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Mobile Money and Income Inequality in Togo

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Abstract: *The objective of this paper is to analyze the impact of mobile money on income inequality in Togo using data from the 2018 Harmonized Household Living Conditions Survey (EHCVM). The Propensity Score Matching method is then used to analyze the impact of mobile money on household expenditures. Our results show that households that use mobile money see an increase in spending compared to households that do not use it. To account for the potential endogeneity bias that may exist between mobile money and spending, we use smooth instrumental variable quantile regression as robustness. Our results reveal that mobile money contributes to increased household spending at all quantile levels of the distribution. The authorities could therefore encourage research and development in the field of digital finance such as mobile money. This could result in the financing of start-ups that innovate in this field.*

Keywords: *Mobile money, income inequality, households, Togo*

JEL: *O16, D63, H31*

1. Introduction

The importance of equality is reflected not only in the Sustainable Development Goals (SDGs) but also in other treaties and actions undertaken at regional and international levels. It is about ensuring that resources are well distributed among different segments of society. Inequality is therefore a major challenge for many developing countries (Piketty, 2014), as it hinders the growth and development of our economies and reduces the impact of policies (Stiglitz, 2015). Exacerbated by the covid-19 pandemic, inequality causes human sight loss, one person every four seconds (Oxfam, 2022). In the face of this situation, achieving the SDGs would be a mere goal set if concrete actions do not follow to reduce these income gaps.

From a theoretical point of view, the issue of inequality has its origins in classical theory with Smith (1776), who maintains that a free market economy

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with minimal state intervention will lead to a natural distribution of income based on the productivity and effort of individuals. Second, the neoclassical labor theory (Marshall, 1890) argues that the distribution of income is determined by the supply and demand for labor. However, in contrast to classical and neoclassical theories, Keynesian theory argues that only state intervention will allow for an equitable distribution of income through economic growth and full employment. As for the institutional theory of Veblen (1898); Acemoglu and Robinson (2001), it asserts that institutions and social norms determine the distribution of income. However, authors such as Durlauf (1996); Sikidmore (2004) argue that despite efforts to reduce income inequality, it still persists in developing countries. However, the technological revolution has the potential to reduce income inequality (Brynjolfsson and McAfee, 2014).

Indeed, the growth of mobile telephony in recent years in Africa and other developing countries has increased significantly (Aker and Mbiti, 2010; Wesolowski *et al.*, 2012). This makes mobile telephony a suitable technology for other innovations (Kikulkwe *et al.*, 2014), such as mobile money. Indeed, mobile money is a service offered by an electronic money issuer to its customers, allowing them to make financial transactions using their cell phone (Loaba, 2022). The introduction of mobile money into the financial system was intended to improve the economic and social situation of the poor by enabling them to make financial transactions.

Thus, mobile money has been recognized in the literature as having a strong potential on households' ability to obtain employment, self-entrepreneurship, receive remittances, save, invest, cope with unexpected shocks, household welfare, and business performance (Kabala, 2023; Hamdan *et al.*, 2019; Aggarwal *et al.* 2020; Batista and Vicente 2020; De Mel *et al.* 2020; Patnam *et al.* 2020; Tabetando and Matsumoto 2020; Ahmed and Cowan 2021; Lee *et al.* 2021a; Lee *et al.* 2021b; Suri *et al.* 2021, Koomson *et al.* 2021; Munyegera and Matsumoto 2016; Islam *et al.* 2018.).

In Togo, a few studies have been conducted in relation to mobile money. These include Afawubo *et al.* (2020) who show that mobile money allows households to cope with shocks. Djahini-Afawoubo *et al.* (2023) find that mobile money contributes to poverty reduction in Togo. In addition, other studies on Togo have looked at inequality. For example, Lawson Body et al (2007); Ametoglo and Guo (2016), argue that income inequality in Togo is higher in rural than in urban areas and that at least 18 percent of overall inequality in 2006 is attributable to inequality between urban areas, but also by education level, place of residence, and gender of the household head. Also, Couchoro and Dout (2019) analyze the dynamics of inequality showing that inequality increased between 2006 and 2015. Thus, in the current state of the literature, there are no studies to our knowledge that have analyzed the relationship between mobile money and income inequality.

This study attempts to answer the following question: What is the impact of mobile money use on income inequality in Togo? To answer this question, the general objective of this paper is to analyze the impact of mobile money use on income inequality in Togo. This study therefore contributes to the existing literature on the relationship between mobile money and income inequality. It will therefore be among the first studies to analyze the link between these two variables in the Togolese context. In addition, in this study, we measure the impact of mobile money use on different household expenditures.

Using 2018 Harmonized Household Living Conditions Survey (EHCVM) data, we use the ''Propensity Score Matching (PSM)'' method and the instrumental variable quantile regression method for robustness. Our results reveal that mobile money increases spending for households that use it in contrast to households that do not use it. In addition, mobile money use increases household income at all quantiles of the distribution, with a larger effect for wealthy households (75th and 90th quantiles).

The rest of this article is structured as follows: the second section presents the methodology and the data. The third section presents the results and then discusses them. The conclusion and policy implications are presented in the last section.

2. Methodology and Data

In this section, the Propensity Score Matching (PSM) method is presented to assess the impact of mobile money on income inequality, and then we present the data.

2.1. Propensity Score Matching Method

The matching method designed for impact evaluation analyses comes from the work of Rosenbaum and Rubin (1983). The main idea of statistical matching is to select a large number of candidates that strongly resemble the units being treated from a large field of potential comparable observations.

2.1.1. Empirical specification of the model

Propensity score matching is used in this study to assess the impact of mobile money use on household expenditure allocation. The method compares households that use mobile money with households that do not. In general terms, the method consists of estimating the following model:

$$Y_i = f(X_i, D_i) + \mu_i \tag{1}$$

The households in the sample can use either mobile money,

$$D_i = 1 \;\; ou \;\; D_i = 0$$

For the household, i, Y represents the different expenditures: (i) food expenditures (ii) non-food expenditures, (iii) housing expenditures and (iv) education expenditures. In this study, we approximate income by annual expenditures for several reasons: first, expenditures allow us to account for so-called non-income earners (Couchoro and Dout, 2019). Second, unlike income whose flows may not be regular, expenditure flows are more regular and more easily identifiable (Friedman, 1957).

2.1.2. Propensity score procedure and estimation of treatment effects

While households that use mobile money differ from non-user households, depending on the baseline covariates, treated households (t) will differ from control households (c), potentially introducing bias into the estimates of the impact of mobile money use. It is therefore preferable to equalize households in groups t and c prior to data analysis (West *et al.*, 2014). We therefore selected 11 key covariates that we believe could have an effect on both mobile money and different expenditures.

However, assume that the conditional independence assumption is not satisfied, but is satisfied if an additional binary variable can be observed. This potential confounder can be simulated in the data and used as an additional covariate in combination with the matching estimator. Comparison of the matched and unmatched estimates on the simulated confounder shows the robustness of the baseline results.

2.1.3. Choice of matching variables

Improving the standard of living of households will increase their purchasing power, which will lead to a decrease in inequality. Indeed, mobile money allows users to regularly transfer funds to relatives, who use it to pay utility bills (water, electricity, telephone, TV subscription, etc.) and pay in supermarkets, restaurants, etc. (Sahay *et al.*, 2015, Suri, 2017). Mobile money is therefore expected to contribute significantly to increasing the rate of access to financial services. It facilitates the daily life of households and enables them to cope with shocks (Riley, 2018).

Thus, we identify the following factors as matching variables: age, religion, cell phone ownership, household size, region, area of residence, non-agricultural land ownership, marital status, level of education, gender and household standard of living.

2.1.4. Construction of propensity scores

We use a probit regression to estimate the propensity scores. The equation is as follows:

$$\textit{The propensity score} = \textit{Predict probit}\ (T = t) \tag{3}$$

$$= b_0 + b_1X_1 + b_2X_2 + \ldots + b_{12}X_{12} \tag{4}$$

where T represents the user household.

In our analysis,

t is the household that uses mobile money and has been recoded 1

c is the household that does not use mobile money has been recoded 0.

X_i is denotes a covariate

We then provided Kernel density estimates of the propensity scores for the mobile money recipient households and the control group samples. Since the two groups may differ on the baseline covariates, we used a group equalization method to obtain an equilibrium.

2.1.5. Comparison group: matching

The main method used is nearest neighbor matching. The matching ratio is 1:1. This matching method consists in selecting a unit in condition t and matching its propensity score with a unit in condition c that has the closest propensity score. The matched pair is removed from the database, and the process continues until all pairs are matched. To avoid a mismatch, we specify a caliper to set a maximum distance between the propensity scores of the two groups. We used a standard deviation of 0.25 standard deviations in propensity scores.

2.1.6. Sensitivity analysis for the matching estimators

The matching method is based on the assumption of conditional independence with observable characteristics. Sometimes this method is not satisfied, when an unobservable characteristic is added to the model in addition to the observable characteristics. In order to test the robustness, we used the sensitivity analysis proposed by Nannicini (2007) and the bounding approach proposed by Becker and Caliendo (2007).

2.1.7. Sensitivity analysis based on simulation

If we assume that the conditional independence hypothesis is not satisfied, but it is if an additional binary variable can be observed. This potential confounder can be simulated in the data and used as an additional covariate in combination with the matching estimator. Comparison of the matched and unmatched estimates on the simulated confounder shows the robustness of the basic results.

2.1.8. Restrictive approach

This involves determining the extent to which an unobservable variable can influence the selection process in order to undermine the implications of the matching analysis (Becker and Caliendo, 2007). Rosenbaum's limits provide evidence on the extent to which meaningful results depend on the conditional independence assumption. To account for the sensitivity of calculating impact by the average treatment effect on treated individuals (ATT), this study also uses nearest neighbor matching, Kernel matching, and radian matching. Indeed, for nearest neighbor matching, a treated individual is matched to an untreated individual on the basis of the nearest propensity score. For Kernel matching, each treated individual is matched to several individuals in the control group, with weights inversely proportional to the distance between the treated and untreated individuals. Finally, for Randian matching, an untreated individual is matched to an individual from the treated group on the basis of the closest propensity score, subject to a certain maximum distance

2.2. Data

In order to analyze the impact of mobile money on income inequality, we use the 2018 Harmonized Household Living Conditions Survey (EHCVM). This is a nationally representative survey that covered 6 171 households in Togo. This survey was conducted by the National Institute of Statistics and Economic and Demographic Studies (INSEED). This survey is nationally representative and includes data on the socio-demographic characteristics of households, data on mobile money, on expenditures and on the well-being of households in Togo.

Our treatment variable here is a dichotomous variable that takes 1 if the household uses mobile money and 0, otherwise. The dependent variables are continuous.

2. Results and Discussion

In this section we present the results of the distribution of the income inequality index by region in Togo. Then, we present the results of the impact of mobile money use on household expenditures in Togo.

2.1. Income Inequality in Togo

The GINI indices used here were calculated by ourselves using the DASP manual. We can therefore see in figure 1 that income inequality is more

Table 1: Descriptive Statistics

Variables	*Description of the variables*	*Observations*	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Total Expenditures	It is the total expenditure of households	6171	1723427	1933723	57429,36	1.80e+07
Food Expenditures	This is the consumption expenditure	6171	869205,7	944453,8	26094,76	5123674
Non-food Expenditures	All other expenditures except consumer expenditures	6171	854220,8	1055569	28424,98	1,49e+07
Education expenses	These are education-related expenditures	6171	1117,6	30749,99	0	835000
Mobile money	Equals 1 if the household uses mobile money and o, otherwise	6171	0,486	0,5	0	1
Household size	The number of people in the household	6171	4,656	3,093	1	21
Age	The age of the head of the household	6171	41,724	11,581	15	99
Gender	Equal 1 if the head of the household is a man and 0 if it is a woman	6171	1,326	0,469	0	1
Marital status	Equals 1 single, 2 married, 3 divorced and 4 widowed	6171	2,194	0,514	1	4
Religion	Equal 1 Muslim, 2 Christian, 3 Animist, 4 Other religion and 5 No religion	6171	2,147	0,667	1	5
Education level	Equal 1 no level, 2 primary level, 3 secondary level and 4 higher level	6171	3,274	1,716	1	4
Region	Equal 0 Lomé commune, 1 Maritime, 2 Plateaux, 3 Centrale, 4 Kara and 5 Savanes	6171	2,562	1,744	0	5
Standard of living	Equal 0 if the household is rich 1 if the household is very poor and 2 if the household is poor	5,983	0,968	0,889	0	2
Place of residence	Equal 1 if the household is in the urban area and 0 if it is in the rural area)	6171	1,713	0,452	0	1
Mobile phone	Equal 1 if the household has a cell phone and 0, otherwise	6170	1,254	0,435	0	1
Non-agricultural land ownership	Equals 1 if the head of the household owns at least one piece of non-agricultural land and 0, otherwise	4052	0,005	0,07	0	1

Source: Author using EHCVM data from 2018 important in the north of the country with the Savanes and Kara regions respectively. This result can be explained in several ways. Indeed, the Savanes and Kara regions are the poorest in the country. The poverty index in the Savanes region increased from 65 percent in 2017 to 65.1 percent between 2018-2019 (EHCVM, 2020). At the same time, the Kara region, which experienced a decrease in its poverty index from 58.2 percent in 2017 to 56.1 percent between 2018-2019 (EHCVM, 2020), still remained the second poorest region in the country, just behind the Savanes region. Added to this is the security crisis marked by terrorist attacks, which leads to population displacements making the daily life of households in these regions even more difficult.

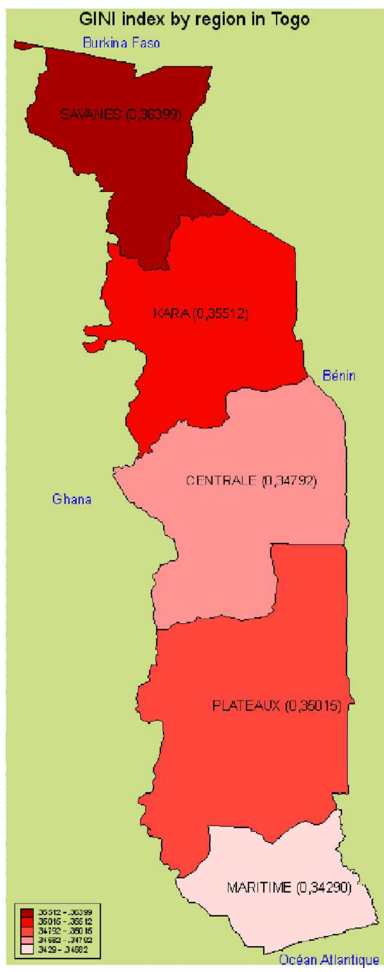

Figure 1: GINI index by region in Togo

Source: Author using EHCVM data from 2018, DIVA-GIS shapefile (https://www,diva-gis,org/gdata)

However, the Maritime region is the most egalitarian in the country with a GINI index of 0.343. This result is understandable insofar as the reduction of inequalities in this region is due to the fact that the Togolese government has worked to implement several projects and programs, such as the National Fund for Inclusive Finance (FNFI)[2], in favor of the poorest populations (especially women), which have had positive impacts. These programs are said to have improved the living conditions of poor households and thereby contributed to the reduction of income disparities in this region.

2.1. Result of propensity score matching (PSM)

To obtain the average treatment effect based on propensity score matching, we first calculate the propensity score, which reflects the probability of being treated, i.e., the probability of using mobile money. To obtain the propensity score, we estimated the participation equation with a probit model (Table 2). In the process of deriving the propensity scores, we use only the observed variables, as it is not possible to control for unobserved variables. Such unintentional omissions could lead to a bias in the estimated propensity score.

Table 2: Result of the participation equation with the probit model.

	(1)
Variables	dy/dx
Household size	0.005*
	(0.003)
Age	0.006***
	(0.000)
Gender (male)	-0.155***
	(0.024)
Marital status	0.016***
	(0.006)
Religion	-0.073***
	(0.008)
Education lavel	-0.001
	(0.010)
Region	0.003
	(0.004)
Standard of living (very poor)	-0.034***
	(0.009)
Place of residence (urban)	0.006
	(0.016)
Ownership of off-farm land	-0.160
	(0.129)
Mobile phone	0.045**
	(0.018)
Observations	4,417

Note: standard errors in parentheses. *** significant at 1 % ; ** significant at 5 %; * significant at 10 %

The probit model estimates in Table 2 reveal that household ownership of a cell phone increases the probability of using mobile money. This shows that the cell phone is an essential element in the mobile money adoption process. This result confirms the Afawubo et al (2020) findings. Household size is an important determinant of mobile money usage. Indeed, households that are relatively large in number of individuals are more likely to use mobile money to receive remittances (Raihan *et al.*, 2021; Randazzo and Piracha, 2019). However, male-headed households are less likely to use mobile money compared to female-headed households.

2.1. Difference-in-means results for each expenditure

The results show that the difference in means is significant for total expenditures and for food expenditures. However, for other expenditures such as non-food expenditures and education expenditures, there is no significance.

Table 3

	Untreated population	*Number of people treated*	*Difference in average*	*Significance at the 5% level (student's t)*
Total Expenditures	2,715	3,484	120071**	t = 5,331
Food expenditures	2,715	3,484	653593.7**	t = 8,4785
Non-Food Expenditures	2,715	3,484	12894.03	t = 1,016
Education expenditure	2,715	3,484	674.0829	t = -0.856

Note: standard errors in parentheses. ** significant at 5 %.

2.1. Presentation of Matching Results (Before and After)

Figure 2 presents the distributions of propensity scores. The first graph on the left (''Raw'') is a kernel density graph that estimates the underlying distributions of propensity scores before matching. The second graph on the right (''Matched'') is a kernel density graph that estimates the underlying distributions of propensity scores after 1:1 matching. Controlled'' represents households without mobile money; ''treated'' represents households with mobile money.

These graphs provide the first indication that we were able to balance the two groups on the propensity scores.

2.2. Mantel Haenszel test

We examine Q_mhþ and Q_mh in the Stata output (Table 4). The upper bounds on the significance levels for gamma = 1.5; 1.6; 1.65; 1.7 and 1.8 are 0.044; 0.024; 0.017; 0.012 and 0.013, respectively. All ranges are significant at

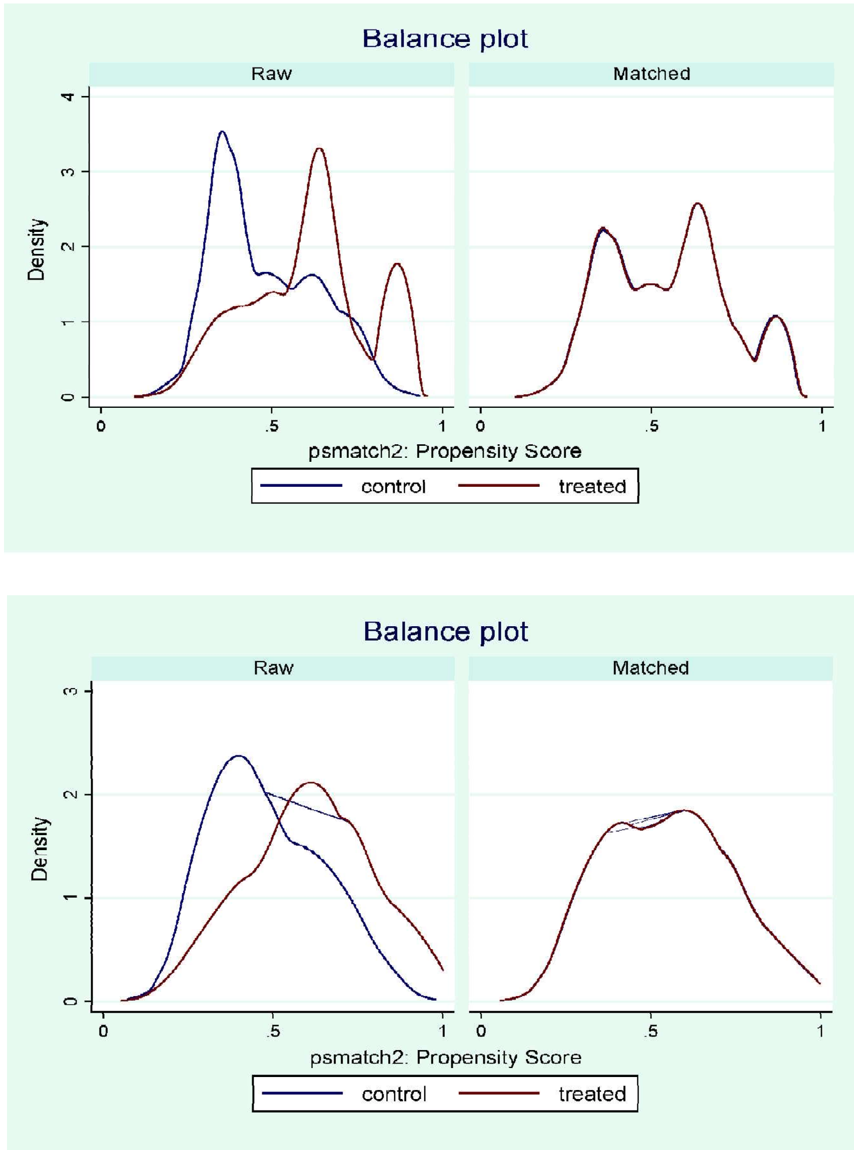

Figure 2: Distribution of Propensity Scores

Source: Author using data from EHCVM 2018

1% from 1.75 onwards. Note that the significance level of the boundaries initially decreases and then increases significantly. Similar trends are obtained regardless of the output considered. Therefore, we can deduce that this study is not very sensitive to any bias.

Table 4: Results of the Mantel Haendel test

Gamma	*Q_mh+*	*Q_mh-*	*P_mh+*	*P_mh-*
1,5	1,844	1,460	0,044	0,072
1,55	1,200	1,599	0,033	0,055
1,6	1,980	1,733	0,024	0,041
1,65	2,111	1,865	0,017	0,031
1,7	2,240	1,992	0,012	0,023
1,75	2,366	2,117	0,008	0,017
1,8	2,488	2,239	0,006	0,013
1,85	2,607	2,357	0,004	0,009
1,9	2,723	2,472	0,003	0,007
1,95	2,838	2,586	0,002	0,005
2	2,950	2,700	0,002	0,003

Gamma: odds of differential assignment due to unobserved factors.
Q_mhþ: Mantel-Haenszel statistic (assumption: overestimation of treatment effect).
Q_mh_: Mantel-Haenszel statistic (assumption: underestimation of treatment effect).
p_mhþ: significance level (assumption: overestimation of treatment effect).
p_mh_: significance level (assumption: underestimation of treatment effect

2.2. *Impact of mobile money on household spending*

To better assess the impact of mobile money on household spending, distinguishing between total spending, food spending, non-food spending and human capital investment spending (education spending). We use three matching criteria (the nearest neighbor criterion, the radian criterion and the Kernel criterion). The results (table 5) show that, on average, mobile money increases overall total expenditure and food expenditure of households in the treatment group compared to households in the control group. This increase is 6%, 21% and 17% respectively for the nearest neighbor, Radian and Kernel methods when using total expenditures. For non-food expenditures, it is 4%, 24% and 20%, respectively for the three criteria. The impact is then significant for the three criteria used. However, there is a lack of significance for non-food and health expenditures.

Table 5: Impact of mobile money on various household expenditures

Expenditure categories	*Observations*	*Treaty*	*Control*	*Nearest neighbor*	*Radius*	*Kernel*
Total expenditure	1903	585	1318	0.063***	0.211***	0.171***
				(0.101)	(0.0472)	(0.050)
Food expenditures	1903	585	1318	0.044***	0.238***	0.207***
				(0.106)	(0.051)	(0.0550)
Non-Food Expenditures	1903	585	1318	0.122	0.205	0.160
				(0.110)	(0.060)	(0.063)
Education Expenditures	1903	585	1318	0.299	0.207	0.224
				(0.153)	(0.087)	(0.094)

Note: standard errors in parentheses. *** significant at 1 %

3.1. Accounting for endogeneity with quantile regression

Drawing on the work of Bang *et al.* (2016) and Sodokin (2021), we hypothesize that the impact of mobile money may differ across the distribution of income captured here by spending. Thus the decision to use mobile money may be correlated with both observable characteristics, such as income level, education level and employment status, and with unobservable characteristics. There is then a bias to the extent that individuals have heterogeneous characteristics (Seng, 2017). Thus, to correct for this potential bias, we use the quantile regression estimator of Koenker and Bassett (1978). The reason we use it is because it is ultimately the best way to answer the question: what is the impact of mobile money on the income distribution, given that the impact of the former is likely to vary with the conditional distribution of the latter." In addition, quantile regression offers the possibility of a more complete view of the statistical landscape and the relationships between stochastic variables, so the interpretability of conditional quantile functions as a natural goal for data analysis is another advantage of this regression (Koenker, 2005).

The model is specified as follows:

$$\begin{aligned} Dtot_i = \beta_0 + \beta_1 MM_i + \beta_3 Householdzise_i + \beta_2 Age_i + \beta_2 Gender_i + \beta_2 Maritus_i \\ + \beta_5 Religion_i + \beta_6 Educ_i + \beta_7 Region_i + \beta_8 Pauvlevel_i + \beta_8 Residence_i \\ + \beta_8 Land_i + \beta_8 Mobilephone_i \\ + \varepsilon_i \end{aligned} \tag{5}$$

In equation (5), *Dtot* the dependent variable and represents total household expenditure, *MM* is the mobile money variable of interest which takes 1 if the household uses mobile money and 0 otherwise. *Householdzise* is the household size. *Age* represents the age of the head of household, *Gender* is sex, *Maritus* is the marital status, Religion is the region, Educ is the level of education, *Religion* is the region, *Educ* is the level of education, *Pauvlevel* is the standard of living of the household, *Residence* is the place of residence of the head of household, *Land* represents non-agricultural land ownership, *Mobilephone* which materializes the possession of the mobile phone.

As suggested by Chernozhukov and Hansen (2008) and following the method used by Bang, and al (2016) and Sodokin (2021), we consider the linear quantile linear model of the income variable Y, conditional on the conditional variable to the treatment variable d, and to a vector of control variables x as follows:

$$Y = q(d, x, u) = \alpha_\tau d + x'\beta_\tau + u, \tag{6}$$

where u represents a non-separable error term. In our case, the treatment variable, d, represents an indicator variable equal to 1 if a household has used mobile money once in the past year, and 0 otherwise. We assume that mobile money is endogenously determined by the following function:

$$d = \delta(x, z, v) = x'\theta_\tau + z'\pi_\tau + v \tag{7}$$

where $\delta(.)$ is an unknown function, z is a vector of excluded instruments that are correlated with the treatment variable, d, but not correlated with the outcome variable (Y), and v is a vector of unobservable characteristics that depends on u. The conditional distribution of u at x and z is assumed to be uniform over the measure (0, 1). $\alpha_\tau, \beta_\tau, y_\tau$

The quantile regression model is the τ^{th} quantile of Y et and identified by:

This leads to the following simplified objective following simplified objective function:

$$\arg_{\alpha_\tau, \beta_\tau, y_\tau} \min \left[E(\rho_\tau[y - \alpha_\tau d - x'\beta_\tau - z'y_\tau]\right), \tag{5}$$

Où $\rho_\tau(\cdot)$ is an absolute function that solves the quantile of Y in the sample.

Our implementation of the estimator derived from this objective function follows that described by Kwak (2010). Thus, following the work of Bang *et al.* (2016) and Sodokin (2021) and Loaba (2022), we use non-agricultural landowner and education level as instruments. In this study, we use the regression, smooth instrumental variable quantile (sivqr) described by Kaplan and Sun (2017). The advantage of this estimator is that it allows for models with multiple endogenous terms, supports a convenient syntax such as for factor variables and the interaction term, and computes a consistent estimator of the IVQR parameters within a reasonable time frame. This is in contrast to the estimators of Kwak (2010) (ivqreg), which allows only one endogenous factor, and Machado and Silva (2018) (ivqreg2), which in turn imposes a location scaling model that may help if well specified, but may lead to inconsistencies if poorly specified. Added to this is the execution time which is about 25 seconds for ''sivqr'' versus a few minutes and more than 20 minutes respectively for ''ivqreg'' and ''ivqreg2''.

2.2. Effect of mobile money on household spending

We present here the Lorenz curves to show the difference between households with mobile money and those without. This curve also allows us to see the different quantiles involved in the income distribution. Next, we present the results of the effect of mobile money received on household income and welfare.

The results show that the distribution of expenditures is less unequal among non-recipient households than among mobile money recipient households, as explained in Figure 3 (Figure 3-a, Figure 3-b). The dotted line in figure 3-b that represents households that use mobile money is slightly above the solid line. These positions show that the funds received via the mobile money channel contribute to the redistribution of Togolese households' income. However, the gap between the two curves is much larger for households that do not use mobile money than for those receiving mobile money transfers. Furthermore, all the curves diverge from 10% of household spending and meet at around 90% of spending, implying a high degree of income equality in the middle of the income distribution.

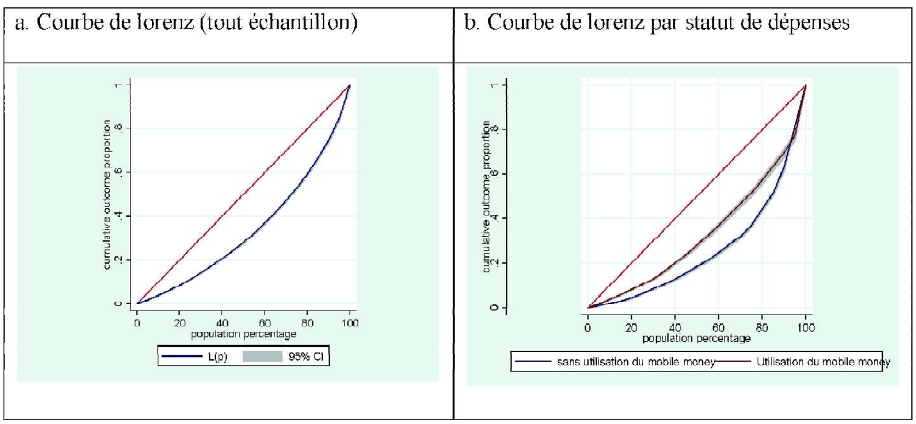

Figure 3: Lorenz curve (entire sample). b) Lorenz curve by mobile money status

Source: Author using data from EHCVM 2018

2.1.1. Validity testing of the instruments

In this section, we present the results of the Ordinary Least Squares (OLS) regression and the "IV/2SLS" instrumental variables method with the various appropriate tests to justify not only the choice of our instruments, but also to justify the endogeneity that exists between mobile money and household income.

Thus, in order to shed light on the effect of mobile money and to test the validity of the instruments, we performed both Ordinary Least Squares (OLS) and Instrumental Variable (IV/2SLS) estimates with our baseline model. The results of these estimates are presented in Table 6. Three important conclusions emerge: first, The probability (Prob > chi2) is less than 1% (0. 0000) allows us to conclude the existence of an endogeneity bias thus justifying the use of the appropriate instrumental variable method to solve this problem; second, the Kleibergen-Paap test for weak instruments takes a value of 14.828 and a P-value of 0.0000 confirming the strength of the instruments; and finally, Hansen's test for the validity of the instruments takes a value of 1.626 and a P-value of 0.2023 confirming the validity of our used instruments.

Table 6: Results of the instrument validity test

		(1)	(2)
Variables		MCO	2SLS
Mobile money		0.188***	4.054***
		(0.018)	(1.132)
Household size		0.137***	0.104***
		(0.004)	(0.014)
Age		0.003***	0.013***
		(0.000)	(0.004)
Gender (Male)		0.048*	-0.570***
		(0.026)	(0.202)
Marital status		-0.032***	0.026
		(0.006)	(0.028)
Religion		0.024***	-0.299***
		(0.009)	(0.112)
Education level		0.061***	-0.463***
		(0.010)	(0.155)
Religion		-0.002	-0.008
		(0.004)	(0.016)
Standard of living (very poor)		-0.028***	0.994***
		(0.010)	(0.310)
Place of residence (urban)		-0.003	-0.031
		(0.016)	(0.056)
Mobile phone		0.064***	0.438***
		(0.018)	(0.139)
Constant		12.879***	9.247***
		(0.056)	(1.129)
Observations		5,982	4,417
R-square		0.323	
Kleibergen-Paap: underidentificationtest)			14.828
			p-value= 0.0006
Kleibergen-Paap (weak instruments test)			F= 21.510
			12.375
Valeurs Stock_Yogo weak ID test critical	10% maximal IV size		19.93
values	15% maximal IV size		11.59
	20% maximal IV size		8.75
	25% maximal IV size		7.25
Hansen J			1.626
			p-value = 0.2023
Endogeneity test			104.330
			p-value = 0,0000

Note: standard errors in parentheses. Two instruments are used: level of education and non-agricultural land ownership. *** significant at 1 % ; ** significant at 5 %; * significant at 10 %.

Table 7 presents the results of the effect of mobile money on household expenditures in Togo. Our results reveal that mobile money contributes to the increase in household income in Togo. This result therefore confirms that of Kikulwe *et al.* (2014), in the Kenyan context. This result is not surprising insofar as mobile money allows users to send and especially receive funds, which can lead to an increase in household income. Also, mobile money allows users to save more money (Loaba, 2022), which can then be used to undertake income-generating activities and thus increase their income. Also, mobile money contributes to increased sales revenue rural areas (Danquah and Iddrisu, 2018), in doing so, it contributes to 11 of the 17 United Nations Sustainable Development Goals (SDGs) (GSMA,

Table 7: Effect of mobile money on household spending

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
VARIABLES	0.10	0.25	0.50	0.75	0.90
Mobile money	1.889***	0.902***	2.127***	4.387**	4.054***
	(0.462)	(0.122)	(0.526)	(1.881)	(1.368)
Household size	0.107***	0.136***	0.124***	0.105***	0.104***
	(0.016)	(0.006)	(0.011)	(0.017)	(0.014)
Age	0.007***	0.004***	0.010**	0.015**	0.013***
	(0.002)	(0.001)	(0.004)	(0.006)	(0.005)
Gender (Male)	-0.445***	-0.204***	-0.369***	-0.574*	-0.570**
	(0.142)	(0.060)	(0.103)	(0.295)	(0.235)
Marital status	0.118**	0.071***	-0.013	-0.024	0.026
	(0.046)	(0.022)	(0.020)	(0.033)	(0.035)
Religion	-0.098**	-0.010	-0.148	-0.390*	-0.299**
	(0.044)	(0.025)	(0.127)	(0.205)	(0.128)
Level of education	-0.236**	-0.088**	-0.459***	-0.578**	-0.463***
	(0.103)	(0.039)	(0.143)	(0.233)	(0.176)
Religion	-0.003	0.003	0.000	-0.003	-0.008
	(0.011)	(0.006)	(0.005)	(0.017)	(0.017)
Standard of living (very poor)	0.531***	0.126**	0.464***	1.019**	0.994***
	(0.182)	(0.050)	(0.128)	(0.448)	(0.376)
Place of residence (urban)	-0.026	-0.013	-0.011	-0.039	-0.031
	(0.040)	(0.022)	(0.021)	(0.058)	(0.055)
Mobile phone	0.233***	0.275***	0.493**	0.494**	0.438**
	(0.079)	(0.051)	(0.193)	(0.226)	(0.177)
Constant	9.242***	11.548***	11.135***	11.251***	34.648***
	(0.755)	(0.196)	(0.539)	(0.892)	(1.401)
Observations	4,417	4,417	4,417	4,417	4,417

Note: The dependent variable is total expenditure and the variable of interest is mobile money. standard errors in parentheses. *** significant at 1% ; ** significant at 5%; * significant at 10%

2017). Furthermore, unlike traditional money transfers, such as mail or hand remittances, which can be costly and time-consuming. Mobile money allows for instant money transfers at lower costs, this can reduce transaction costs by 10-20% for user households, which can increase their disposable income (Banque Mondiale, 2012).

However, the results reveal that mobile money use benefits richer households (75th and 90th quantiles) more than poor households (10th and 25th quantiles) in Togo. This result can be explained in several ways. First, the fees associated with using mobile money may be higher for poor households that conduct low-value transactions, while wealthy households may be able to negotiate lower fees for high-value transactions. Also, mobile money is a relatively new technology in the country and requires digital skills to use, so poor households may be at a disadvantage in terms of these skills compared to rich households. In addition, it is possible that the use of mobile money will accentuate existing income gaps between rich and poor, as richer households have more resources to invest in income-generating assets and may use mobile money to facilitate these investments, while poorer households may use mobile money only for consumption transactions.

Conclusion

The objective of this paper was to analyze the impact of mobile money use on income inequality in Togo. To do so, we used the Propensity Score Matching method and quantile regression with instrumental variables as robustness. Our results reveal that the income of mobile money user households increases compared to non-user households. In addition, we find that mobile money use positively affects household expenditures at all quantiles of the distribution. Given these results, it would be important for the government and businesses to encourage the adoption of mobile money by offering financial incentives or facilitating access to this technology. This could help households increase their income and improve their spending. Also, authorities can work with mobile money service providers to reduce barriers to using the technology, such as high fees or security concerns. This could encourage more households to adopt mobile money and enjoy its benefits. In addition, authorities can consider programs to support low-income households to benefit from this technology. This can be done through the establishment of a social registry, which will better identify poor households that are eligible for these programs. In addition, mobile money is a relatively young technology that can still evolve. The authorities could therefore encourage research and development in this area. This could mean funding start-ups that innovate in this area.

Note

1. Created in January 2014, the FNFI aims to strengthen the financial and operational capacities of decentralized Financial Service Providers. The FNFI works in synergy with all stakeholders and partners while remaining in line with the Government's overall vision for grassroots development and the inclusive finance sector in Togo.

References

Acemoglu, D., Johnson, S., & Robinson, J. A. 2001. The colonial origins of comparative development/ : An empirical investigation. *American economic review*, *91*(5), 1369 1401.

Afawubo, K., Couchoro, M. K., Agbaglah, M., & Gbandi, T. 2020. Mobile money adoption and households' vulnerability to shocks/ : Evidence from Togo. *Applied Economics*, *52*(10), 1141 1162.

Aggarwal, S., Brailovskaya, V., & Robinson, J. 2020. Cashing in (and out)/ : Experimental evidence on the effects of mobile money in Malawi. *AEA papers and proceedings*, *110*, 599 604.

Ahmad, A. H., Green, C., & Jiang, F. 2020. Mobile money, financial inclusion and development/ : A review with reference to African experience. *Journal of Economic Surveys*, *34*(4), 753 792.

Aker, J. C., & Mbiti, I. M. 2010. Mobile phones and economic development in Africa. *Journal of economic Perspectives*, *24*(3), 207 232.

Ametoglo, M. E. S., & Guo, P. 2016. *Inequality, poverty and inclusive growth in TOGO/ : An Assessment of the Survey Data*.

Batista, C., & Vicente, P. C. 2020. Adopting mobile money/ : Evidence from an experiment in rural Africa. *AEA Papers and Proceedings*, *110*, 594 598.

Becker, S. O., & Caliendo, M. 2007. Sensitivity analysis for average treatment effects. *The stata journal*, *7*(1), 71 83.

Breza, E., Kanz, M., & Klapper, L. F. 2020. *Learning to navigate a new financial technology/ : Evidence from payroll accounts*. National Bureau of Economic Research.

Brynjolfsson, E., & McAfee, A. 2014. *The second machine age/ : Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Chernozhukov, V., & Hansen, C. 2008. Instrumental variable quantile regression/ : A robust inference approach. *Journal of Econometrics*, *142*(1), 379 398.

Couchoro, M. K., & Dout, H. 2019. Dynamique des Inégalités de Revenu au Togo entre 2006 et 2015. *African Development Review*, *31*(4), 476 491.

Danquah, M., & Iddrisu, A. M. 2018. Access to mobile phones and the wellbeing of non-farm enterprise households/ : Evidence from Ghana. *Technology in Society*, *54*, 1 9.

De Mel, S., McIntosh, C., Sheth, K., & Woodruff, C. 2022. Can mobile-linked bank accounts bolster savings? Evidence from a randomized controlled trial in sri lanka. *The Review of Economics and Statistics*, *104*(2), 306 320.

Djahini-Afawoubo, D. M., Couchoro, M. K., & Atchi, F. K. 2023. Does mobile money contribute to reducing multidimensional poverty? *Technological Forecasting and Social Change*, *187*, 122194.

Durlauf, S. N. 1996. A theory of persistent income inequality. *Journal of Economic growth*, *1*, 75 93.

Friedman, M. 1957. *Theory of the consumption function*. Princeton university press.

Hamdan, J. 2019. *The impact of mobile money in developing countries*.

Islam, A., Muzi, S., & Rodriguez Meza, J. L. 2018. Does mobile money use increase firms' investment? Evidence from Enterprise Surveys in Kenya, Uganda, and Tanzania. *Small Business Economics*, *51*, 687 708.

Kabala, E. 2023. Dynamics of Mobile Money Entrepreneurship and Employment in Kitwe, Zambia. In *Global Labour in Distress, Volume I: Globalization, Technology and Labour Resilience* (p. 387 391). Springer.

Kaplan, D. M. 2022. Smoothed instrumental variables quantile regression. *The Stata Journal*, *22*(2), 379 403.

Kaplan, D. M., & Sun, Y. 2017. Smoothed estimating equations for instrumental variables quantile regression. *Econometric Theory*, *33*(1), 105 157.

Kikulwe, E. M., Fischer, E., & Qaim, M. 2014. Mobile money, smallholder farmers, and household welfare in Kenya. *PloS one*, *9*(10), e109804.

Koenker, R. 2005. *Quantile regression* (Vol. 38). Cambridge university press.

Koenker, R., & Bassett Jr, G. 1978. Regression quantiles. *Econometrica: journal of the Econometric Society*, 33 50.

Koomson, I., Bukari, C., & Villano, R. A. 2021. Mobile money adoption and response to idiosyncratic shocks/ : Empirics from five selected countries in sub-Saharan Africa. *Technological Forecasting and Social Change*, *167*, 120728.

Kwak, D. W. 2010. Implementation of instrumental variable quantile regression (IVQR) methods. *Michigan State University*.

Lawson Body, B. K., Baninganti, K., Homevoh, E., & Lamadokou, E. A. 2007. Comparative analysis of poverty and inequality in Togo/ : A multidimensional approach based on a wealth index. *Poverty and Economic Policy Research Network Working Paper No. PMMA-2007-10*.

Lee, J. N., Morduch, J., Ravindran, S., & Shonchoy, A. S. 2022. Narrowing the gender gap in mobile banking. *Journal of Economic Behavior & Organization*, *193*, 276 293.

Lee, J. N., Morduch, J., Ravindran, S., Shonchoy, A., & Zaman, H. 2021. Poverty and migration in the digital age/ : Experimental evidence on mobile banking in Bangladesh. *American Economic Journal: Applied Economics*, *13*(1), 38 71.

Loaba, S. 2022. The impact of mobile banking services on saving behavior in West Africa. *Global Finance Journal*, *53*, 100620.

Marshall, A. 1898. Distribution and exchange. *The Economic Journal*, *8*(29), 37 59.

Munyegera, G. K., & Matsumoto, T. 2016. Mobile money, remittances, and household welfare/ : Panel evidence from rural Uganda. *World Development*, *79*, 127 137.

Nannicini, T. 2007. Simulation-based sensitivity analysis for matching estimators. *The stata journal*, *7*(3), 334 350.

Oxfam. 2022. Les inégalités tuent.

Patnam, M., & Yao, W. 2020. *the real effects of mobile money/ : Evidence from a large-scale fintech expansion*.

Piketty, T., & Saez, E. 2014. Inequality in the long run. *Science*, *344*(6186), 838 843.

Raihan, S., Uddin, M., & Ahhmed, S. 2022. Impact of foreign remittances on the household spending behaviour in Bangladesh. *Migration and Development*, *11*(3), 1104 1126.

Randazzo, T., & Piracha, M. 2019. Remittances and household expenditure behaviour/ : Evidence from Senegal . *Economic Modelling*, *79*, 141 153.

Sahay, R., Èihák, M., N'Diaye, P., & Barajas, A. 2015. Rethinking financial deepening/ : Stability and growth in emerging markets. *Revista de Economía Institucional*, *17*(33), 73 107.

Seng, K. 2017. *Considering the effects of mobile phones on financial inclusion in Cambodia*.

Skidmore, T. E. 2004. Policy Issues Brazil's Persistent Income Inequality/ : Lessons from History. *Latin American Politics and Society*, *46*(2), 133 150.

Smith, A. 1776. 1976. An Inquiry into the Nature and Causes of the Wealth of Nations. *The Glasgow edition of the works and correspondence of Adam Smith*, *2*.

Sodokin, K. 2021. Comparative analysis, cash transfers, household investment and inequality reduction in Togo. *Applied Economics*, *53*(23), 2598 2614.

Stiglitz, J. E. 2012. *The price of inequality/ : How today's divided society endangers our future*. WW Norton & Company.

Suri, T. 2017. Mobile money. *Annual Review of Economics*, *9*, 497 520.

Suri, T., Bharadwaj, P., & Jack, W. 2021. Fintech and household resilience to shocks/ : Evidence from digital loans in Kenya. *Journal of Development Economics*, *153*, 102697.

Tabetando, R., & Matsumoto, T. 2020. Mobile money, risk sharing, and educational investment/ : Panel evidence from rural Uganda. *Review of Development Economics*, *24*(1), 84 105.

Veblen, T. 1898. The beginnings of ownership. *American Journal of Sociology*, *4*(3), 352 365.

Wesolowski, A., Eagle, N., Noor, A. M., Snow, R. W., & Buckee, C. O. 2012. Heterogeneous mobile phone ownership and usage patterns in Kenya. *PloS one*, *7*(4), e35319.

West, S. G., Cham, H., Thoemmes, F., Renneberg, B., Schulze, J., & Weiler, M. 2014. Propensity scores as a basis for equating groups/ : Basic principles and application in clinical treatment outcome research. *Journal of consulting and clinical psychology*, *82*(5), 906.