximately 155 districts in Mozambique (Equation 1); b) To identify the determinants of Mobile Money usage by individuals and discuss how findings reflect the impact of economic inequality on the use of Mobile Money.

Firstly, we use an ordinary least square model (OLS) complemented by a classic quantile regression model following the approach employed by Demir et al (2022) as referred in the previous section. Specifically, OLS only estimates how the predictor variables are related to the mean value of the dependent variable while quantile regression, allows researchers to model the predictors against different locations and measurements of the dependent variable. Statistically, we consider dependent variable as the Mobile Money ($MobMoney$)

[1] Also see Shifa and Ranchhod (2019)

rates variable at district level. The explanatory variables are the Gini (Gini) of the average asset index. The asset index is a continuous variable estimated using the uncentred principal component analysis method proposed by Wittenberg & Leibbrandt (2017). We consider a set of nine durable goods mostly used in both rural and urban in Mozambique with reliable data provide in the 2017 population census dataset (Radio, Television, Telephone, Computer, Iron, Refrigerator, Car, Motorcycle, and Bicycle). Then, the Gini indices of the asset index are estimated for each of the 155 districts. The control variables (CV) represent the average rates of access to basic services (electricity, improved water and sanitation) and individuals' characteristics, specially, literacy and primary education completion rates by districts. The linear regression model is presented in equation 1.

$$MobMoney_i = \beta_0 + \beta_2 Gini_i + \beta_1 CV_i + \varepsilon_i \tag{1}$$

Secondly, we employ a quantile regression approach to investigate the influence of economic inequality on Mobile Money utilization, while still accounting for the control variables outlined in equation 1. Quantile regression enables researchers to assess the impact of income inequality across the entire range of Mobile Money usage rates, with specific attention to districts spanning from the lowest to the highest Mobile Money usage rates. The quantile estimator is obtained by solving the optimization problem in equation 1.1 for $\alpha - th$ quantile $(0 < \alpha < 1)$ which y_i is the dependent variable and x_i is a k by 1 vector of explanatory variables (Altunbaş and Thornton 2019; Demir et al. 2022). The dependent and explanatory variables are the same as in equation 1.

$$min \sum_{i \in \{i: y_i \geq x_i' \alpha\}} \alpha \left| y_i - x_i' \Omega \right| \sum_{i \in \{i: y_i \geq x_i' \alpha\}} 1 - \propto \left| y_i - x_i' \Omega \right| \tag{1.1}$$

In a third step we run a probit model to test and identify the determinants of Mobile Money use by individuals in Mozambique. The model is adopted from Jossefa (2011, 21–24) with some modifications. The author presents the determinants of access and use of financial services in Mozambique. We employ the approach from this study with little modifications and highlighting three variables categories: i) individual characteristics ($indivual\_char$): gender, age, education, marital status; ii) socioeconomic characteristics ($socioecon\_char\_char$): asset ownership and access to basic services; iii) geographical characteristics ($geog\_char$): province and area of residence (rural or urban). Other studies provide a foundation for these variables as well (Amoah, Korle, and Asiama 2020; Llanto and Rosellon 2017; Nampewo et al. 2016; Zins and Weill 2016). As robustness check we also run a linear probability model for equation 2.

$$MobMoney_i \quad \alpha + \beta \; indivual\_char_i + \sigma \; socioecon\_char\_char_i + \varphi \; geog\_char_i + \mu_i \quad (2)$$

Results

Brief Overview of Economic Inequality and Use of Mobile Money in Mozambique

The maps in **Error! Reference source not found.** depict the district-level spatial distribution of Mobile Money usage rates and the level of inequality measured by the Gini index of the average asset index. In general, districts in the northern and central regions, as well as the interior of the southern region, exhibit low levels of Mobile Money usage (less than 5%). The majority of these districts also have high Gini indices, ranging between 78% and 88%. The descriptive statistics in **Error! Reference source not found.** reveal significant variation among the 155 districts. The Mobile Money usage rate ranges from as low as 0.2% to as high as 37%, with an average of 6%. Economic inequality, as measured by the Asset Index Gini, displays substantial variability, ranging from 30.0% to 88%, with a mean of 79%. Literacy rates also vary considerably, ranging from 16.8% to 79%, with an average of 41%. Access to electricity ranges from 0.0% to 91%, with an average of 15%. Additionally, the rates of improved water access vary from 5.9% to 97%, while improved sanitation access rates range from 6.1% to 99%. These statistics illustrate the diverse landscape of these variables across the districts, providing a foundation for further analysis and insights into their relationships.

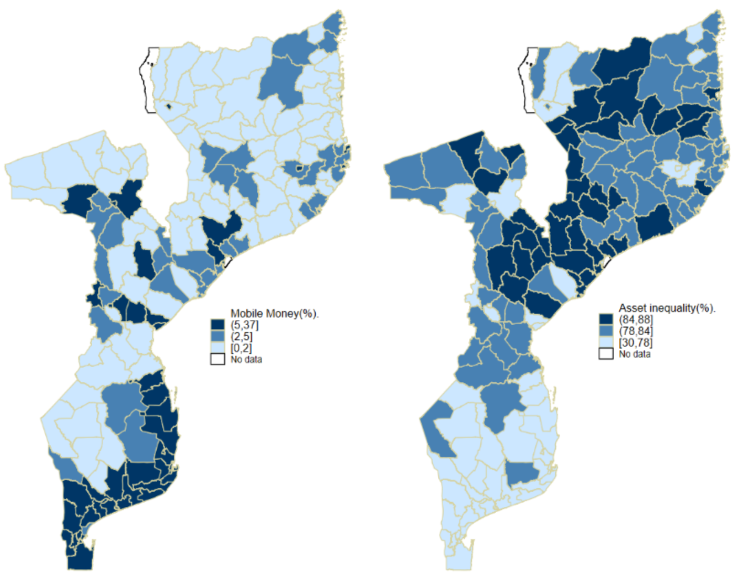

Figure 1: Mobile Money usage rates by district in Mozambique, 2017
Source: Illustrated by the authors based on 2017 population census data

Table 1: Table Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Mobile Money	155	6%	0.074	0.2%	37%
Asset index Gini	155	79%	0.081	30.0%	88%
Literacy rate	155	41%	0.136	16.8%	79%
Electricity access	155	15%	0.192	0.0%	91%
Improved water	155	45%	0.216	5.9%	97%
Improved sanitation	155	33%	0.24	6.1%	99%

Source: Authors' estimations based on 2017 population census data

Empirical Results

While we conducted various tests to investigate the factors determining access and utilization of Mobile Money services, our primary focus in this discussion centres on the final model, where one of the explanatory variables for Mobile Money service rates is the level of asset inequality across districts in Mozambique. To gain a more comprehensive understanding of the impact of inequality on the adoption of mobile money, we performed Ordinary Least Squares (OLS) regression and quantile regression at the 0.25th, 0.5th, and 0.75th percentiles. The outcomes are presented in Table 2, and several noteworthy observations emerge. Firstly, it is essential to note that the strength of the association between inequality and district mobile money rates displays statistically significant difference from the OLS coefficients across all quantiles. Secondly, it is worth noting that inequality emerges as a significant explanatory factor for districts situated within the 0.5th and 0.75th percentiles of the distribution of Mobile Money usage rates in the first model. The coefficients obtained from the quantile regression exhibit a negative sign, indicating that as inequality, measured by the asset Gini index, increases, there is a corresponding decrease in the adoption and utilization of mobile money services. In Table 2, we only show the estimates from the model using logarithms to allow a more intuitive explanation. Specifically, the OLS coefficient suggests that a 1% increase in the Gini index results in 1.73% percentage reduction in the mobile money usage district rate. Furthermore, this coefficient appears to increase compared in quantiles as 1% increase of the Asset index Gini increases the reduction of mobile money district usage rate by more than 2%.

Thirdly, among the control variables, both literacy rate and access to electricity emerge as significant explanatory variables of mobile money usage in both OLS and quantile regressions. Literacy has statistical significance across all quantiles and the OLS estimates suggest that a 1% increase in the district's literacy rate is associated with a 1.74% increase in the mobile money usage rate. Regarding electricity, a 1% increase in access to electricity through the public grid is associated to a 0.32% rise in the district's mobile money usage rate. However, access to improved water and sanitation coefficients are not statistically significant, and the coefficients in the quantile regression do not differ significantly from those in the OLS.

Upon considering all other these factors, the results from the quantile regression analysis suggest that inequality is primarily relevant to Mobile Money adoption in districts with higher Mobile Money usage rates. For instance, the average usage rate at the 0.5th quantile is approximately 4% per district, while at the 0.75th quantile, the average rate stands at 17% per district. This range encompasses districts with mobile money usage rates as low as 17% and as high as 37%. It is also important to note that OLS regression aims to model the conditional mean value of the dependent variable (Mobile Money). However, it is widely recognized that mean values can be strongly influenced by extreme cases, potentially introducing bias to the estimates and undermining the overall conclusions. In this study, the overall conclusion remains relatively consistent, with the primary distinction being observed between quantile regression and OLS at the lower quantiles. In the first quantile, the inequality coefficient is statistically not different from zero as an explanatory variable for mobile money usage.

Table 2: OLS and quantile regression estimates (N = 155).

		Regressors in logarithms			
		(1)	(2)	(3)	(4)
VARIABLES		OLS	025	05	075
Asset index Gini		-1.729***	-2.198***	-2.064***	-2.122***
		(0.528)	(0.714)	(0.575)	(0.460)
Literacy rate		1.439***	1.409***	1.142***	1.151***
		(0.296)	(0.401)	(0.323)	(0.258)
Electricity access		0.323***	0.372***	0.385***	0.228***
		(0.0804)	(0.109)	(0.0875)	(0.0700)
Improved water		-0.0488	-0.124	-0.0725	0.157
		(0.136)	(0.184)	(0.148)	(0.118)

Improved sanitation		-0.0505	-0.0744	0.0211	0.0862
		(0.141)	(0.191)	(0.154)	(0.123)
Constant		-1.788***	-2.183***	-1.895***	-1.655***
		(0.281)	(0.380)	(0.306)	(0.245)
Observations		153	153	153	153
R-squared		0.678			
* Significantly different OLS and quantile regression coefficient from zero at the 5% significance level; *** p<0.01, ** p<0.05, * p<0.1 ++: Significantly different quantile regression coefficients from OLS coefficients at the 5% significance level.					

Although the results presented in this section are pertinent in understanding the relationship between economic inequality and the use of Mobile Money at spatial level, it is essential to acknowledge their limitations, primarily due to the limited number of observations and the unavailability of data that would allow for comparisons across different years. In this case, we considered approximately 155 districts in Mozambique for which at least the 2017 population census provides reliable data. To assess the robustness of the results, we also estimated the determinants of Mobile Money usage[2] using the entire dataset from 10% sample of the census, which includes observations from over 2.6 million individuals. The results are presented in Table 3.

Overall, the data indicate that the determinants of Mobile Money usage include age, geographic location, asset ownership, and individual characteristics such as literacy, proficiency in the official language (Portuguese), and educational level. The significance of the estimated coefficients and their magnitude is similar in both the probit and linear probability models.

Regarding individual characteristics, for age, the results suggest that individuals in the 18 to 24 age group have a 0.1% higher probability of using a mobile money service than individuals aged 25 to 59. However, individuals aged 60 and older have a 4% lower

[2] In line with the findings regarding the determinants of mobile money usage, we also examined the factors influencing mobile phone ownership. Despite the differences in coefficients magnitudes, results suggest that the determinants of mobile phone ownership appear to be the same as those influencing mobile money usage. In this case, we also took advantage of the data from the most recent survey the 2019/20 Household Budget Survey (IOF2019/20) (National Institute of Statistics, 2021). The primary distinction of this survey is that, despite providing data on mobile phone ownership, it does not include information on the usage of mobile money or any other financial system services.

probability than adults aged 25 to 59[3]. Speaking Portuguese increases the chances by approximately 2.4%, and completing secondary education increases the likelihood of using Mobile Money by 9%, while completing the last grade of primary education increases the chances by 5%, compared to individuals with no completed educational level.

Concerning household characteristics, having access to electricity increases the probability of using Mobile Money by about 1.3%. In contrast to the first spatially estimated model, the determinants tests suggests that access to improved sanitation and improved water have a significant positive impact on the use of mobile money services. Access to improved water increases the probability of using mobile money services by about 2%, while access to sanitation increases it by approximately 1.7%.

Regarding asset ownership, having a mobile phone, TV set, refrigerator, and computer is positively associated with the use of Mobile Money. For instance, owning a mobile phone increases the chances of using mobile money by 15.8%, owning a computer increases it by 0.9%, and owning a TV set increases the chances by 1.5%.

The location of the household also plays a statistically significant role in the determinants of Mobile Money usage. The results suggest that individuals living in rural areas have a 3% lower probability of using mobile money compared to those in urban areas. Living in coastal provinces such as Nampula, Zambézia, and Inhambane increases the chances of using Mobile Money compared to Maputo city. For example, compared to Maputo city, living in Nampula increases the chances of using Mobile Money by about 1.1%, while living in Zambézia increases the chances by 0.3%. However, residing in inland provinces such as Niassa, Tete, and Manica tends to reduce the likelihood of using Mobile Money compared to Maputo city. In this case, living in Niassa decreases the chances of using Mobile Money by 5%, while living in Manica reduces the chances by about 2.7%.

Table 3: Empirical results from the probit and linear probability regressions (Mobile Money as dependent) data from census 2017

VARIABLES	Probit (coefficients)	Probit Marginal effects	Linear Probability (coefficients)
Gender: Female	0.0746***	0.00756***	0.00558***

[3] In this case, the age coefficient shows the difference in the effect of age when comparing the groups (7-17, 18-24, and 60+) to the age group of 25-59. Financial inclusion survey indicates that the use of Mobile Money services in Mozambique is primarily driven by cash withdrawals, deposits, and transfers. These services are mostly used by individuals who are formally or informally employed and have secondary or higher education (Financial Sector deepening Mozambique and FinMark Trust 2020). We assumed that individuals would have at least completed secondary education by the aged 25 using World Bank Development indicators standard.

Age: 7 to 17		-0.507***	-0.0495***	-0.0357***
Age: 18 to 24		0.0462***	0.00511***	0.00178***
Age: 60+		-0.492***	-0.0482***	-0.0499***
Province	Niassa	-0.576***	-0.0522***	-0.0863***
	Cabo Delgado	-0.435***	-0.0409***	-0.0814***
	Nampula	0.112***	0.0119***	-0.0424***
	Zambezia	0.0325***	0.00339***	-0.0445***
	Tete	-0.177***	-0.0177***	-0.0586***
	Manica	-0.277***	-0.0271***	-0.0816***
	Sofala	-0.0152*	-0.00157*	-0.0486***
	Inhambane	0.276***	0.0302***	-0.0180***
	Gaza	-0.216***	-0.0214***	-0.0931***
	Maputo Province	0.286***	0.0313***	0.0454***
Assets and basic services	Rural	-0.346***	-0.0361***	-0.0383***
	Mobile phone	1.569***	0.158***	0.196***
	Sanitation	0.171***	0.0172***	0.00764***
	Improved water	0.204***	0.0206***	0.0257***
	Electricity	0.131***	0.0132***	0.0352***
	Housing	0.0690***	0.00695***	-0.00773***
	TV set	0.150***	0.0154***	0.0194***
	Computer	0.0949***	0.00976***	0.0427***
	Fridge	0.0128**	0.00129**	0.0233***
	Car	-0.177***	-0.0172***	-0.0365***

Education	Literate	0.0111	0.00111	-0.00546***
	Speak Portuguese	0.240*	0.0245**	0.0135**
	Not to speak Portuguese	-0.162	-0.0150	0.00192
	Primary (EP1)	-0.0695***	-0.00604***	-0.0173***
	Primary (EP2)	0.155***	0.0146***	-0.00261***
	Secondary (ESG1)	0.484***	0.0505***	0.0542***
	Secondary (ESG2)	0.823***	0.0942***	0.192***
	Vocational school	1.048***	0.126***	0.339***
	University	0.713***	0.0792***	0.270***
		(0.0114)	(0.00147)	(0.00376)
Constant		-2.832***		0.0725***
		(0.129)		(0.00694)
Observations		1,874,277	1,874,277	1,874,277

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Conclusion

The findings presented in this study address three research questions: how does economic inequality impact the usage of Mobile Money services at the spatial level? what are the determinants of the utilization of these services by individuals, and how does this reflect the impact of economic inequality on Mobile Money usage?

Firstly, at the spatial level, both quantile regression and OLS regression demonstrate that economic inequality, as measured by asset ownership index and access to basic services, has a statistically significant impact on explaining the adoption and usage of Mobile Money services. Specifically, considering the 155 districts in Mozambique, the Gini index of asset ownership, the literacy rate, and access to electricity are the primary factors associated with Mobile Money usage. To estimate the asset index, we employed the uncentred principal component analysis method (Shifa and Ranchhod 2019; Wittenberg and Leibbrandt 2017), and for access rates to basic services, we used the proportion of the population with access to these services (electricity, improved water, and sanitation) by district. The results suggest that a 1% increase in the Gini index of asset ownership index per district is associated with a 1.73% reduction in the district's Mobile Money usage rate. Conversely, a 1% increase in literacy rates and access to electricity is associated to an increase in the district's Mobile Money usage rate by 1.4% and 0.3%, respectively.

Secondly, the fact that quantile regression suggests that the coefficients of inequality, access to electricity, and literacy rate are not statistically different from those in OLS coefficients reinforces the relationship these variables have in explaining Mobile Money usage across all quantiles. In other words, the negative association between inequality and Mobile Money usage may be valid for nearly all districts, regardless of their individual Mobile Money usage rates. In the models using non-logarithm Mobile Money usage rates, the statistically not different from zero Gini index coefficient in the first quartile may be associated with the low Mobile Money usage rates. In this quantile, the average usage rate among the 40 districts is 1%, with a minimum of 0% and a maximum of 2%. Therefore, factors other than asset inequality may play a more substantial role in explaining Mobile Money usage.

Descriptive statistics at the quartile level indicate that higher Mobile Money usage quartiles are associated with higher district electrification rates. This observation suggests that, at the spatial level, the inequality in the distribution of basic services such as electricity may be linked to the inequality in Mobile Money usage. For example, the first and second quartiles have average electricity access rates of 4% and 5%, respectively. The average Mobile Money usage is 1% in the first quartile and 2% in the second quartile. In contrast, the third and fourth quartiles have electrification rates of 14% and 36%, respectively. The average Mobile Money usage rates are 4% and 17%, respectively. A similar trend is observed for literacy rates. However, the trend differs concerning access to improved water and sanitation, where, for instance, the first quartile has an improved water access rate of 37%, while the second has a lower rate of 34%. Access to sanitation is 20% in the first quartile and 18% in the second.

Thirdly, at the individual level, asset ownership, access to basic services, gender, and residential location also have a statistically significant relationship with the probability of using Mobile Money services. The results from the probit model with categorical variables provide a multidimensional analysis perspective of the impact of inequality on access to basic services, assets, and opportunities. For example, individuals with assets such as a TV set, mobile phone, and refrigerator are more likely to use Mobile Money. To illustrate, owning a mobile phone increases the marginal probability of using Mobile Money by 15% compared to not having one. Regarding access to basic services, having access to electricity, improved water, and improved sanitation also significantly increases the probability of individuals using Mobile Money. These findings are also related to the opportunities available to individuals based on their regions of residence. For instance, compared to the capital city, Maputo city, residing in the far northern provinces (Cabo

Delgado and Niassa) and in the interior of the central provinces (Tete and Manica) of Mozambique is associated with a lower probability of using Mobile Money. Living in Niassa and Cabo Delgado is associated with a nearly 5% reduction in the chances of using Mobile Money, while residing in Tete and Manica is linked to a reduction of approximately 2%.

Several policy implications can be drawn from this study. For instance, quantile regression suggests that economic inequality, as measured by asset ownership, is a statistically significant factor in explaining Mobile Money usage. A higher inequality index is associated with a lower adoption rate of Mobile Money. This finding has policy implications for Mozambique. Firstly, while policymakers aim to increase Mobile Money usage rates to reduce inequality in access to the financial services and reduce social disparities (Bank of Mozambique, 2016a), the findings of this study suggest that inequality in sectors as electricity and education may also negatively affect efforts to increase financial inclusion through Mobile Money usage. In other words, the relationship between inequality and Mobile Money usage may be bidirectional. Therefore, efforts to enhance financial sector inclusion, whether through Mobile Money or other financial products or services, should be complemented by efforts to reduce inequality in other areas, such as access to education and electricity. Secondly, as indicated by the descriptive statistics from the quantile regression, the fact that the top quartile of districts with the highest Mobile Money usage rates also have a higher Gini index suggests that the increased usage of these services may not necessarily contribute to greater wealth distribution. This observation is also supported by other studies suggesting that inequality in income and asset distribution can even increase with financial deepening (Ashenafi and Dong 2022; Turégano and Herrero 2018).

This study has several limitations. Firstly, inequality is measured from a perspective of a very limited list of assets to which individuals have access. However, the asset index is not the only measure of inequality, and the use of money metric measures such as average household consumption or income is missing. Unfortunately, the census database does not provide data that would allow us to capture the monetary dimension of the population. Secondly, the use of the Gini index as a measure of inequality can be biased due to the limitations of the index itself. For example, the sample size of the population and the small number of districts in Mozambique can influence the results shared in this study (Shifa and Ranchhod 2019). In addition to these limitations, endogeneity may be part of the limitations and criticism of this study, as the economic literature on financial inclusion often considers the analysis in the opposite direction, i.e., it examines how inequality is impacted by the use of Mobile Money (Ashenafi & Dong, 2022; Demir et al., 2022). However, the aim of this article is the opposite and analyse how these services are affected by economic inequality.

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