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ESSAYS ON DIGITAL FINANCE, FINANCIAL INCLUSION AND POVERTY ALLEVIATION IN WAEMU

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DEDICATION

To my family, especially:

Odile

Nadège, Bénie, Mercy, Eldad

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ABSTRACT:

Financial Inclusion is not an objective per se, but only to the extent that it helps alleviate poverty. This thesis aims then at investigating the mechanisms through which digital finance may solve the multiple financial market imperfections by improving financial Inclusion and alleviate poverty in developing countries. We estimated first a random effect model and a system GMM and found that beyond the specific effects of mobile phone penetration and Internet usage, the joint use of these two technologies is very key to financial inclusion in the WAEMU countries. Secondly, we made a cluster analysis and a logistic regression to investigate respectively the macroeconomic and microeconomic driving factors of mobile money adoption. We found that illiteracy, underemployment as well as the lack of mobile infrastructure are the main macroeconomics bottlenecks for digital finance adoption. In addition, the age, gender, education level, poverty status as well as the ownership of bank account are the main microeconomics driving factors of digital finance adoption in WAEMU. Finally, we estimated the probability of lifting out of poverty in WAEMU with a recursive bivariate probit model and concluded that both mobile led financial inclusion and bank led financial inclusion are essential for sustainable poverty alleviation in WAEMU. The findings from these essays suggest to governments to support both Mobile Network Operators (MNOs) and Financial Institutions to deliver financial services through digital technologies to last miles. This requires then a flexible regulation toward the digital finance business in WAEMU.

***Keywords**: Digital Finance, Financial Inclusion, cluster, Logit, GMM, Recursive Bivariate probit, WAEMU*

RÉSUMÉ

L’inclusion financière n’est pas l’objectif ultime mais seulement dans la mesure où elle permet de réduire la pauvreté. Cette thèse vise à cet effet à examiner les mécanismes par lesquels la finance digitale peut résoudre les multiples imperfections des marchés financiers en induisant de facto l'inclusion financière et la réduction de la pauvreté dans les pays de l’UEMOA. L’estimation du modèle à effets aléatoires et du Modèle de Moments Généralisés en système montrent qu'au-delà des effets spécifiques de la pénétration du téléphone mobile et de l'utilisation d'Internet, l'utilisation simultanée de ces deux technologies est très importante à l'inclusion financière dans les pays de l'UEMOA. Ensuite, à l'aide d’une l’analyse de groupage (cluster) et d’une régression logistique, nous trouvons que l’analphabétisme, le chômage ainsi que le manque d'infrastructures mobiles sont les principaux obstacles structurels à l'adoption de la finance digitale. L’âge, le genre, le niveau d’instruction, le statut de pauvreté et même la détention de compte bancaire sont quant à eux les déterminants microéconomiques de l’adoption de la finance digitale. Enfin, l’estimation d'un modèle probit bivarié récursif montre qu’il est important que les opérateurs de téléphonie mobile et les institutions financières collaborent pour une meilleure inclusion financière gage de la réduction de la pauvreté dans l'UEMOA. Les résultats suggèrent aux autorités publiques d’élaborer des stratégies permettant aux opérateurs de téléphonie mobile et aux institutions financières formelles de fournir des services financiers à tous. A cet effet, une réglementation flexible et appropriée en faveur du secteur de la finance digitale est nécessaire.

Mots-clés: *Finance Digitale, Inclusion Financière, Cluster, Logit, GMM, probit bivarié Récursif, UEMOA*

ABBREVIATIONS & ACRONYMS

ARCEP-Benin	:	Autorité de Régulation des Communications Electroniques et de la Poste du Benin
BBPR	:	Broad Banking Penetration Rate
CGAP	:	Consultative Group to Assist the Poor
DFTF	:	Digital Finance Task Force
FI		Financial Inclusion
FIA	:	Financial Inclusion Action
FIAP	:	Financial Inclusion Action Plan
G20	:	Group of Twenty
GRFSU	:	Global Rate of Financial Services Utilization
GMM	:	Generalized Method of Moments
GPFI	:	Global Partnership for Financial Inclusion
GSMA	:	GSM Association
ITU	:	International Telecommunication Union
MFIs	:	Microfinance Institutions
MNO	:	Mobile Network Operators
M-PESA	:	Mobile-PESA

OECD	:	Organization for Economic Co-operation and Development
SMS	:	Short Message Service
SWIFT	:	Society for Worldwide Interbank Financial Telecommunication
UNCDF	:	United Nation Capital Development Fund
UN	:	United Nation
WAEMU	:	West African Economic and Monetary Union
WB	:	World Bank

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SUMMARY

GENERAL INTRODUCTION

General Introduction

1.1. Theoretical background

Theoretical debates relating economic development to finance is not new in the economic literature (Schumpeter, 1911; McKinnon, 1973; Shaw, 1973; Levine, 2005; Allen et al., 2016, Beck et al., 2018; Ky et al., 2021). The contemporary financial inclusion debate is predicated on the understanding that inclusive financial systems tend to alleviate poverty through the stimulation of economic growth within communities and nations (Beck et al., 2009; Tita & Aziakpono, 2017). The seminal work of Schumpeter (1911) highlights the importance of financial development on economic growth and indirectly on poverty reduction. In the same vein, McKinnon (1973) and Shaw (1973) in providing arguments against policies of financial repression, emphasized the role of the financial sector in increasing the volume of savings by creating appropriate incentives for the sake of economic development. However, the McKinnon-Shaw theory has been criticized by several economists including Stiglitz (1989) who predicted that financial liberalization would slow down economic growth. Stiglitz (1989) criticized financial liberalization on the theoretical background of market failures in financial markets. Nonetheless, Silber (1983) and King and Levine (1993) emphasized the role of innovation in the financial sector in accelerating financial inclusion.

Financial inclusion refers to a condition in which everyone has access to financial services provided by formal institutions and is able to use at least one formal account to perform financial transactions at an affordable cost (World Bank, 2016; Klapper & Singer 2014). Such formal accounts could include a bank account, nonbank account or mobile money account to save, borrow, access insurance products, make payments, transfers or receive remittances (Demirgüç-Kunt et al., 2018). Financial inclusion ensures not only access to financial services but also promotion of economic growth and development of a culture of saving especially in rural areas (Dube et al., 2014). However, the financial market in sub-Saharan African (SSA) countries have generally been described as underdeveloped, risk averse, highly concentrated in urban areas, and skewed against the poor (Allen et al., 2016; Aterido, et al., 2013; Kuada, 2016). The imperfections of the financial market impede poor people who generally lack collateral and credit history to access financial services (Banerjee & Newman, 1993; Aghion & Bolton, 1997). Poor people need financial capital in order to move out of the poverty trap (Li et al., 2020; Mader and Sabrow, 2019; Bongomin et al., 2018; Demirguc-kunt et al., 2017; Oumar et al., 2017; Barret et al, 2016). Being in the poverty trap is bad to an individual, a family, a

community and even a nation. It implies the existence of a vicious circle where poverty and underdevelopment grow worse over generations (Todaro & Smith, 2012).

The dominant poverty trap models in the literature revolve around multiple dynamic equilibrium which arise from multiple financial market failures[1] (MFMF) that makes the poor to choose behaviors that reinforce their initial poverty status (Barrett et al., 2016). The existence of Multiple Financial Market failure (MFMF) should not be controversial as it is well established that market failures regularly impact the lives of the poor and more specifically that a lack of financial products including saving, remittance, insurance and credit perpetuates poverty by trapping poor households in low risk and low yield activities (Dercon and Christianse, 2011). If poor households are excluded from the credit market or if they lack socially mediated access to capital, then discrete jumps enabled by strategic borrowing may not be possible (Carter and Barret, 2006).

In the face of exclusion from financial market, a poor household's only option would be to move forward slowly with an autarkic saving strategy by reducing consumption or extra spending (withdrawing children from school, no hospital, etc.). If the poor household opts not to undertake extraordinary savings, it then settles into a poverty trap. Beyond the poverty trap, there exists a threshold at which wealth dynamics bifurcate which might induce the market imperfection especially the financial market that is a condition for risk to lead to persistent poverty[2] (Barrett et al., 2016). Furthermore, Lybbert et al. (2004) together with Stiglitz and Weiss (1981) state that the persistence of the poverty is due to information asymmetric problems. Stiglitz and Weiss (1981) show that the price of credit may affect the nature of the transaction, and may therefore not clear the market. The result is derived from an adverse selection effect and an incentive effect. Indeed, adverse selection and moral hazard induce the financial system to ration credit while the process of poverty alleviation requires financial institutions to provide financial services to poor people in order to smooth their consumption and cope with other needs (Toindepi, 2016; Lybbert et al., 2004).

To cope with financial market failure, there is a need to implement innovative financial tools to improve access to formal financial services (World Bank, 2020; Ozili, 2018; King and

[1] **Financial market failures** refers to situations where financial markets fail to operate efficiently; causing lost economic output and reductions in the value of national wealth.

[2] The persistent poverty results from the chronic poverty that households face in presence of information asymmetric problems.

Levine, 1993; Silber, 1983). For instance, in China, non-bank structures are now operating within the financial sector (Ghose, 2016). Such a penetration is informed by the fact that formal banking sector is less developed in the developing countries. In those countries, less than a third of adults have a bank account and even those who own one do not necessarily use it (Demirguc-kunt et al., 2013). The limited use of financial services is due to the distance that people have to travel to access a financial institution, the lack of financial services that meet their needs, and the lack of identity document(s) to create an account (Bakhshi, 2016). To overcome these barriers, non-bank institutions including mobile Network operators (MNO) take the advantage of mobile financial innovation to digitally provide financial services to the unbanked and underserved individuals.

Literature has shown how the digital revolution has contributed significantly to social advances, such as expanding financial inclusion of unbanked customers in developing countries (Gabor and Brooks, 2017, Chatterjee, 2020; Wellalage et al., 2020; Ozili, 2020, 2018). The digitalization of finance is defined as the use of digital technologies in order to create new business models and to provide new revenue and value-producing opportunities (Wellalage et al., 2020; Ozili, 2018; Gomber et al., 2017). It is the process of moving into a digital business and the integration of digital technologies into everyday life (UN-DFTF, 2019). From a practitioner's viewpoint, digital financial inclusion is a digital access to, and the use of, formal financial services by the excluded and underserved population. It is a financial service delivered through mobile phones, personal computers, the internet or cards linked to a reliable digital payment system (Manyika et al., 2016; Ozili, 2018). It entails a bunch of new financial products, financial businesses, finance-related software, and novel forms of customer communication and interaction delivered by Fintech companies and innovative financial service providers (GSMA, 2014; CGAP, 2015; Gomber et al., 2017).

Digital finance, combined with the change in consumers' behavior has attracted many players into the financial industry who use different financial technology-driven innovations to deliver financial services without leaving anyone behind. For Chatterjee (2020) the digital technologies, which hinge on strong telecommunications infrastructure can contribute to economic growth by improving productivity, reducing transaction costs, promoting innovation and development, and also by developing the financial sector. They have been considered essential in providing access to markets, decreasing transaction costs, and increasing income for a significant proportion of people living in developing countries (Mora-Rivera & García-

Mora, 2020; Banerjee and Duflo, 2020; Mushtaq & Bruneau, 2019; Sayer, 2018; Lybbert & Wydick, 2018; Galperin and Viecens, 2017).

These technologies include mobile technologies, Blockchain or Distributed Ledger Technology, cryptocurrencies, the Internet of Things, Cloud computing, artificial intelligence and biometric technology (OEDC, 2018). Blockchain technology for example, has the potential to speed up and reduce the cost of transactions, give individuals more control over their personal data, reduce or remove the need for costly intermediaries (Makhdoom et al., 2018; International Telecommunication Union [ITU, 2017]). It is rapidly developing in emerging countries because of its dependency on cutting edge technology. Similarly, mobile payment platforms appear to be a promise for a greater financial inclusion in the middle and less developed countries where poor people are present in vast majority (OEDC, 2018). Digital technology is crucial for providing financial access due to the fact that most financially excluded people hold at least one mobile phone as an asset and that the provision of financial services through this technology could accelerate the financial inclusion of the poor (World Bank, 2014).

The digitalization is changing the global economy, and indeed many aspects of peoples' lives. It is changing the fundamentals of finance, from the basics of digitization in delivering cheaper and faster data to inform financing decisions, to supporting greater access to financial services and enabling citizens to be more centrally involved in every aspect of finance, to the reinvention of the meaning and role of money itself, and the ways in which our global financial system is governed (Chu, 2018; Ozili, 2018; Chen et al., 2020**).** As we move into the digital economy, financial technology has started to take up some roles traditionally played by large financial institutions. In some cases, digital technology can reduce transaction costs, expand transaction scope, and empower peer-to-peer transactions, spurring a new wave of innovation in FinTech (Chen et al., 2020). Ozili (2018) shows that digital finance impacts financial inclusion through the access of vulnerable communities to financial services as well as through the profitability of banks due to the benefit reaping from the non-installation of new branches. Similarly, Chu (2018) finds mobile technology to be a springboard for digital financial inclusion.

Access to financial services through digital technologies appears to be key in reducing poverty and improving well-being. This is confirmed by a number of recent studies **(**Li et al., 2019; Mader and Sabrow, 2019; Bongomin et al., 2018; Demirguc-kunt et al., 2017; Oumar et al., 2017; Barret et al, 2016) as well as reports by international organizations (CGD, 2016; WB,

2014; UN, 2006) which state that provision of financial services at low-cost boosts economic growth and lifts the poor from poverty. Indeed, the digital financial inclusion allows the poor to improve their productivity, to smooth their consumption, to create employment and develop small business. Digital finance can drive greater expansion of financial services to non-financial sectors, and the expansion of basic services to individuals since most of the disadvantaged people own a mobile phone (World Bank, 2014, 2020). It also helps them face their children's need as far as health and education spending are concerned (Ozili, 2018). With access to affordable and secure digital financial services, there will be a shift from cash-based and informal transaction to a formal digital financial transaction platform. Taking it differently, digital financial inclusion improves the welfare of individuals and businesses that have a reliable digital platform with which to access funds in their bank accounts to carry out financial transactions (CGAP, 2015).

The expected benefits of the digital financial inclusion can be fully realized if the cost of obtaining a digital transactional platform including mobile phones, personal computers and related devices by poor individuals is negligible or low. Increased digital financial services channeled to rural and poor communities can improve access to finance for bank customers in rural and poor communities who cannot conveniently access banks located in the formal sector due to poor transportation networks and long queuing hours in banking halls, and will reduce bank customers' presence in bank branches and reduce cost because bank would cost-efficiently maintain fewer branches, and the lower costs would have positive effects for bank profitability and financial inclusion in rural and poor communities.

In addition, easy-to-use digital finance can provide a more convenient platform for individuals to carry out basic financial transactions such as paying for electricity and water bills, and transferring money to family and friends etc. If digital finance platforms are easy-to-use, users of digital financial services can help inform and persuade their peers in the formal and informal sector to take advantage of digital financial services, leading to greater number of individuals using digital finance thereby leading to greater financial inclusion and poverty reduction. Greater digital finance can also lead to greater financial inclusion if users are able to persuade their peers including those in informal sector to effectively adopt digital finance for their daily transaction (Ozili, 2018). In addition, inclusive digital financial services mean that poor people can store and increase savings, cope with unexpected economic shocks, access social benefits more cheaply, and make investments in economic opportunities that can lead them out of poverty (UN, 2016).

Besides its effect on individuals, digital finance contributes to increasing the performance of the financial sector. This is evidenced by Scott et al. (2017) who found in examining the impact on bank performance of the adoption of SWIFT, that this innovation had a large effect on profitability and a significant network effect on performance. Moreover, digital finance contributes to boosting national aggregate since the access to a diversified financial product will surely increase expenditure and thereby the gross domestic product (Ozili, 2018). In light of this background, it is very important to focus on the issue of digital financial inclusion as a solution to the multiple financial market failures that leads to severe poverty in developing countries. Yet, very few studies are devoted to the digital financial inclusion and poverty nexus in developing countries. The existing empirical studies have most of the time focused on the direct and the indirect effect of financial inclusion on poverty alleviation through economic growth. This is obviously due to the lack of household panel data that could help analyze the poverty and financial inclusion nexus.

1.2. Problem statement and Research Questions

More than 1.7 billion of adults worldwide do not have a formal bank account and about 80% of poor people are excluded from the formal financial system. Women are overrepresented among the world's unbanked. About 980 million of them do not have an account, accounting for 56% of all unbanked adults globally (Demirguc-Kunt et al**,** 2017). Similarly, the financial exclusion rate as well as the poverty rate is the highest in developing countries (UNCDF, 2015). Those without an account, men as well as women, tend to be concentrated among poorest households. Globally, about a quarter of unbanked adults live in the poorest 20 percent of households within their economy, about twice the share living in the richest 20 percent in Africa. In that context, most of the sub-Saharan countries expressed the need to improve their financial system through saving mobilization and investment in productive sectors (Beck and Hesse, 2006; Were and Wambua, 2013).

The World Bank (2018) notes that, while financial inclusion is generally on the rise, the gains have been uneven across countries. Globally, only around 3.8 billion people (or 69% of the global adult population) owned bank accounts in 2018 (World Bank, 2018). Smartphone ownership has also generally increased, but again, growth of mobile technology both within and across countries has been uneven, with developing countries having the largest inequality (Silver and Johnson, 2018; World Bank, 2018). Moreover, around 1.8 billion people (or 31% of the global adult population) do not have any form of financial identity, and this is often

amplified by the lack of access to the internet and electricity, crucial indicators for social and financial inclusion and well-being, especially in Africa and Asia (Cozzi et al., 2018; World Bank, 2018).

It is then worth noting that financial development through the extension of financial services has benefited to the relatively less poor because of the requirement of collateral prior to the credit (Beck et al., 2009). This situation is often called financial market failure or imperfection. Nowadays, it constitutes a big challenge for policymakers in developing countries. In fact, the United Nations expects digital financial inclusion to become a priority since it enables countries to achieve the Sustainable Development Goals of 2030, and Fintech is anticipated to extend the financial market reach, notably to those that are excluded and underserved (Mogaji, 2019). For the World Bank (2020), financial inclusion is a building block of both poverty reduction and opportunities for economic growth, with access to digital financial services as critical for joining the new digital economy. As we move into the digital economy, financial technology has started to take up some roles traditionally played by large financial institutions. In some cases, digital technology can reduce transaction costs, expand transaction scope, and empower peer-to-peer transactions, spurring a new wave of innovation in FinTech (Chen et al., 2019).

In the WAEMU countries, the challenge is the same and needs appropriate measures. These WAEMU countries had witnessed for a couple of decades an upward trend of their gross domestic product but had unfortunately registered during the same period, the highest rate of poverty (on average 47%) compared to their peers developing countries. This situation may probably be caused by the high inequality of resources and opportunities (Todaro and Smith, 2012; BCEAO[3], 2015). As a matter of fact, the central bank of this region has recently targeted some policy measures in order to overcome the chronic and persistent poverty in the WAEMU countries. For the sake of illustration, since 2010, the loan interest rates have dropped from 8.4 % to 6.9 % in nominal terms and from 7 % to 6 % in real terms. Likewise, the deposit interest rate has increased from 5 % to 5.4 % in nominal terms and from 3.77 % to 4.4 % in real terms (BCEAO, 2015). However, the proportion of financially excluded people is still high in those countries. Moreover, recent studies have shown that the financial inclusion rate in the WAEMU countries is among the lowest in Africa (GSMA, 2015; UNCDF, 2015) as only 34.5% of WAEMU adults possess an account in a formal banking sector**.** This low financial inclusion is

[3] **BCEAO** : **B**anque **C**entrale des **E**tats de l'**A**frique de l'**O**uest, is the Central bank of WAEMU States.

due to the lack of financial education, geographical coverage of banking infrastructures as well as issues related to identification (GSMA, 2016).

However, the growth of ICTs with the usage of 3G and 4G Internet connectivity is impressive in those countries. For example, the mobile penetration rate in Benin was 83.81% in 2015 and 88% in 2016 compared to 67% in 2013 (UNCDF, 2016). In addition, from 130,000 in 2010 the numbers of Internet users were almost 2 million in 2014. As a result, the financial inclusion enabled by digital technology proves to be very important in the WAEMU countries. For that purpose, the central bank has aimed to financially include 75% adult population by 2020 and has been encouraging digital finance (BCEAO, 2015). Yet, the adoption of digital financial services is still low albeit the adoption of mobile phone in WAEMU is among the highest in the world (GSMA, 2016). This is because many countries in WAEMU including Benin, Togo, Niger and Guinea-Bissau are nascent digital financial markets with very low digital transaction (CGAP, 2016). Indeed, considering the low financial inclusion rate in WAEMU (17 % on average) and the high poverty rate (47% on average) (BCEAO, 2018), one can say that financial exclusion might be the major obstacle for the economic development and poverty alleviation in the WAEMU countries. As a matter of fact, tremendous policies should be implemented in order to get poor people lifted out of the chronic and persistent poverty in the WAEMU countries.

This thesis entails three essays. Through these essays, we answer this main research question: How can digital finance accelerate financial inclusion and alleviate poverty in WAEMU countries? More specifically, this dissertation answers the followings research questions: Was digital technology the missing piece for financial Inclusion in WAEMU? What are the macroeconomic and microeconomic factors driving adoption of digital finance in WAEMU? How does digital financial inclusion impact poverty in WAEMU?

1.3. Objective of the thesis

This thesis aims to investigate the mechanisms by which digital finance may improve financial inclusion and poverty alleviation in WAEMU. Specifically, it aims to:

i. Analyze the effect of digital technologies on financial Inclusion in WAEMU;
ii. Identify the bottlenecks for digital finance adoption in WAEMU;
iii. Analyze the effect of digital financial inclusion on poverty alleviation in WAEMU.

1.4. Main contribution of the thesis

This thesis contributes to the relevant literature on finance and poverty as follows. First, in addition to the usual determinants, it incorporates the joint use of mobile phone and internet as a relevant accelerating driver of financial inclusion. As such, it enriches the literature by combining ICT variables and macroeconomic variables in the analysis of the driving factors of financial inclusion in WAEMU. Second, to the best of our knowledge, this is the first study on the WAEMU countries that empirically combines microeconomic and macroeconomic factors in the analysis of digital finance adoption. Most existing studies separately focus on either the macroeconomics or the microeconomic determinants of innovation adoption (Soumaré et al, 2016; Evans, 2016). Third, there is still a controversy about how digital finance really affects poverty in developing countries. Some pieces of evidence have focused on the positive impact of digital finance on poverty in developing countries. Yet, most of these studies consider digital finance including mobile money as a key element of financial inclusion and thus assess the impact of financial inclusion either directly or indirectly on poverty. This thesis clearly shows that beyond digital data, digital financial inclusion has both a direct and indirect effect on poverty.

Beyond the theoretical and empirical contribution, this thesis has also the merit to have a methodological value added to the literature. To our knowledge very few studies have assessed the determinant as well as the effect of digital finance on poverty using rigorous econometric methods. In this study, we aim to fill these gaps in the literature by taking advantage of a rich dataset from the World Bank containing information on thousands of adult populations in the WAEMU region. We specifically employ the system generalized method of moments (GMM), a cluster analysis combined with a Logit and a conditional Logit regression and a recursive bivariate probit model as estimation strategies. These methods address the issues of endogeneity and selection bias emanating from observed and unobserved heterogeneity. The estimation with the GMM allows for efficient estimators, incorporates the memory effect, corrects the simultaneous bias between the variables of interest, and control and traces the dynamics of behaviors and their possible heterogeneity (Wooldridge, 2001). The cluster analysis allows to consider the structural determinants of the adoption of digital finance in WAEMU. Last but not the least, the recursive bivariate probit allows to consider the dual causality between digital financial inclusion and poverty and to estimate the direct and indirect effect of digital financial inclusion on poverty in WAEMU.

1.5. Organization of the thesis

This dissertation is organized into three essays preceded by a general introduction and followed by a general conclusion. The general introduction presents the theoretical background and the problem of the study. The three essays present the substance of the empirical part of this thesis. Indeed, the first essay investigates the impact of digital technologies on financial inclusion in WAEMU. Using data from BCEAO (2017) and ITU (2017) over the period 2006-2017, we estimated first a random effect model and thereafter a system GMM devised by Arrelano-Bover/ Bundell-Bond. Findings show that beyond the specific effects of mobile phone penetration and Internet usage, the joint use of these two technologies is very key to financial inclusion in the WAEMU countries. In the second essay, we investigated the bottlenecks for digital finance adoption using both country and individual level data respectively from the World Development indicators (2017) and the World Bank Global Findex (2017) database. We first made a cluster analysis and then a logistic regression to investigate respectively the macroeconomic and microeconomic driving factors of mobile money adoption. We found that illiteracy, underemployment as well as the lack of mobile infrastructure are the main bottlenecks for digital finance adoption.

In examining the microeconomic factors affecting the adoption of mobile money in the WAEMU countries, we found in line with existing evidences that being old, female, uneducated, relatively poor and even unbanked decreases the likelihood of adopting digital finance in WAEMU**.** The third essay presents the impact of the digital financial Inclusion on poverty alleviation in WAEMU. Using the World Bank's Findex (2017) database, we estimated the probability of lifting out of poverty in WAEMU with a recursive bivariate probit model that addresses the endogeneity issues raised from the probit model. Findings show that both mobile led financial inclusion and bank led financial inclusion are essential for sustainable poverty alleviation in WAEMU. In addition, the change in poverty status can be indirectly due to certain key-driven factors of mobile money adoption including the ownership of mobile phones and education achievements which are conducive to digital financial inclusion. We wind up the thesis with a general conclusion.

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ESSAY I

Financial Inclusion in WAEMU: Was digital technology the missing piece?[4]

Abstract

Like most International Institutions, the Central Bank of West African States (BCEAO) considers universal access to finance vital to empowering disadvantaged people. In this regard, this essay assesses the accelerating role of digital technologies using mobile phone penetration and internet usage as broad indicators, on the dynamics of financial inclusion in WAEMU. Using data from BCEAO and ITU databases over the period 2006-2017, we estimated first a random effect model and thereafter a system GMM to address the endogeneity issue arising from the static model. Findings show that beyond the specific effects of mobile phone penetration and Internet usage, the joint use of these two technologies is very key to financial inclusion in the WAEMU countries. We thus urge policy makers to take steps towards enhancing the availability, accessibility, affordability of digital financial services and to design flexible legislation pertaining to mobile financial services providers in order to accelerate financial inclusion in WAEMU.

JEL Code: C01, G29, O10, O30

Résumé

A l'instar des institutions internationales, la Banque centrale des Etats de l'Afrique de l'Ouest (BCEAO) a fait de l'inclusion financière son cheval de bataille pour sortir les pauvres de leur précarité. Cet essai vise à cet effet à évaluer le rôle accélérateur de la technologie digitale dans la dynamique de l'inclusion financière dans l'UEMOA. A l'aide des données secondaires de la BCEAO et de l'ITU portant sur les pays de l'UEMOA couvrant la période 2006-2017 nous avons estimé premièrement un modèle à effet aléatoire et par la suite un modèle dynamique avec le système GMM pour corriger l'endogénéité dont souffre le modèle statique. Les résultats de nos estimations montrent qu'au-delà des effets mitigés de la technologie mobile et de l'internet, l'usage simultané de ces deux technologies est très capital à l'inclusion financière dans les pays de l'UEMOA. Il urge alors des politiques en faveur de la disponibilité, de l'accessibilité et de la législation de ces technologies pour une meilleure inclusion financière digitale.

Mots clés : Inclusion financière, Technologie Digitale, GMM, UEMOA

Code JEL: C01, G29, O10, O3

[4] This essay is a joint work with Wautabouna OUATTARA and Denis ACCLASSATO HOUENSOU. A slightly different version of this essay is published in Cogent Economics & Finance

2.1. Introduction

Financial development including financial inclusion, is widely discussed in literature as being crucial for economic development (Schumpeter, 1911; Silber, 1983; Levine, 2005; Beck et al., 2018). The theoretical debates concur on the fact that a developed financial system enables access to broad finance through efficient capital allocation and proposes efficient investment choice. Indeed, financial inclusion is increasingly becoming part of the top priority agenda of most of international organizations. For instance, the United Nations (UN) has made financial inclusion a priority issue for economic development by 2020 (UN, 2006). The World Bank too has made universal access to finance a central pillar of the global fight against poverty (World Bank, 2016).

For the G20, policies that promote the expansion of banking services can be a major tool for financial inclusion by facilitating access to deposit, credit and payment services (Busch, 2017). Similarly, the 2017's Financial Inclusion Action Plan (FIAP) reaffirmed the G20's commitment to advancing financial inclusion for the benefit of all disadvantaged people (GPFI, 2017). In the same vein, the Central Bank of West African States has set a target of 75% of adults to be financially included by 2020 (BCEAO, 2015). To this end, several reforms have been implemented to boost financial inclusion in that region. These reforms consisted of providing infrastructure conducive for banking activities, supporting the activities of microfinance institutions and developing digital finance including electronic money (BCEAO, 2017).

Digital finance, also known as fintech, has great potential to broaden access to financial services by lowering costs, reducing information asymmetries and enabling more transparency (Gabor & Brooks, 2017; Zhonga & Jiang, 2020). Today, the relevance of digital finance and the issue of exclusion from traditional finance are attracting the attention of policymakers and academics (Bachas et al., 2018; Ozili, 2018). The development of ICT triggered what is now referred to as the fourth industrial revolution. This fourth industrial revolution poses enormous changes in all aspects, particularly in the financial systems with financial inclusion becoming a central component of development policy around the globe. A focal highlight illuminates the crucial role of inclusive financial systems in reducing extreme poverty and fostering sustainable growth and development in countries (Oumar, et al., 2017). Information and communication technologies (ICT), which hinge on strong telecommunications infrastructure, can contribute to

economic growth by improving productivity, reducing transaction costs, promoting innovation and development, and also by developing the financial sector (Chatterjee, 2020).

In addition, a number of empirical studies have highlighted the accelerating role of digital technologies in financial inclusion. Most empirical studies have evidenced the effect of digital technology on financial inclusion and the mechanism through which digital finance may alleviate financial exclusion (Morawczynski, 2009, Lapukeni, 2015; Fernández-Olit et al., 2020; Zhonga & Jiang, 2020; Wellalage et al., 2020). For example, Mushtaq and Bruneau (2019) find that ICT diffusion positively impacts financial inclusion. Similarly, Zhonga and Jiang (2020) show that digital finance including internet finance can weaken the exclusiveness of traditional finance and reduce the asymmetry in investment and borrowing exclusion levels in traditional financial markets. Wellalage et al. (2020) find that the average financial inclusion of entrepreneurs using digital technology in their business is approximately higher than their counterparts who do not use digital technology. In fact, according to Morawczynski (2009), the mobile finance increases savings and especially the financial empowerment of women. Similarly, Klein and Mayer (2011) argue that mobile banking services provide an electronic payment register to the financially excluded people who otherwise preferred cash transactions.

However, while about two billion people worldwide still lack access to formal financial services (Demirguc-Kunt et al., 2017), most of the financially excluded people hold a mobile phone as an asset (GSMA, 2017). Information and Communication Technologies (ICT) like smartphones and broadband internet are therefore very important for developing access to secure and affordable financial services such as payments, domestic and international transfers, insurance, credit and savings (Patwardhan et al, 2018; Arner, 2018). To this end, Jim Yong Kim, the 12th president of the World Bank had issued a call for action towards universal financial inclusion by 2020 (UFA2020) especially through the issuance of bank cards and mobile money. This ought to involve public and private stakeholder to provide technologies to last miles at an affordable price.

Digital financial inclusion can make a difference for underserved low-income households, as well as for small and medium enterprises (SMEs). Digital financial services can make life easier for clients by allowing them to make small transactions and better manage their expenditures and incomes. Financial services including payment, transfer, savings and credit provided by the digital transaction platform as well as data collected on the users of those services can enable providers to offer additional financial services tailored to the needs of their customers. Moreover, digital financial inclusion can also reduce the risk of loss, costs, theft or

other financial crimes pertaining to cash transactions (GSMA, 2017). According to the World Bank (2018), many people in the world do not have access to financial services irrespective of advances made in development. Largely, there is uneven access to financial services globally (Demirgüç-Kunt et al., 2018). Digital finance appears as a technological innovation that has emerged as a solution to inaccessibility of financial services (World Bank, 2018). It refers to the provision of financial services through technology such as mobile phones (Demirgüç-Kunt et al., 2018; Gai et al., 2018).

However, considering the WAEMU countries, characterized by low financial inclusion and high mobile telephony penetration through the extension of mobile phone network over rural areas (GSMA, 2018), digital finance appears to be the ultimate solution to financial and social exclusion. Specifically, mobile money is a powerful tool for integrating disadvantaged people into the formal financial sector (GSMA, 2015). Yet, according to BCEAO (2018), 21.9 million individuals in WAEMU had an electronic financial account in compared to 11 million in 2013. The number of bank accounts from 2.6 million in 2006 to around 7.8 million in 2014 while e-money rose dramatically from 366,000 in 2010 to 16 million in 2014. The number of electronic money service points improved from zero points of service in 2009 to 24,300 points of service in 2014 (BCEAO, 2016). Despite this positive trend in digital finance, financial inclusion in WAEMU compared to other regions remains very low to achieve the Sustainable Development Goals.

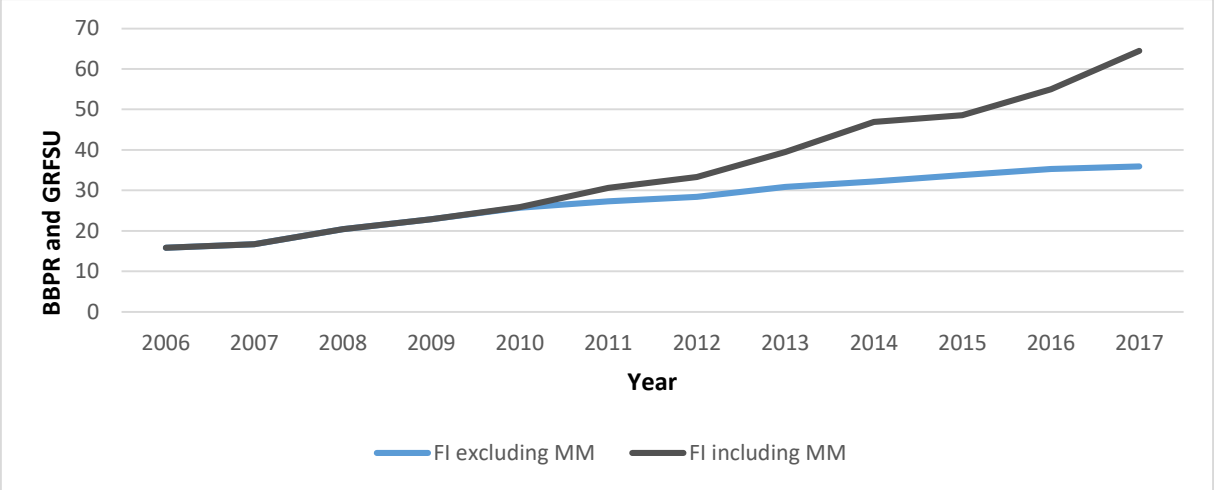
This essay assesses the impact of financial services enabled by digital technologies on financial inclusion in WAEMU. The main hypothesis of this essay is that digital technologies accelerate financial inclusion in WAEMU. It contributes to the few and emerging literature that examines the role of technological innovation in financial services (Beck & Frame, 2018; Fostel & Geanakoplos, 2016; Silber, 1983). Insights from the discussions in this paper can improve our understanding of the functions of digital finance providers and can also help regulators understand the relationship between Fintech, digital finance and financial inclusion. Findings of this essay show that the advent of digital technologies has contributed significantly to financial inclusion in WAEMU. In addition, the dynamics of financial inclusion differ across countries and the effect of mobile phones and Internet users on financial inclusion is perceived differently from one country to another. It stands out that the availability of the Internet on mobile phones promotes greater financial inclusion than the mobile phone per se. Therefore, beyond the traditional financial services provided by digital technologies including payment,

savings, credit, mobile technologies are well designed to offer last generations' financial services.

The rest of this essay is organized as follows. Section 2.2 presents the state of financial inclusion in the WAEMU countries. Section 2.3 summarizes the related literature while the methodology and data are presented in the section 2.4. We conclude this study with a concluding remark and some policy recommendation in the section 2.5.

2.2. State of Financial Inclusion in WAEMU

The financial ecosystem of WAEMU is characterized by a diversity of stakeholder including among others banks, microfinance institutions (MFIs) and Mobile Network Operators (MNOs). Like bank and microfinance institutions, mobile network operators are increasingly entering the financial market to reap the benefit of their infrastructure potential to offer financial services. This helps fill the financial services gap left by financial institutions. In fact, the banking sector has been developing these last decades with about 144 financial institutions including 126 banks and 18 credit institutions in WAEMU. In addition, nearly 600 microfinance institutions and 38 mobile phone enabled financial services have been created (BCEAO, 2018). WAEMU also has postal financial services and rapid transfers' institutions. Figure 2.1 displays the dynamics of financial inclusion in terms of Broad Banking Penetration Rate (BBPR) and Global Rate of Financial Services Utilization (GRFSU) in WAEMU.



Note: GRFSU: *Global Rate of Financial Services Utilization****; BBPR:*** *Broad Banking Penetration Rate*

Figure 2.1: *Financial Inclusion Dynamics in WAEMU*

Source: *Author, 2019*

Broad Banking Penetration Rate (BBPR) in Figure 2.1 measures the percentage of adults that have accounts in banks, postal services, National Savings Fund, national treasure as well as at microfinance Institutions. However, the advent of mobile money in 2008 in most of the WEAMU countries has changed the magnitude of the financial inclusion. The Financial Inclusion appears then as an extension of the Broad Banking Penetration Rate to the percentage of the adult population holding an electronic account especially mobile banking and mobile money account. From 15.8% in 2006, the broad Banking Penetration Rate increased to 35.9% in 2017 whilst the Global Rate of Financial Services Utilization (GRFSU) increased to 64.5% over the same period. This implies that mobile financial services filled a gap of 28.6%. Thus, the advent of electronic money and especially mobile banking and mobile money in WAEMU has contributed significantly to the expansion of financial services to last miles.

According to the 2018 report of the Central Bank of the WAEMU's States, in 2017, Benin was the best performing country in WAEMU as far as Broad banking penetration (BBPR) and the Global Rate of Financial Services Utilization (GRFSU) are concerned. With 27.2% for BBPR and 82,1% for GRFSU rate in 2017, Benin was followed by Togo with 24.3% and 79.6%, Burkina Faso with 22.2% and 68.8%, Senegal with 19.6% and 64.1%, Ivory Coast with 16.6% and 60.7%. These statistics are very striking because of the reverse trend witnessed by the usual leading countries such as Ivory Coast and Senegal. However, experts argued that there are a number of strategies designed and implemented by the government of Benin in terms of expanding financial access to disadvantaged people (BCEAO, 2017). They also argued that Benin had the higher ratio of point of services (POS) in WAEMU. With 371 POS for 1000 Km squares, it was followed by Togo and Senegal with respectively 265 and 206 POS for 1000 Km squares. Niger lagged behind with nearly 17 POS for 1000 Km squares (BCEAO, 2017).

However, taking into account the socio economics characteristics, the above trend changes considerably. The disparity between countries may reveal the specificities of legal, sociological, cultural or religious norms or may even result from income or education gap between these countries. Indeed, out of 50,494,200 electronic money accounts, Côte d'Ivoire alone accounts for 37.92%, followed by Burkina Faso, Mali, Benin and Senegal, which each detains more than 13% of electronic money subscribers in WAEMU. However, Bissau Guinea has the lowest rate in WAEMU with less than 0.74% of electronic money account holders (Figure2).

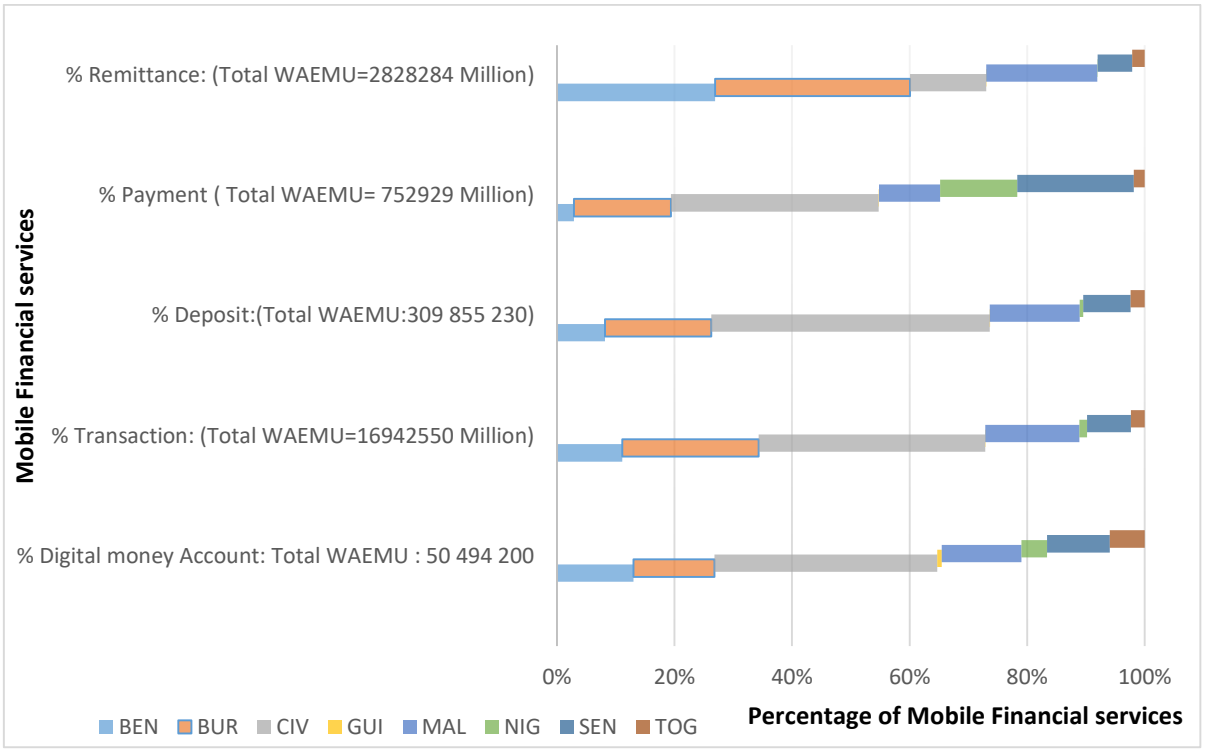


***Figure 2.2**: Mobile Financial Services in WAEMU*

Source: Author, 2019

In addition, beyond the adoption of banking and electronic financial services, the financial inclusion can also be measured through the utilization of financial services (Figure2.2). Thus, the simple increase in the banking penetration of adults' populations leads to an effective inclusion if and only if the financial account holders use them for savings, payment, and transfer as well as for credit purposes. From the Figure 2.2, it appears that the total amount of mobile financial transaction operated in WAEMU in 2017 was about 16,942,550 million FCFA in value. Nearly 38.56% of that transaction was operated in Côte d'Ivoire followed by Burkina Faso with over 23.21% and then Mali, Benin, Senegal with 16.01%, 11.09%, and 7.44%, respectively. However, Bissau Guinea and Togo have poorly performed with less than 3% of the total mobile financial transactions. This disparity has changed slightly in terms of payment where Côte d'Ivoire is still the leading country in that region with more than 35.35% of digital payments, followed by Senegal with nearly 19.87%. On the contrary, Côte d'Ivoire is relegated to the fourth place behind Burkina Faso with 33.14%, Benin with 26.93%, and Mali with 18.87% as far as domestic transfers are concerned. It stood out a positive correlation between transfer and the rate of poverty which indicates the issue of social security network enabled by domestic transfers in those countries.

2.3. Literature review

Prior to discussing the theoretical and empirical literature on the financial inclusion and technology nexus, we present a summary note on the concept and the challenge of financial inclusion in this section.

2.3.1. Financial Inclusion: Concept and Challenges

Financial inclusion can be defined as an access to and use of appropriate, accessible and affordable financial services (Klapper and Singer 2014). Although it is the most accepted definition, there are many other definitions of the financial inclusion. For the Global Partnership for Financial Inclusion, it refers to a state in which all working age adults have effective access to credit, savings, payments, and insurance from formal service providers. "Effective access" involves convenient and responsible service delivery, at a cost affordable to the customer and sustainable for the provider, with the result that financially excluded customers use formal financial services rather than existing informal options (GPFI, 2017). Financial services are delivered by a range of providers, most of them private, and reach everyone who can use them, including disabled, poor, rural, and other excluded populations. According to Dube et al (2014), financial inclusion ensured not only access to financial services but also promotes economic growth and the culture of savings in rural areas. A large body of research has evidenced the positive impact of financial inclusion on development through the accessibility, security and affordability of financial services.

For Park and Mercado (2015), financial inclusion appears as a critical element that induces inclusive growth since access to finance allows the economic agent to make long-term consumption and investment decisions, participate in productive activities and deal with shocks. Similarly, Patwardhan et al. (2018) show that financial inclusion is not an end per se but rather a means to an end. However, the conventional financing system that is expected to play this role has a number of limitations that lead to an inadequate delivering of financial services to the disadvantaged populations (Sapovadia, 2018). One of these limitations is the lack of infrastructure to provide banking services (Gas, 2017). Indeed, following the initiatives of Muhammad Yunus' Grameen Bank in the 1970s, a range of solutions were found to advance financial inclusion in the 1980s (Nhavira, 2015). They consisted in multiplying the installations of Automatic Tellers Machines (ATM) in rural areas. Similarly, Brown et al. (2016) argued that the proximity of bank branches to populations is very critical for financial inclusion.

However, the implementation of this banking infrastructure had proved to be very costly for Banks, given the small size of their clientele and the large costs of investing in banking infrastructure (David-West, 2016). For illustrative purposes, the Reserve Bank of India considered that, it is impossible to have Automatic Tellers Machines (ATM) in all villages because of the high-cost pertaining to these infrastructures. Moreover, physical transactions with financial institutions are often subject to manipulation, error and omission (Sapovadia, 2018). However, Dupas et al. (2016) empirically tested the effect of expanding access to the basic bank account in Uganda, Malawi and Chile. They show that as the number of deposits increased, there was no clear effect on the increase or the decrease in savings and income. Even better, Karlan et al. (2016) emphasized on the challenges of financial market imperfections and deviations for a broad access to finance. All these authors are unanimous on the importance of digital technology for an effective financial inclusion.

2.3.2. Digital Technology and Financial Inclusion

Financial market imperfections impede poor people who lack collateral and credit history to access financial services (Banerjee and Newman, 1993; Aghion and Bolton, 1997). Theoretical literature has fundamentally emphasized the importance of financial development for an economy (Schumpeter, 1911; Levine, 2005). These precursors argue that a developed financial system enables access to broad finance through efficient capital allocation and proposes efficient investment choice. Schumpeter (1911) in his theory of economic development showed the importance of innovation and credit for economic agents. For Levine (2005) a broad financial development induces economic growth. Thus, financial intermediation provides information on investment opportunities, directs savings towards investments and manages the risk associated with those investments.

The theory relating digital technology and financial inclusion is very nascent and begins with the fact that most financially excluded people hold at least one mobile phone as an asset and that the provision of financial services through this technology could accelerate the financial inclusion of the poor (World Bank, 2014). Ozili (2018) shows that digital finance impacts financial inclusion through the access of vulnerable communities to financial services as well as through the profitability of banks due to the benefit reaping from the non-installation of new branches. Similarly, Chu (2018) finds mobile technology to be a springboard for digital financial inclusion. Indeed, he shows that key-driven factors of the proliferation of mobile technology such as the accessibility, availability and affordability of an open financial

ecosystem are also the driven factors of a strong and sustainable digital financial inclusion (Chu, 2018).

Mobile technology is perceived as a better alternative to address the imperfections of the formal finance (Alexandre and Eisenhart, 2013). For example, the Global Partnership for Financial Inclusion emphasized on the development and the rapid penetration of digital innovations in finance to accelerate the delivering of financial services. Similarly, by investigating the impact of remittances on financial inclusion in El Salvador on 937 households using instrumental variable technology, Anzoategui et al. (2014) find a positive impact of remittances on financial inclusion in terms of increased household deposits, but unfortunately non-significant and robust effect on credits. For these authors, strong financial inclusion through digital technology can reduce the costs of sending and receiving transfers, which could further motivate migrants to send and households to receive remittances. Ravi and Gakhar (2015) in the same vein, show that the comparative advantage in terms of infrastructure and customers' network allows digital technologies to accelerate access to financial services.

Access to credit via digital technologies is a promise for financial inclusion. Thus, using the mobile phone to make credit can help predict credit payments by households and avoid defaults. Sinha and Highet (2017) argue that mobile technology in developing countries is conducive to an effective penetration of the financing system to the underserved populations. For example, prior to the introduction of MPESA in Kenya, only 26.4% of adults had access to formal financial services in 2006. This rate increased to 66.7% in 2013 (Muthiora, 2015). However, beyond the adoption of a digital technology, a complete digital inclusion of an economy requires the extension of telecommunications services to the poor in rural areas, which is very important to provide a platform of digital communication between clients and mobile money agents in rural areas.

The digital inclusion urges the provision of a system of payment on the basis of this established telecommunication services controlled by regulation to clarify the requirements regarding the "know your client" and the legal status of mobile money agents (Arner, 2018). And finally, access for the poor to all their financial and non-financial needs online (Koh et al., 2018). The authors also argue that the positive effects of digital finance on well-being are perceived through access to, savings accounts, social and institutional inclusion, and access to a diverse and improved range of financial services such as payments, savings and micro credits.

However, given the rapid development of mobile technology in developing countries, many studies have highlighted the accelerating role of mobile technology in financial inclusion and inclusive development in Africa (Fernández-Olit et al., 2020; Zhonga & Jiang, 2020Cull et al., 2018; Lapukeni, 2015; Beck et al., 2014; Andrianaivo and Kpodar, 2012). For example, Andrianaivo and Kpodar (2012), investigated the impact of mobile phone on economics growth on 44 African countries from 1988 to 2007. They found, using a GMM system that the rapid expansion of mobile phones positively and significantly impacts economic growth through financial inclusion. Similarly, Beck et al. (2014) in a study on the financial behavior of Kenyan households found that holding a mobile phone improves the likelihood of accessing financial services in Kenya. Moreover, the Mobile Money Global Event organized by the GSMA in Tanzania in 2017 confirms these results and shows that the progress of the adoption and effective use of mobile money in recent decades is a promise for the decades ahead (GSMA, 2017).

Digital technology is all the more important as it accelerates international transfer operations as far as cost and delivering time are concerned. To this end, a study by the World Bank in 2016 showed that the traditional transfer system charges nearly 10% as transfer fees for a minimum delivering time of one day while the Bit Pesa in East Africa and the Rebit in the Philippine charge less than 3% as transfer fee for an immediate delivering (WB, 2016). For example, the sender in UK buys and sends some bit coins which are immediately transformed in Kenyan Shilling at reception in Kenya by the recipient (Sapovadia, 2018). Similarly, Alampay et al. (2017) in a systematic review of 2,758 empirical studies on the impact of mobile financial services in middle and low-income countries find that mobile financial services users receive higher amount of transfer than non-users. Moreover, they find that mobile money induces an increase in savings. In the same vein, Jack and Suri (2014) show that people are increasingly using MPESA to save. They also note that transfers via MPESA are fast, instantaneous and cheaper.

Besides, during an idiosyncratic shock or an unfortunate event, individuals benefit some transfers from their relatives through mobile money (Jack and Suri, 2014). Mobile money not only reduces transaction costs and promotes financial inclusion but also increases individuals' savings, particularly for health emergencies (Ky, Rugeminttwari, & Sauviat, 2018) and agricultural investment in fertilizer (Batista & Vicente, 2020), and even reduces poverty with a more pronounced outcome for female-headed households (N'dri & Kakinaka, 2020; Suri & Jack, 2016). Mobile money has also reduced informal savings practices which consisted to save

monies under mattresses or participate to tontine systems, resulting in an increased demand for banking services (Osafo et al., 2018; Jack and Suri, 2014).

In investigating the impact of mobile money on household transfer in Uganda, Munyegera and Matsumoto (2014) find, that MPESA users and in particular individuals working in cities and having relatives in villages make more transfers than non-users of MPESA. Similarly, Ghosh (2012) shows that people in Uganda use their electronic wallet to save money. In Bangladesh, a guide prepared by Sinha and Highet (2017) on the financial inclusion of women through digital technologies shows that the use of these technologies has increased transfer amounts, women's savings and even access to credit; which creates many opportunities for the empowerment of these women. In addition, online payments are becoming increasingly important. This is in line with the 2015's World Bank report entitled "Innovative Digital Payment Mechanisms Supporting Financial Inclusion", which shows that mobile money is not only a transfer tool but also induces saving, access to microcredit and increased international transfers (Gas, 2017).

2.4. Methodology

2.4.1. Estimation strategy

This study aimed at assessing the impact of digital technologies on the dynamics of financial inclusion in WAEMU. The study followed the theoretical approach devised by Andrianaivo and Kpodar (2012) who investigated the relationship between financial inclusion and mobile phone using an econometric model presented as follows:

$$FI_{it} = \alpha_0 + \alpha_1 ICT_{it} + X'\beta + \varepsilon_{it} \qquad \textbf{2. 1}$$

Where FI_{it} denotes the log of financial inclusion, ICT_{it} denotes the log of *ICT* indicators including mobile phone and internet subscribers, X is a matrix of other control variables such as broad money M2, GDP per capita, population, inflation rate and ε_t denotes a one way random error term.

The estimation strategy used in this study passed through two main steps. We first estimated a fixed or random effect model and then the Hausman test (1979). However, the very short time dimension of our study already suggests the relevance of the random effect model (Andrianaivo and Kpodar, 2012). In addition, the random effect model imposes the strict exogeneity of independent variables meaning that they must be uncorrelated with both country

and time specific effects. Otherwise, the random effect model becomes biased and inconsistent (Baltagi, 2008). Moreover, we conducted the Breusch-Pagan Lagrange multiplier (LM) test that helps us decide between a random effects regression and a simple OLS regression. The null hypothesis in the LM test is that variances across entities is zero. This is, no significant difference across units (i.e. no panel effect) (Baltagi, 2008). We estimated this static model just to assess the effect of the implementation of digital finance on financial inclusion in WAEMU.

The second steps of the estimation strategy and the most important was considering the dynamics in the analysis of the relationship between financial inclusion and digital technologies in WAEMU. To this end, a dynamic panel model was estimated. According to Baltagi (2008), most macroeconomic relationships are dynamic in nature and one of the advantages of panel data modeling is to allow the researcher to fully understand the dynamics of adjustments. The interest of introducing dynamics in this analysis is to, capture the dynamic effects of current and previous shocks in the model (Hsiao, 1986), control the unobserved and missing variables as well as allow the identification of country specific effects (Arellano-Bond, 1991). Therefore, the GMM system was estimated because the financial inclusion may depend on its previous values which are absent in the model and can create the problem of endogeneity.

In a simple way, a dynamic panel model can be presented as follows:

$$y_{i,t} = \delta y_{i,t-1} + \gamma x_{i,t} + \mu_{i,t} \qquad \textbf{2. 2}$$

Where δ and γ are scalars and $\mu_{i,t}$ is the individual effect. The empirical specification of the dynamic panel model can be written as follows:

$$FI_{it} = \alpha_0 + \alpha_1 FI_{i,t-1} + \alpha_2 DMM_{i,t} + \alpha_3 ICT_{i,t} + \sum_{j=4}^{p} \alpha_j x_{ijt} + \varepsilon_{i,t} \qquad \textbf{2. 3}$$

Where $FI_{i,t}$ denotes the financial inclusion and is measured by the Global Rate of Financial Services Utilization (GRFSU) and the Broad Banking Penetration Rate (BBPR). $FI_{i,t-1}$ denotes the first period lagged value of the financial inclusion. $DMM_{i,t}$ is a dummy variable that takes 1 from the year when the Money mobile for unbanked is implemented. ICT refers to the number of mobile phone holders and Internet users. x_{ijt} denotes other control variables including Broad money (M2), Inflation rate, population, GDP per capita, Net interest rate and Bank Branch. However, in including the lagged of the dependent variable in the model, the dynamic panel regression is characterized by two sources of temporal persistence: self-correlation due to the presence of the lagged dependent variable among regressors and

individual effects characterizing heterogeneity among individuals (Baltagi, 2008). The literature has identified a number of issues that could impede the robustness of the model. Several estimation techniques such as the Arellano & Bond (1991) GMM system, Arellano & Bover (1995) and Blundell & Bond (1998) are proposed to solve these problems.

This study used the Blundell and Bond (1998) approach rather than the Arellano & Bond (1991) one because the first approach is more appropriate when the number of panel periods is very short. In addition, the validity of the used instruments must be verified to ensure that the results are valid. According to Roodman (2009), the GMM system must be used with great care and several tests must be done to ensure the consistency of the results especially when the number of periods is small and the number of instruments is high. This is because many instruments would result in biased results (Roodman, 2009). We thus adopted the two stage GMM system of Windmeijer (2005) with robust option pertaining to our small sample sizes.

2.4.2. Data and descriptive statistics

The data used in this study was mainly drawn from the Central Bank of West African States (BCEAO, 2017) database and the International Telecommunication Union (ITU) database (2017). This study included eight (08) WAEMU countries over the periods 2006 to 2017. The choice of these countries was based on the sharing of a similar currency that is the CFA franc. This then concedes a very crucial homogeneity in the analysis of the effect that monetary and financial innovations can have on financial inclusion. Although very short, the time period of the study is justified by the availability of data over this period. We could have used the monthly or quarterly data to get a larger sample, but the unavailability of those data has bounded the sample to 12 years and 8 countries either 96 observations.

Table 2.1 displays the descriptive statistics. From that table, it stands out that on average the financial inclusion measured by the Global Rate of Financial Services Utilization (GRFSU) and the Broad Banking Penetration Rate (BBPR), is respectively 29.67% and 15.53% with standard deviation of 20.06% and 10.02 showing the high variability of the financial inclusion rate across the WAEMU countries and over the period of the study. In addition, this variability is confirmed by the banking infrastructure potential which has an average of about 109 points of banking services across these countries. Indeed, the access to banking financial services in WAEMU is still very low because of the demographic structure of the population as well as the issue of financial education. It can also be supported by the large gap between the deposit and credit rate at plays in that region. Thus, the net interest gap deviation from than average (4.11%)

is critical to discourage access to banking financial services. For example, the share of credit allocated to the private sector by banks is on average 18.66% of GDP, with a maximum share of 37.86% for the most banked economies like Côte d'Ivoire and Senegal. Access to credit in WAEMU is highly constrained because of the requirement of collateral to ensure repayment, albeit credits is key to allowing the development of micro enterprises and the creation of sustainable jobs. This low access to credit services supports the low financial inclusion rate of African countries in general and WAEMU countries in particular. Besides, the GDP per capita is also patchy across the WAEMU countries. Assessing, on average, at 276,061 FCFA, this level of per capita income peaks in some countries at 703,175 FCFA. The WAEMU's economies also have a major advantage in terms of broad money and inflation. In fact, the broad money, that is to say the entire fiduciary currency plus the quasi-currency, is on average 1762.696 billion FCFA per country, for a maximum amount of 8574.9 billion FCFA. This confirms the adequacy of the total amount of money needed in accordance of the dynamics of these economies.

Through monetary policies, this leads to the stability of the currency and, in turn, the low inflation rate in WAEMU region (2.20% on average). On the other hand, the WAEMU countries have diverse demographic structures with an average population of around 12 million while the employed labor force is nearly 4876951. However, some evidences pointed out that one of the areas where Africa has been successful is the mobile technology and in particular mobile phone access. In fact, the number of mobile phone users is nearly 58.27 while those who use internet are about 5.25 users per 100 inhabitants. This confirms the major role of information and communication technologies in the development of developing countries in general and in WAEMU countries in particular.

Table 2. 1:*Descriptive statistics*

Variable		Mean	Std. Dev.	Min	Max	Obs	
Financial Inclusion Rate (GUFS)	overall	0.296	0.200	0.008	0.821	N =	96
	between		0.160	0.061	0.500	n =	8
	within		0.132	0.077	0.688	T =	12
Financial Inclusion (BBPR)	overall	0.155	0.100	0.004	0.391	N =	96
	between		0.096	0.030	0.285	n =	8
	within		0.042	0.035	0.260	T =	12
Broad Money	overall	1762.69	1662.22	53.2	8574.90	N =	96
	between		1479.33	174.24	4905.44	n =	8
	within		909.91	-1128.34	5432.15	T =	12
DMM	overall	0.562	-	0	1	N =	96
	between		0.124	0.333	0.666	n =	8
	within		0.484	-0.104	1.229	T =	12
Bank Branch	overall	109.11	57.08	13.59	253.52	N =	96
	between		47.01	3 3.02	175.19	n =	8
	within		36.11	-1.28	187.43	T =	12
Bank Net Interest Rate	overall	0.041	0.016	0	0.082	N =	96
	between		0.009	0.027	0.055	n =	8
	within		0.013	0.013	0.090	T =	12
% of credit in GDP	overall	0.186	0.078	0.021	0.378	N =	96
	between		0.069	0.082	0.278	n =	8
	within		0.043	0.050	0.286	T =	12
Population	overall	1.26e+07	5964995	1494603	2.2e+07	N =	96
	between		6220670	1678110	2.0e+07	n =	8
	within		1168380	9561238	1.5e+07	T =	12
Phone owners per 100	overall	58.272	32.92	3.53	149.06	N =	96
	between		19.68	27.60	81.73	n =	8
	within		27.22	-11.18	125.61	T =	12
Internet subscribers per 100	overall	5.253	5.71	0.2940	38.44	N =	96
	between		3.61	1.25	11.53	n =	8
	within		4.60	-3.31	33.60	T =	12
Inflation rate	overall	0.0220	0.0257	-0.0224	0.1130	N =	96
	between		0.0038	0.0155	0.0257	n =	8
	Within		0.0254	-0.0185	0.1179	T =	12
Labour	overall	4876951	2189155	624090	8540700	N =	96
	between		2282589	711127.3	7801634	n =	8
	Within		430666.9	3636702	5660476	T =	12
GDP per capita	Overall	276061.6	172965.2	384.2886	703175.2	N =	96
	Between		182209.2	536.3627	605623.5	n =	8
	Within		23685.68	200783	373613.3	T =	12

Source: Author, 2019

2.5. Results and Discussion

Prior to the estimation results of the GMM, we present the estimation results of the fixed and random effect model followed by the Hausman and the Breusch-Pagan Lagrange multiplier (LM) tests (Table A.1.4A and A.1.4B, in appendix I). The Hausman and the Breusch-Pagan Lagrange multiplier (LM) tests support the random effect estimation. We use the Global Rate of Financial Services Utilization (GRFSU) and the Broad Banking Penetration Rate (BBPR) as proxies for financial inclusion. The random effect model results show at first glance that the advent of digital technologies is non-essential for financial inclusion. On the contrary, it came out from the results of the random effect model that the introduction of mobile money services in WAEMU countries is very critical for financial inclusion albeit the confused effect of digital technologies in that region. Indeed, this effect is about 5.99% with a degree of significance of 10%. Besides, the share of credit in GDP granted to the private sector affects positively at 5% level the financial inclusion in WAEMU. This shows the importance of credit for small businesses to grow and its effect on savings behavior of those people. However, although the specific effect of mobile phone and internet on financial inclusion is negative in the static model, the interaction variable of mobile phone and Internet is very conducive to financial inclusion. It positively impacts at 10% level the dynamics of the financial Inclusion in WAEMU. In addition, some variables including the Broad money, population, labor, Bank branch were expected to positively impact the dynamics of financial inclusion. Unfortunately, those variables are either negatives or non-significantly positive in the random effect model. Although paradoxical, these results justify the possible endogeneity problem often raised in static models. Therefore, considered as more robust than the Arellano and Bond method, the Arrelano-Bover/Bundell-Bond system will help address this endogeneity by regressing in the model the endogenous variable on its first period lagged value and on the first period lagged values of some predetermined variables as well as on other exogenous regressors (Maddala, 1983). Table 2.2 displays the estimation results of the Arrelano-Bover/Bundell-Bond Dynamic Model. Indeed, considered as very crucial in the dynamic models, the coefficient of the lagged endogenous variable is significant at 1% level and lies between 0 and 1.

This coefficient indicate that the financial inclusion rate of the previous periods significantly determines the current financial inclusion rate and suggests a catch-up effect. A null coefficient would indicate a complete catch-up while a coefficient between 0 and 1 indicate a partial catch-up. Economically, these coefficients indicate that countries with strong financial inclusion tend to cover most of their past financial inclusion gap. The estimates of the dynamics

model (column 1) show that digital finance including mobile money and mobile banking technologies positively and significantly affects the dynamics of the overall financial inclusion (GRFSU) in the WAEMU countries at 10% level. This impact is also predetermined by the development of mobile phones penetration coupled with the broadband Internet access across the WAEMU countries. Indeed, phone and internet variables are all considered as potential instruments in the dynamic models. Although results show a negative effect of the internet penetration on financial inclusion, the use of that technology jointly with mobile phones is very important for massive financial inclusion. Moreover, the negative effect of the internet on financial inclusion indicates that this technology is not yet widely adopted in the WAEMU countries due to the constraints of accessibility, availability and affordability pertaining to it.

In fact, consistent with Evans (2016) that investigated the determinants of financial inclusion in Africa using two dynamic panel approaches, we find that mobile phone access positively but not significantly affects financial inclusion in WAEMU. In addition, our findings are in line with those of Andrianaivo and Kpodar (2012) who indicated that the Information and Communication Technologies are a vehicle for financial inclusion and, in turn, induce inclusive development. Unfortunately, contrary to results of Sarma and Pais (2011) and Allen et al. (2014) indicating that, access to Internet is a key element in the digital economy and has led to the acceleration of financial inclusion, the coefficients related to the density of Internet users per 100 has overturned this accelerating role of ICT on financial inclusion.

Though counterintuitive, this result aligns with the realities of developing countries where access to online banking services other than mobile banking is not yet well established in the banking culture of these populations. In fact, people often prefer mobile money to internet banking services because of its practicability and security. But it still urges to point out that the interaction Mobile phone-internet increases the financial inclusion (GRFSU) by 1.01% but negatively the BBPR by 3%. This interaction, although its magnitude is not very significant, indicates that the ease with which people can access their account online in a touch on their smart phone is very critical for mobile money expansion but may hamper the sustainability and efficiency of financial institutions in providing financial services for the disadvantaged people. To this end, it appears however that the availability and accessibility of mobile phones coupled with the use of the Internet is very crucial for financial inclusion for the disadvantaged people in developing countries. This is evidenced in Kenya where the M-PESA that fundamentally relies on mobile phone, has changed the financial landscape of Kenya (Ndung'u, 2018; Jack and Suri, 2011).

Table 2. 2*: *Estimation Results

VARIABLES	Financial Inclusion	
	(1)	(2)
	GRFSU	**BBPR**
Lagged. Financial Inclusion	0.972***	0.789***
	(0.048)	(0.089)
Dummy Mobile Money	0.025*	-0.004
	(0.014)	(0.004)
Bank Net Interest Rate	-0.213	-0.412 **
	(0.268)	(0.199)
Lagged. Net Interest Rate	-0.238	0.084
	(0.198)	(0.148)
Credit part in GDP	0.092	0.327***
	(0.089)	(0.065)
Inflation	0.314***	0.071*
	(0.095)	(0.041)
Lagged. Inflation	0.218	0.084
	(0.182)	(0.092)
Broad Money (Log)	0.018	-0.024***
	(0.023)	(0.007)
Phone subscribers (log)	0.000	0.002
	(0.010)	(0.003)
Internet users per 100 (log)	-0.054***	0.001
	(0.016)	(0.006)
Interaction phone-internet (log)	0.010**	-0.003**
	(0.003)	(0.001)
Labor (log)	0.080*	0.013
	(0.043)	(0.033)
Bank Branch (log)	0.006	0.034***
	(0.027)	(0.013)
GDP per capita (log)	-0.000	0.004**
	(0.003)	(0.002)
Population (log)	-0.088**	0.006
	(0.038)	(0.031)
Constant	0.075	-0.356***
	(0.249)	(0.110)
Observations	88	88
Number of Countries	8	8
Wald	9551.69	1165.33
AR(1) p.value	0.0505	0.0196
AR(2) p.value	0.5337	0.3774
Sargan test p.value	0.9169	0.8027
Number of Instruments	166	166

GRFSU: Global Rate of Financial Services Utilization
BBPR: Broad Banking Penetration Rate

Source: Author, 2019

However, these authors indicate that without digital technologies, the financial inclusion in Africa and by the way in WAEMU countries would be a myth. This is because the entry of new players other than banks into the financial services market is made possible by the dynamics of Information and Communication Technologies in Africa (GSMA, 2016). In

addition, several other variables significantly drive the financial inclusion in WAEMU. We have among other, the population; the broad money (M2), the bank branch, the number of employees and the inflation rate. Indeed, results of the dynamic panel estimation indicate that population growth is strongly unfavorable to GRFSU. This result is unfortunately in contrast to those of Allen et al. (2014) who have shown that population growth is one of the key determinants of financial inclusion. These results indicate that in developing countries, like WAEMU, demography generates more poor people who do not necessarily have access to formal financial services. However, with digital technologies enabled financial services such as mobile phone, these excluded populations can easily and adequately access financial services. Moreover, like Andrianaivo and Kpodar (2012), results of the dynamic model show that the broad money is a key-driven factors of access to financial services. This because with large amount of money, bank and other financial institutions will be willing to provide loan to people at low interest rate.

However, it is worth noting that the previous financial inclusion rates are very determinant in the current financial inclusion level. This because the coefficient related to the lagged of financial Inclusion is 97.2 and significant at 1% level. Besides, we found that the advent of digital technology has no significant effect on the banking financial inclusion in WAEMU. Indeed, neither the coefficient of the dummy of mobile money implementation nor those of mobile phone subscribers and internet penetration are significant in the model of Broad Banking Penetration Rate (BBPR). Yet, there are others specific factors including the part of credit in the GDP, the inflation rate, the number of bank branches as well as the GDP per capita that boost the bank-led financial inclusion in WAEMU.

2.6. Concluding remarks

The objective of this study was to assess the effect of digital technologies on the financial inclusion in WAEMU countries. Using data from the BCEAO and the ITU databases, we first estimated a static panel model and then a dynamic panel model to address the endogeneity problems often raised in static models. From the estimation results, it appears that the advent of digital technology has contributed significantly to financial inclusion in WAEMU. In addition, the dynamics of financial inclusion differ from one country to another and the effect of mobile phone and internet on financial inclusion is perceived differently across countries in the WAEMU region. The results show that the simultaneous use of Internet and mobile phone is more conducive to financial inclusion than the separate use of these technologies. This is

because, beyond mobile money, the digital inclusion of an economy through the adoption of second and third generations of mobile money services are becoming increasingly a major issue in the WAEMU countries.

Furthermore, payments and other online transactions require strong internet connectivity. In addition, online banking services are made possible by the use of the internet on smartphones and take a large part of digital finance in developing countries. Moreover, it can be seen that beyond digital technology, the net interest rates at plays in the banking system, the amount of credit granted to the private sector as well as the amount of money in circulation in an economy are all key driven factors of financial inclusion in WAEMU. To this end, we urge policy makers to promote the use of digital technologies by making them affordable, available and accessible even in the remote areas. Furthermore, the extension of communication networks in rural areas is a big issue. This may pass by the development of infrastructure conducive to innovation. Moreover, public awareness of adopting second and third generation mobile money services is very critical to a digital inclusion of all WAEMU economies. Given the comparative advantage in terms of infrastructures of mobile telephone operators, it would also be advantageous for banks and microfinance institutions to change their business model by collaborating more with Mobile Network Operators. The States as well as the Central Bank should consider making the regulation governing digital financial services flexible in order to encourage new players to enter into the digital finance market. Furthermore, that regulation may lead to data protection for clients.

However, having established the importance of digital technologies for the financial inclusion process in the countries of WAEMU, it is important for one to question why the adoption of those technologies, especially the mobile money is very low in that region. This may help policymakers to implement appropriate policies towards stakeholders in order to accelerate digital financial inclusion in WAEMU and in developing countries in general.

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Appendix I

A1.1. Descriptive Statistics

```
. xtsum fi fibank var51 DMM Branch depo bankNIR credi Population Phone Intern
> et Inflation Labour GDPc
```

Variable		Mean	Std. Dev.	Min	Max	Observations	
fi	overall	.2967423	.200652	.00861	.82142	N =	96
	between		.1601091	.0616342	.5008242	n =	8
	within		.1326445	.0779414	.6885448	T =	12
fibank	overall	.1553459	.1002586	.00437	.3914	N =	96
	between		.0966295	.0309636	.285924	n =	8
	within		.0423755	.0353019	.2608219	T =	12
var51	overall	1762.696	1662.219	53.2	8574.9	N =	96
	between		1479.332	174.2417	4905.442	n =	8
	within		909.9155	-1128.346	5432.154	T =	12
DMM	overall	.5625	.4986825	0	1	N =	96
	between		.124004	.3333333	.6666667	n =	8
	within		.4848585	-.1041667	1.229167	T =	12
Branch	overall	109.1082	57.07867	13.5929	253.524	N =	96
	between		47.00807	33.02326	175.1991	n =	8
	within		36.11209	-1.282102	187.4331	T =	12
depo	overall	.209756	.0828607	0	.407812	N =	96
	between		.0688522	.1120753	.3254732	n =	8
	within		.0517125	-.0453307	.2949355	T =	12
bankNIR	overall	.0411234	.0164543	0	.0824376	N =	96
	between		.0097959	.027326	.0558045	n =	8
	within		.0136343	.0137974	.0900906	T =	12
credi	overall	.1866503	.0782267	.0217516	.378689	N =	96
	between		.0690417	.0829474	.2785596	n =	8
	within		.0436418	.0504977	.2867797	T =	12
Popula~n	overall	1.26e+07	5964995	1494603	2.27e+07	N =	96
	between		6220670	1678110	2.07e+07	n =	8
	within		1168380	9561238	1.55e+07	T =	12
Phone	overall	58.27245	32.91903	3.530778	149.0691	N =	96
	between		19.68089	27.60336	81.72787	n =	8
	within		27.22453	-11.18052	125.6137	T =	12
Internet	overall	5.253083	5.71358	.294034	38.44	N =	96
	between		3.609492	1.255546	11.53431	n =	8
	within		4.596207	-3.314465	33.60063	T =	12
Inflat~n	overall	.0220156	.0257546	-.0224802	.1130504	N =	96
	between		.0038565	.0155369	.0257317	n =	8
	within		.025498	-.0185085	.117967	T =	12
Labour	overall	4876951	2189155	624090	8540700	N =	96
	between		2282589	711127.3	7801634	n =	8
	within		430666.9	3636702	5660476	T =	12
GDPc	overall	276061.6	172965.2	384.2886	703175.2	N =	96
	between		182209.2	536.3627	605623.5	n =	8
	within		23685.68	200783	373613.3	T =	12

A1.2. Fixed Effect estimation results

```
. xtreg fi DMM credi bankNIR lnmm lnlabour lnbranch  lngdpc Inflation lnpop lnp
> op lnphone lninternet interphoneInternet,fe
note: lnpop omitted because of collinearity

Fixed-effects (within) regression               Number of obs      =         96
Group variable: CountNum                        Number of groups   =          8

R-sq:                                           Obs per group:
     within  = 0.8011                                         min =         12
     between = 0.0163                                         avg =       12.0
     overall = 0.0740                                         max =         12

                                                F(12,76)           =      25.51
corr(u_i, Xb)  = -0.8759                        Prob > F           =     0.0000
```

fi	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
DMM	-.0039529	.0315137	-0.13	0.901	-.0667179	.0588121
credi	.4352476	.3576712	1.22	0.227	-.2771162	1.147611
bankNIR	-1.338196	.7059936	-1.90	0.062	-2.744304	.0679121
lnmm	.2380616	.0444615	5.35	0.000	.1495089	.3266143
lnlabour	.2474292	.3180348	0.78	0.439	-.385992	.8808503
lnbranch	.0217872	.0549801	0.40	0.693	-.0877152	.1312896
lngdpc	.1516899	.1473716	1.03	0.307	-.1418261	.4452058
Inflation	.18947	.3171588	0.60	0.552	-.4422065	.8211466
lnpop	-.4006986	.4226346	-0.95	0.346	-1.242448	.4410511
lnpop	0	(omitted)				
lnphone	-.1206382	.0433886	-2.78	0.007	-.2070541	-.0342223
lninternet	-.0253547	.059273	-0.43	0.670	-.143407	.0926977
interphone~t	.0219294	.0122884	1.78	0.078	-.002545	.0464039
_cons	-.2039114	6.555123	-0.03	0.975	-13.25957	12.85175
sigma_u	.40516689					
sigma_e	.06613808					
rho	.97404539	(fraction of variance due to u_i)				

```
F test that all u_i=0: F(7, 76) = 15.93                     Prob > F = 0.0000
```

A1.3. Random Effect estimation results

```
. xtreg fi DMM credi bankNIR lnmm lnlabour lnbranch  lngdpc Inflation lnpop lnp
> op lnphone lninternet interphoneInternet,re
note: lnpop omitted because of collinearity

Random-effects GLS regression                   Number of obs     =         96
Group variable: CountNum                        Number of groups  =          8

R-sq:                                           Obs per group:
     within  = 0.7048                                         min =         12
     between = 0.8486                                         avg =       12.0
     overall = 0.7856                                         max =         12

                                                Wald chi2(12)     =     304.06
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

fi	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DMM	.0599317	.0348627	1.72	0.086	-.0083979	.1282613
credi	1.160104	.3029412	3.83	0.000	.5663498	1.753857
bankNIR	-2.693935	.8684384	-3.10	0.002	-4.396043	-.9918273
lnmm	.1191817	.0454883	2.62	0.009	.0300263	.2083372
lnlabour	-.0548052	.1351345	-0.41	0.685	-.319664	.2100536
lnbranch	.0673002	.0473597	1.42	0.155	-.025523	.1601235
lngdpc	-.0046055	.0089178	-0.52	0.606	-.022084	.0128731
Inflation	.1770777	.4401545	0.40	0.687	-.6856092	1.039765
lnpop	-.0412432	.1268418	-0.33	0.745	-.2898486	.2073622
lnpop	0	(omitted)				
lnphone	-.0845429	.0347404	-2.43	0.015	-.1526327	-.016453
lninternet	-.0848276	.0722476	-1.17	0.240	-.2264303	.0567752
interphone~t	.0174154	.0158992	1.10	0.273	-.0137464	.0485771
_cons	.9040977	.5984206	1.51	0.131	-.2687851	2.07698
sigma_u	0					
sigma_e	.06613808					
rho	0	(fraction of variance due to u_i)				

A1.4A. Hausman Test

```
. hausman fe re
```

	Coefficients (b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
DMM	-.0039529	.0599317	-.0638846	.
credi	.4352476	1.160104	-.724856	.1901455
bankNIR	-1.338196	-2.693935	1.355739	.
lnmm	.2380616	.1191817	.1188799	.
lnlabour	.2474292	-.0548052	.3022343	.2878972
lnbranch	.0217872	.0673002	-.045513	.0279262
lngdpc	.1516899	-.0046055	.1562953	.1471015
Inflation	.18947	.1770777	.0123923	.
lnpop	-.4006986	-.0412432	-.3594554	.4031515
lnphone	-.1206382	-.0845429	-.0360953	.0259938
lninternet	-.0253547	-.0848276	.0594729	.
interphone~t	.0219294	.0174154	.0045141	.

```
                b = consistent under Ho and Ha; obtained from xtreg
     B = inconsistent under Ha, efficient under Ho; obtained from xtreg

  Test:  Ho:  difference in coefficients not systematic

              chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                       =  -123.34    chi2<0 ==> model fitted on these
                                     data fails to meet the asymptotic
                                     assumptions of the Hausman test;
                                     see suest for a generalized test
```

A1.4B. Breusch-Pagan Lagrange multiplier (LM)

	var	Sd=sqrt (var)
fi	9.09e+18	3.02e+09
e	7.82e+18	2.80e+09
u	1.13e+18	1.06e+09

```
Test: Var(u) = 0

                    chi2(1) = 3.67

                    Prob > chi2 = 0.063
```

A1.5. Robust fixed effect estimation results

```
. xtreg fi DMM credi bankNIR lnmm lnlabour lnbranch  lngdpc Inflation lnpop lnp
> op lnphone lninternet interphoneInternet,fe robust
note: lnpop omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =         96
Group variable: CountNum                        Number of groups  =          8

R-sq:                                           Obs per group:
     within  = 0.8011                                         min =         12
     between = 0.0163                                         avg =       12.0
     overall = 0.0740                                         max =         12

                                                F(8,7)            =          .
corr(u_i, Xb)  = -0.8759                        Prob > F          =          .

                                (Std. Err. adjusted for 8 clusters in CountNum)
```

fi	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
DMM	-.0039529	.0330696	-0.12	0.908	-.0821502	.0742444
credi	.4352476	.3262912	1.33	0.224	-.3363083	1.206804
bankNIR	-1.338196	.5853753	-2.29	0.056	-2.722389	.0459967
lnmm	.2380616	.122225	1.95	0.092	-.0509545	.5270777
lnlabour	.2474292	.284824	0.87	0.414	-.4260726	.920931
lnbranch	.0217872	.0517822	0.42	0.687	-.1006583	.1442327
lngdpc	.1516899	.203523	0.75	0.480	-.3295655	.6329452
Inflation	.18947	.1861146	1.02	0.343	-.2506211	.6295612
lnpop	-.4006986	.394347	-1.02	0.343	-1.333181	.5317839
lnpop	0	(omitted)				
lnphone	-.1206382	.0448072	-2.69	0.031	-.2265903	-.0146861
lninternet	-.0253547	.0711493	-0.36	0.732	-.1935959	.1428866
interphone~t	.0219294	.0129022	1.70	0.133	-.0085795	.0524383
_cons	-.2039114	6.168819	-0.03	0.975	-14.79085	14.38303
sigma_u	.40516689					
sigma_e	.06613808					
rho	.97404539	(fraction of variance due to u_i)				

```
.
```

A1.6. Robust Random Effect estimation results

```
. xtreg fi DMM credi bankNIR lnmm lnlabour lnbranch  lngdpc Inflation lnpop lnp
> op lnphone lninternet interphoneInternet,re robust
(71 missing values generated)
note: lnpop omitted because of collinearity

Random-effects GLS regression                   Number of obs     =         96
Group variable: CountNum                        Number of groups  =          8

R-sq:                                           Obs per group:
     within  = 0.7048                                         min =         12
     between = 0.8486                                         avg =       12.0
     overall = 0.7856                                         max =         12

                                                Wald chi2(7)      =          .
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =          .

                                 (Std. Err. adjusted for 8 clusters in CountNum)
```

fi	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
DMM	.0599317	.0486342	1.23	0.218	-.0353896	.1552529
credi	1.160104	.5169781	2.24	0.025	.1468451	2.173362
bankNIR	-2.693935	1.874542	-1.44	0.151	-6.367969	.9800989
lnmm	.1191817	.0803235	1.48	0.138	-.0382494	.2766128
lnlabour	-.0548052	.0604335	-0.91	0.364	-.1732526	.0636423
lnbranch	.0673002	.0500175	1.35	0.178	-.0307323	.1653327
lngdpc	-.0046055	.019106	-0.24	0.810	-.0420526	.0328416
Inflation	.1770777	.2163522	0.82	0.413	-.2469649	.6011202
lnpop	-.0412432	.0440191	-0.94	0.349	-.1275191	.0450327
lnpop	0	(omitted)				
lnphone	-.0845429	.0360265	-2.35	0.019	-.1551536	-.0139321
lninternet	-.0848276	.0759921	-1.12	0.264	-.2337694	.0641143
interphone~t	.0174154	.0104391	1.67	0.095	-.0030449	.0378756
_cons	.9040977	.940749	0.96	0.337	-.9397365	2.747932
sigma_u	0					
sigma_e	.06613808					
rho	0	(fraction of variance due to u_i)				

A1.7. Estimation results system GMM

```
. xtdpdsys fi DMM credi lnmm lnlabour lnbranch  lngdpc Inflation lnpop , lags(1
> ) maxldep(1) maxlags(1) pre(bankNIR   Inflation , lag(1,.))pre(credi lnmm lnp
> hone lninternet interphoneInternet) vce(robust) artests(2)
note: credi dropped because of collinearity
note: lnmm dropped because of collinearity
note: Inflation dropped because of collinearity

System dynamic panel-data estimation            Number of obs     =         88
Group variable: CountNum                        Number of groups  =          8
Time variable: Year
                                                Obs per group:
                                                              min =         11
                                                              avg =         11
                                                              max =         11

Number of instruments =    166                  Wald chi2(7)      =    9551.69
                                                Prob > chi2       =     0.0000
One-step results
```

fi	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
fi						
L1.	.9721972	.0483293	20.12	0.000	.8774736	1.066921
bankNIR						
--.	-.2134737	.2681525	-0.80	0.426	-.7390429	.3120955
L1.	-.2383723	.1980528	-1.20	0.229	-.6265488	.1498041
Inflation						
--.	.3143188	.0954096	3.29	0.001	.1273195	.5013181
L1.	.2177506	.181529	1.20	0.230	-.1380396	.5735408
credi	.0927565	.0895744	1.04	0.300	-.082806	.2683191
lnmm	.0180859	.0229979	0.79	0.432	-.0269891	.0631608
lnphone	.0004695	.0109349	0.04	0.966	-.0209624	.0219014
lninternet	-.0540402	.016634	-3.25	0.001	-.0866422	-.0214381
interphone~t	.0100726	.0039513	2.55	0.011	.0023283	.0178169
DMM	.0256705	.0144066	1.78	0.075	-.002566	.0539069
lnlabour	.0802924	.0436036	1.84	0.066	-.005169	.1657538
lnbranch	.0066773	.0273225	0.24	0.807	-.0468738	.0602285
lngdpc	-.0006445	.0036908	-0.17	0.861	-.0078783	.0065892
lnpop	-.0881005	.0386212	-2.28	0.023	-.1637966	-.0124044
_cons	.075303	.2492228	0.30	0.763	-.4131648	.5637707

```
Instruments for differenced equation
        GMM-type: L(2/2).fi L(1/1).L.bankNIR L(1/1).L.Inflation L(1/1).credi
                  L(1/1).lnmm L(1/1).lnphone L(1/1).lninternet
                  L(1/1).interphoneInternet
        Standard: D.DMM D.credi D.lnmm D.lnlabour D.lnbranch D.lngdpc
                  D.Inflation D.lnpop
Instruments for level equation
        GMM-type: LD.fi LD.bankNIR LD.Inflation D.credi D.lnmm D.lnphone
                  D.lninternet D.interphoneInternet
        Standard: _cons
```

A1.8. GMM Post estimation test

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-1.9557	0.0505
2	.62241	0.5337

H0: no autocorrelation

```
. estat sargan
Sargan test of overidentifying restrictions
        H0: overidentifying restrictions are valid

        chi2(150)     =  126.6768
        Prob > chi2   =    0.9169
```

Financial inclusion excluding Digital Finance (BBR)

```
. xtdpdsys fibank DMM credi lnmm lnlabour lnbranch  lngdpc  lnpop , lags(1) maxldep(1) m
> lags(1) pre(bankNIR   Inflation  , lag(1,.))pre(credi lnmm lnphone lninternet interphon
> nternet) vce(robust) artests(2)
note: credi dropped because of collinearity
note: lnmm dropped because of collinearity

System dynamic panel-data estimation            Number of obs     =         88
Group variable: CountNum                        Number of groups  =          8
Time variable: Year
                                                Obs per group:
                                                              min =         11
                                                              avg =         11
                                                              max =         11

Number of instruments =    166                  Wald chi2(7)      =    1165.33
                                                Prob > chi2       =     0.0000
One-step results
```

fibank	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
fibank						
L1.	.7898791	.0898767	8.79	0.000	.6137239	.9660343
bankNIR						
--.	-.4125043	.1993322	-2.07	0.039	-.8031883	-.0218204
L1.	.0847042	.1489707	0.57	0.570	-.2072729	.3766813
Inflation						
--.	.0717468	.0417461	1.72	0.086	-.0100741	.1535677
L1.	.0847932	.0925466	0.92	0.360	-.0965948	.2661812
lnmm	-.0246492	.0075583	-3.26	0.001	-.0394632	-.0098352
lnphone	.0021055	.0036969	0.57	0.569	-.0051402	.0093513
lninternet	.0016725	.006249	0.27	0.789	-.0105753	.0139204
interphoneInternet	-.003303	.0015667	-2.11	0.035	-.0063737	-.0002323
DMM	-.0047465	.0043185	-1.10	0.272	-.0132106	.0037176
credi	.3274087	.0657842	4.98	0.000	.198474	.4563434
lnlabour	.0134072	.0338608	0.40	0.692	-.0529588	.0797732
lnbranch	.0347925	.01327	2.62	0.009	.0087837	.0608012
lngdpc	.0044437	.0022329	1.99	0.047	.0000673	.00882
lnpop	.0069869	.0310505	0.23	0.822	-.0538708	.0678447
_cons	-.3560309	.1109093	-3.21	0.001	-.5734092	-.1386527

```
Instruments for differenced equation
        GMM-type: L(2/2).fibank L(1/1).L.bankNIR L(1/1).L.Inflation L(1/1).credi
                  L(1/1).lnmm L(1/1).lnphone L(1/1).lninternet
                  L(1/1).interphoneInternet
        Standard: D.DMM D.credi D.lnmm D.lnlabour D.lnbranch D.lngdpc D.lnpop
Instruments for level equation
        GMM-type: LD.fibank LD.bankNIR LD.Inflation D.credi D.lnmm D.lnphone
                  D.lninternet D.interphoneInternet
        Standard: _cons
```

```
. estat abond

Arellano-Bond test for zero autocorrelation in first-differenced errors
```

Order	z	Prob > z
1	**-2.3333**	**0.0196**
2	**.88267**	**0.3774**

H0: no autocorrelation

```
. estat sargan
Sargan test of overidentifying restrictions
        H0: overidentifying restrictions are valid

        chi2(150)     =  135.108
        Prob > chi2   =    0.8027
```

ESSAY II

Is there a bottleneck for Digital Finance adoption? An empirical evidence from mobile money in WAEMU[5]

Abstract

This essay aims at investigating the driving factors of mobile money adoption and the policies package that may alleviate the bottlenecks of the low digital financial inclusion in that region. Using both country and individual level data respectively from the World Development indicators (2017) and the World Bank Global Findex (2017) database, we made first, a cluster analysis to investigate the macroeconomic driving factors of mobile money adoption. We found that country characteristic such as literacy rate, labor force, mobile infrastructure and even banking infrastructure in terms of numbers of ATM per 100000 people are the main macroeconomic determinants of mobile money adoption. We estimate thereafter a logistic regression to examine the microeconomic factors affecting the adoption of mobile money in the WAEMU countries. Findings show in line with existing evidences that being young, man, educated, relatively richer and even banked increases the likelihood of adopting mobile money in WAEMU. They support the view that policies favoring mobile technologies accessibility, affordability as well as flexible legislations towards mobile money providers may boost the penetration of the digital finance in WAEMU.

***Key-words*:** *Mobile money - Cluster Analysis - dendrogram - Clogit - WAEMU*
JEL Code: G21; O16

Résumé

Cet essai a pour objectif de rechercher les facteurs déterminant l'adoption de la finance digitale en occurrence le mobile money ainsi que les politiques adéquates à réduire les goulots d'étranglement de l'inclusion financière dans l'UEMOA. Nous utilisons à cet effet les données macroéconomiques (WDI, 2017) et un échantillon constitué de 8000 adultes enquêtés courant 2017 dans l'UEMOA par la banque mondiale (FINDEX, 2017) pour estimer, après avoir fait une analyse statistique de groupage un modèle Logit approprié à cette analyse. Il ressort des résultats que le niveau d'instruction, la population active, les infrastructures bancaires et de GSM ainsi que le nombre de guichets automatique par 100000 habitants sont les déterminants macroéconomiques de l'adoption du Mobile money. Par ailleurs, au niveau microéconomique, le fait d'être jeune, homme, bien instruit et relativement riche et ayant même un compte dans une institution financière impacte positivement et significativement la probabilité d'adoption du mobile money dans l'espace UEMOA. Il ressort donc que les politiques en faveur de l'accès ainsi que la flexibilité des législations à l'endroit des fournisseurs des services de mobile money vont permettre une adoption massive de la finance digitale dans les pays de l'UEMOA.

***Mots clés* :** *Mobile money – Analyse de groupage - Dendrogramme - Clogit - UEMOA*
***Code JEL** : G21; O16*

[5] This essay is joint work with Wautabouna OUATTARA and Denis ACCLASSATO HOUENSOU. A slightly different version of this essay is published in Transnational Corporation Review

3.1. Introduction

Many technological adoption theories including the technology acceptance model (TAM) have been developed to study the framework of innovation adoption (Hubert et al., 2019; Narteh et al., 2017; Davis et al., 1989). Indeed, Davis et al. (1989) observe that the TAM is a simple and parsimonious model. It's used in many studies because of its practicability and simplicity (Chong et al., 2012). However, the introduction of innovative financial products such as mobile money will then enable poor to access saving, credit and insurance product and then correct the financial market failure and poverty issues in developing countries (Fanta et al., 2016). Indeed, the mobile phone usage has tremendously grown in developing countries especially in sub-Saharan Africa (IUT, 2016). Its diffusion has been seen as a powerful tool to overcome the financial infrastructure gap in developing world (Andrianaivo and Kpodar, 2012). Mobile phone subscription grew at an average rate of 208 % per annum in Sub Saharan Africa compared to 46% per annum in East Asian and Pacific, 24% in Europe and 12% in North America (World Bank, 2012). This has put the developing world at a leading position of mobile phone adoption (Andrianaivo and Kpodar, 2012; Fanta et al., 2016).

According to the World Bank (2018), many people in the world do not have access to financial services irrespective of advances made in development. Largely, there is uneven access to financial services globally (Demirgüç-Kunt et al., 2018). One technological innovation that has emerged as a solution to inaccessibility of financial services is fintech (World Bank, 2018). Fintech refers to the provision of financial services through technology such as mobile phones (Demirgüç-Kunt et al., 2018; Gai et al., 2018). In this study, we focus on mobile money, a form of fintech innovation that enables financial transactions through mobile devices (Donovan, 2012). The World Bank (2018) indicates that the mobile phone is accelerating the rise in financial inclusion globally. Thus, mobile money is highly regarded as an essential game changer in deepening financial inclusion (Senyo et al., 2020). In addition, mobile money services are widely available, with remote areas able to participate, and there is no need for a physical branch to enable transaction performance as compared to traditional banks (Demirgüç-Kunt et al., 2018). Furthermore, it offers convenience, low transaction cost and wide accessibility (Maurer, 2012) as transactions can be performed instantly from anywhere, at any time and at a relatively low service charge.

The ubiquitous nature of mobile phone and other advantages it affords have made this technology suitable for developing digital services to the unbanked population in developing

countries especially in Africa. For the sake of illustration, in 2013, there were 203 million of mobile money customers and 61 million active customers (GSMA, 2013). In the same vein, Demirguc-Kunt et al (2015) in their study find that mobile money account ownership increases from 24% in 2011 to 34% in 2014 and showed that the growth in mobile money account especially in sub-Saharan Africa is a main vehicle for financial development via financial inclusion. Plus, the development of ICT with the usage of 3G and 4G internet connectivity is impressive. Similarly, recent studies have shown that financial inclusion rates in the WAEMU countries are among the lowest in Africa (GSMA, 2015; UNCDF, 2015). In fact, only 34.5% of adult population in WAEMU possesses an account at a formal financial institution. This low financial inclusion is due to a number of factors including the low adoption of digital finance by people albeit the high penetration of mobile phone and Internet in that region (GSMA, 2016).

However, the digital financial inclusion rate of WAEMU (17%) is very low compared to that of east African countries including Kenya where the financial inclusion rate is 69% and the digital financial inclusion is 67% (UNCDF, 2016). It results that financial exclusion and particularly digital financial exclusion may be the major obstacle for economic development and poverty alleviation in WAEMU. As a matter of fact, tremendous policies should be implemented for its sustainable adoption. In addition, special policy should be directed to its ecosystem which is still characterized by the predominance of first generation mobile financial services where the mobile phone platform serves for transfers between users and later payments and settlement (Ndung'u, 2018) and impeded by the issue of illiteracy, utility bill payment, security and digital credit (ITU, 2016; Totolo, 2018; Ndung'u, 2018).

This essay aims to identify the main reasons for which a technological innovation like the mobile money in WAEMU is still poorly adopted and contribute to policy implementation conducive to financial inclusion and poverty alleviation in this economic region. Indeed, due to the virtual nature of mobile money transactions, some people are hesitant in using the innovation (Baganzi and Lau, 2017). In addition, majority of the unbanked are people without formal education (Demirgüç-Kunt et al., 2018), as a result, some may find the adoption and the use of mobile money innovation difficult. The study hypothesizes that socio economic as well as structural factors drive the adoption of mobile money in WAEMU.

Therefore, this essay contributes to the literature that focus on the intention to use innovations including mobile money (e.g., Chauhan, 2015; Narteh et al., 2017) in many ways. First, most previous mobile money studies (e.g., Baganzi and Lau, 2017; Narteh et al., 2017;

Osei-Assibey, 2015) have largely focused on technological factors while there is relative silence on socio economic and structural factors. This essay updates the existing literature by incorporating this aspect in the determinant of mobile money adoption. Second, to the best of our knowledge, this study is among the first to investigate both the macroeconomic and microeconomic driving factors of mobile money adoption in WAEMU. Thus, we take advantage of the rich national and household level data to make a cluster and a logistic analysis to investigate. The findings of this paper indicate that being young, man, educated, relatively richer and even banked increases the likelihood of having a mobile money account in WAEMU. They also reveal that some countries such as Côte d'Ivoire, Mali, Senegal and Burkina Faso are performing well as far as digital finance penetration is concerned because of policies and structural factors pertaining to them.

The rest of the paper is organized as follows. Section 3.2 presents a panorama of mobile money adoption in WAEMU followed by the related literature in Section 3.3. Section 3.4 describes the methodology and Section 3.5 presents the empirical results and discussion. We end the study with a concluding remark in Section 3.6.

3.2. Mobile money Landscape in WAEMU

The architecture of mobile money in WAEMU is expanding unevenly across the eight countries although all those countries are under the same regulation for electronic money. The digital financial services (DFS) market of each country displays different dynamics, financial access structure, challenge and customer needs resulting to different opportunities and country specific response. Nearly half of the total mobile money account and their transaction were in Côte d'Ivoire as a result of the government support for digital financial services expansion. For instance, in 2015, the number of mobile money account owners in Côte d'Ivoire was 9.8 million while it was just 1.9 million in Niger (CGAP, 2016). It's also obvious that the DFS usage in WAEMU is relatively low with regard to their potential as far as mobile phone penetration is concerned. Barely 7.5% of adults in WAEMU possessed a mobile money account as for 2014 Findex statistics. The reasons of this low utilization vary across countries and within a country. In Côte d'Ivoire and Senegal for instance, some factors including insufficient revenue, the transaction cost, the understanding of clients as well as the consumer readiness are the major reasons of the low adoption of mobile money. The Figure 3.1 displays the dynamics of the mobile money landscape in WAEMU compared to the average of Sub Saharan Africa (SSA) between 2014 and 2017.

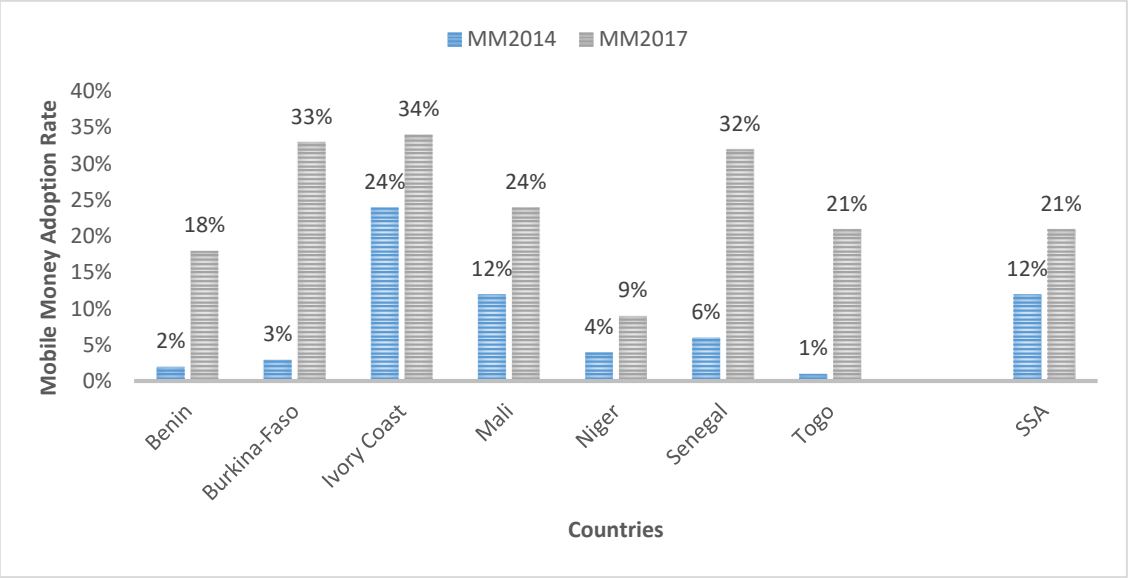

Figure 3. 1*: Mobile money landscape dynamics in WAEMU*

Source: Author, 2019

On average, WAEMU countries are witnessing a growing rate of mobile money adoption. In fact, from 12% in 2014, the mobile money adoption rate was nearly 21 % in 2017. However, this performance was above the average of Sub Saharan African countries. Therefore, from 2014 to 2017, the mobile money has emerged seriously in WAEMU region. For instance, in 2015, 22 million people or nearly a quarter of the population of WAEMU subscribed to mobile financial services. Togo with 1% of mobile money penetration rate presented the lowest growth in the region while the well-performed country was Côte d'Ivoire with 24% as of 2014. This dynamism has changed slightly over the years till 2017 when the less performed country became Niger with 9% and the well performed was still Ivory Coast followed by Burkina-Faso (33%) and Senegal (32%). So, Côte d'Ivoire is a success story of mobile money penetration in WAEMU but Senegal has the most crowded and diverse provider ecosystem for mobile money.

From this figure, WAEMU countries can be classified as countries with very low mobile money penetration rate such as Niger, Togo, Benin and somehow Mali and countries with high mobile money penetration rate such as Côte d'Ivoire, Senegal and Burkina Faso. The low penetration rate of the first group of countries is justified by the fact that they are nascent digital financial market in which the infrastructural gap is high. In this group, although the mobile money penetration rate of Niger is the lowest, it is worth noting that digital financial transactions are high in that country.

3.3. Literature review

The recent rapid expansion of mobile phone has generated a large number of researches as well as great expectation on its potentiality to contribute to financial inclusion**.** After presenting the theoretical debate on the adoption of technologies, we present the empirical studies that analyze the innovation's characteristic and benefits they provide to users in order to predict the potential adoption of such an innovation.

3.3.1. A theoretical analysis of new technologies adoption

The success of a technology is greatly influenced by the individuals' willingness to adopt a particular technology (Tan et al., 2012). Thus, technology acceptance has proven to be an essential requirement for its successful implementation (Al-Emran et al., 2016; Davis, 1989; Venkatesh et al., 2012). The research community's interest in this issue has led to the development of a series of theories and models of technology acceptance, which analyze individuals' perceptions of the determinants of technology acceptance and causal relationships between these factors and intentions to use the technology (Venkatesh et al., 2003). There are several theories pertaining to the adoption of a new technology as innovation that have been used in recent studies (Patil et al., 2019, Dwivedi et al., 2017; Kapoor et al., 2014; Chong et al., 2012). They include the innovation diffusion theory (IDT), the theory of reasoned action (TRA); the technology acceptance model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the theory of planned behavior (TPB).

A common element of these theories is that the adoption of a technology and especially the mobile money is a complex and multifaceted process. In details those theories and models are presented as follows:

3.3.1.1.Innovation Diffusion Theory (IDT)

There exist according to Roger (1983) five perceived interests that an innovation has to provide to users in order to be adopted: the relative advantage, the compatibility, the complexity, the observability and the trialability. Indeed, for an innovation to attract new users with its relative advantage, it should be perceived as better than its predecessor. This advantage can be financial profitability, social prestige, or other perceived gains by potential users. Similarly, the perceived compatibility is the extent to which an innovation is perceived by potential adopters to be in accordance with their existing values, past experiences, and current needs. In other words, for an innovation to diffuse successfully, it should fit well with the

cultural norms of a social system. Social values and cultural beliefs, information and ideas presently held by potential adopters, and the current needs and situations influence perceived compatibility. In opposite, complexity suggests that when an innovation is viewed as hard to understand and use, its adoption uncertain. A high degree of complexity can lead to a high degree of frustration among potential and new adopters, in addition to rejection, discontinuance, and misuse of the innovation. By trialability Roger means the extent to which an innovation may be experimented by potential adopters on a limited basis. It is a key factor because in trying out an innovation, the adopter gives a sense to it while realizing how it works. More importantly, trialability allows the adopter to return to the previous state without bearing too much cost. In other words, trialability reduces uncertainty and risks, increasing the likelihood of trial adoption. The observability as far as it is concerned refers to how visible the positive results of an innovation are to others in the social system.

3.3.1.2.Theory of Reasoned Action (TRA)

The theory of reasoned action by Fischbein and Ajzen (1975), Ajzen and Fischbein (1980) as well as Bagozzi (1982) states that customers are rational agent when it comes to considering the implication of their actions. TRA is a versatile behavioral theory and models the attitude-behavior relationships. This theory maintains that individuals would use a technology if they could see that there would be positive benefits associated with using them.

3.3.1.3.Technology Acceptance Model (TAM)

Technology Acceptance Model (Davis, 1989) was the first model to mention psychological factors affecting technology acceptance and it was developed from the Theory of Reasoned Action (TRA) by Davis (1989). Davis (1989) developed and validated better measures through TAM for predicting and explaining technology use. It considers that the process of adoption of a particular technology by a customer can be driven essentially by the customer’s voluntary intention to accept and use the technology. TAM posits that perceived usefulness and perceived ease of use determine an individual's intention to use a system with the intention to use serving as a mediator of actual system use. Perceived usefulness is also seen as being directly impacted by perceived ease of use. The underlying links between two key constructs and users’ attitudes, intentions and actual technology usage behavior, were specified using the theoretical underpinning of the TRA. Attitude and perceived usefulness jointly determine the behavioral intention while attitude is determined by perceived usefulness and perceived ease of use.

3.3.1.4.The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh, Davis and Davis (2003) based on criticism of the predictive capacity of TAM. It entails four core determinants of intention and usage, and up to four moderators of key relationships. Including the performance expectancy, the effort expectancy, the social influence and the facilitating conditions. Its aim is to determine user acceptance and usage behavior on technology. Attitude toward using technology, self-efficacy, and anxiety are theorized not to be direct determinants of intention. The key moderators in the model are gender, age, voluntariness, and experience. From a theoretical perspective, UTAUT provides a refined view of how the determinants of intention and behavior evolve over time (Venkatesh et al., 2003). UTAUT hypothesizes that performance expectancy, effort expectancy, and social influence affect behavioral intention, which, together with facilitating conditions, affects use behavior. Moreover, the model posits that different combinations of gender, age, experience, and voluntariness of use moderate the effects of these key constructs on behavioral intention and use behavior.

3.3.1.5.Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (Ajzen, 1985, 1991) is a successor of TRA and it introduced a third independent determinant of intention, perceived behavior control (PBC). It is determined by the availability of skills, resources, and opportunities, as well as the perceived importance of those skills, resources, and opportunities to achieve outcomes.

In short, theories and models including TRA, TPB, TAM, and UTAUT are very popular and are being used worldwide in different studies. Davis et al. (1989) observe that the TAM is a simple and parsimonious model. It's used in many studies because of its practicability and simplicity (Chong et al., 2012). The goal of TAM is to provide a theoretical model explaining the determinants of user acceptance of technology (Davis et al., 1989). The model suggests that several factors influence individuals' decisions about using a system. Thus, TAM argues that system usage is determined by individual's Behavior intention, and the latter is jointly determined by two specific beliefs, perceived usefulness and perceived ease of use.

TAM model has been extensively replicated and validated by many researchers with different technologies, situations, and tasks. In general terms, TAM has maintained its consistency, reliability and validity in explaining users' information systems acceptance behavior, and has successfully explained the adoption of numerous systems, such as e-learning,

social networks, e-commerce, online banking, use of e-HRM or m-learning, among others (Tan et al., 2012; Venkatesh and Davis, 2000). However, the original TAM presents some limitations to explain the relationship between a system and users' behavior towards system acceptance, since the model only includes two antecedents: perceived usefulness and perceived ease of use (Cheung and Vogel, 2013). In addition, another criticism of the model refers to the lack of antecedents of the major TAM constructs (Lee et al., 2003).

TRA model though has some limitations including a significant risk of confounding between attitudes and norms since attitudes can often be reframed as norms and vice versa. The second shortfall of this theory is the assumption that when someone forms an intention to act, they will be free to act without limitation. In practice, constraints such as limited ability, time, environmental or organizational limits, and unconscious habits will limit the freedom to act. However, there is also a growing recognition that additional explanatory variables are needed for TRA. The theory of planned behavior (TPB) has extended the theory of reasoned action in emphasizing on the absence of difference between customers who consciously control their actions compared to those who do not. TPB has been the explicit theoretical basis for many studies over various contextual settings.

Generally, Technology Acceptance Model (TAM) specifies general determinants of individual technology acceptance and therefore can be and has been applied to explain or predict individual behaviors across a broad range of end user technologies and user groups (Davis et al., 1989). Simultaneously TAM computing compared favorably with TRA and TPB in parsimonious capability. However, TAM is easier to use than TPB, and provides a quick and inexpensive way of gathering.

3.3.2. Empirical analysis of the Mobile Financial Technologies adoption

Numerous recent studies on mobile payments have applied the theory of Acceptance Model (Kim et al., 2010; Shaw, 2014; Sánchez-Prieto, Olmos-Migueláñez and García-Peñalvo, 2016; Baganzi & Lau, 2017; Narteh et al., 2017) as well as other models such as the Technology Diffusion Theory (Kapoor et al., 2014, Li et al., 2014); the Unified Theory of Acceptance and Use of Technology (Patil et al., 2019, Dwivedi et al., 2017, Rana et al., 2016, 2017, Slade et al., 2015, Venkatesh et al., 2003). For instance, in investigating mobile money adoption in Uganda, Baganzi and Lau (2017) used the TAM. Similarly, Narteh et al. (2017) combined the TAM with the DOI to investigate mobile money adoption. Indeed, Patil et al. (2019) used a meta-analysis based on 23 studies and found that attitude, cost, mobility and innovativeness are

the main driven factor of consumers' intention to adopt digital system. Similarly, Dwivedi et al. (2017) combined a structural equation modeling with a meta-analysis approach on 1600 observations to empirically test the Unified Theory of Acceptance and Use of Technology (UTAUT). Like Rana et al. (2017), they found that attitude is key in the adoption and use of new technologies. In the same vein, Slade et al. (2015) investigated factors affecting non-users' intention to adopt remote mobile payment in UK by using a structural equation modeling on a sample of 208 individuals. They found that innovativeness and perceived risk are among the main determinants of technology adoption.

However, Kapoor et al. (2014) by testing the Roger's Technology Diffusion theory found with the help of a meta-analysis technique that the trialability and the observability are key in the technology adoption. Indeed, the mobile money services are mainly SMS based services and very simple to be used. Although it does not really require any learning, its effective adoption and use could require some preexisting knowledge on financial services in general. Plus, Mobile Money services provides some advantages to the users and all the community by bridging the lack of banking infrastructures and expanding financial services to the last miles.

Furthermore, the migration of people from rural to urban areas imposes the need for distant money transfers. In the case banking system does not exist, mobile money could be a helpful solution to the distant money transfer. Besides, innovation is generally compatible with past experiences to be adopted. For the mobile money, this compatibility with past experiences can be related to the need of financial knowledge and experience to ensure adoption of mobile money services (Kapoor et al., 2014). The need of financial literacy can also be linked to the perceived trialability of the innovation. Financial literacy, especially financial experience, appears to be primordial to mobile money adoption as a trial of this new service. It is a real advantage for mobile money service providers who know they will meet their demand by offering new financial services (Camner and Sjöblom, 2009).

Moreover, potential users can face internal and external factors which act as a major constraint on behavior called the volitional control factors. A lack of individual abilities and skills for the innovation use can disturb the relation between the intentional behavior and the effective behavior. Furthermore, the potential users perceived self-efficacy (Shareef et al., 2018; Saini, 2014; Kabir, 2013; Khraim et al., 2011) which is the perceived and the self-confidence of potential users of their ability to use the innovation, can also be a constraint to adoption and usage. The volitional control factors and the self-efficacy perception depend on

the level of education of individuals. The potential user of mobile money services must be literate because most of mobile money services are SMS based services and people have to know reading and writing to use mobile money (Sathye et al., 2018; Afawubo et al., 2017; Buku and Meredith, 2013; Merrit, 2011).

However, most prior mobile money studies (e.g., Baganzi and Lau, 2017; Narteh et al., 2017; Osei-Assibey, 2015) have largely focused on technological factors while there is relative silence on socio economics antecedents (Senyo et al., 2016). For instance, in investigating mobile money adoption in Uganda, Baganzi and Lau (2017) focus on factors that predict intention to use mobile money services. Similarly, Chauhan (2015) and Osei-Assibey (2015) also investigated factors that influence the intention to adopt mobile money in India and Ghana respectively. As a result, factors that influence intention to use mobile money services are well established.

Individuals also need to have a high level of education to be confident in their self-efficacy necessary to adoption (Hove and Dubus, 2019; Kiconco et al., 2018, Afawubo et al., 2017). Indeed, using a three step probit model to identify the socioeconomic driven factors of individuals that do not adopt M-PESA and do not use it for saving purpose in Kenya, Hove and Dubus (2019) found that poor, non-educated and women are more likely to not adopt this technology. Similarly, Kiconco et al. (2018), investigating the skill perspective of Mobile Money adoption and use in Uganda, found that education is key in the process of mobile money adoption. In the same vein, Afawubo et al. (2017), investigating the socio economics determinant of mobile Money adoption process using an ordered logit model on a sample of 5197 individuals in Togo, found that the ability to read, write as well as having an account at bank or at other financial institutions affect the mobile money adoption process.

3.4. Methodology: Cluster and logistic analysis

This study makes use of a cluster and a logistic analysis to respectively investigate the macroeconomic and microeconomic driven factors of mobile money adoption in WAEMU. The theoretical framework of this study lies on the Technology Acceptance Model (TAM) by Davis (1989).

3.4.1. Cluster Analysis

A Cluster analysis consists of determining the natural groupings of observations. Also called classification, this process is used by researchers to conduct discriminant analysis, which is related but not the same. Ward (1963) using an error-sum of square presented a general hierarchical clustering approach where groups were formed to maximize an objective function. Ward's method of clustering became synonymous with using the error-sum-of-squares criteria and is obtained by using the L2squared dissimilarity option. The objective of this cluster analysis for mobile money adoption in WAEMU is to regroup countries according to their level of adoption and the number of years spent since the first Mobile Money for Unbanked (MMU) was launched in order to merge countries with homogenous adoption characteristics. Therefore, it will be possible to determine in which group there is the highest rate of adoption and describe characteristics from these groups.

To do this, the Ward's minimum variance method is used. It has been chosen preferably from other hierarchical cluster algorithms because of its better predictive potential tested and attested in numerous studies based. At the beginning, the number of clusters is unknown and this analysis starts by attributing each country to a distinct cluster. Clusters are progressively merged according to a minimized variance between two clusters. Ward's method for cluster stops when it remains only one cluster. To determine the optimal number of clusters, different methods can be used. In this analysis, two of them have been tested: The Duda and Hart index and the realization of a dendrogram. The Duda and Hart Index is defined as:

$$DH = {J_1^2(m)}\Big/{J_2^2(m)} \qquad \textbf{3. 1}$$

Where $J_1^2(m)$ is the within-cluster sum of squared errors of the *mth* cluster; $J_2^2(m)$ the within cluster sum of squared distances when the *mth* cluster is optimally divided into two. The value of the Duda and Hart Index is high and the value of the Pseudo T-squared is low when the number of groups is optimum. The Index result is completed and checked by a visual confirmation via the dendrogram. Dendrogram graphically presents the information concerning which observations are grouped together at various levels of similarity or dissimilarity. At the bottom of the dendrogram, each observation is considered its own cluster. Vertical lines extend up for each observation, and at various similarity or dissimilarity values, these lines are connected to the lines from other observations with a horizontal line. The observations continue to combine until, at the top of the dendrogram, all observations are grouped together.

3.4.2. Logistic analysis

We use a logistic regression technique to examine the individual characteristics factors affecting the adoption of mobile money in WAEMU. This technique is employed to find the model which would best fit in describing the relationship between the dichotomous characteristic of interest ($account\_mm_i$) and the independent variables (Z_i).The Logistic regression has been recognized as a new approach to obtain more precise estimates on the level of adoption in social sciences (Maddala, 1983; Adeogun et al., 2008). Using a Maximum Likelihood estimation approach, we estimate the following model:

$$account\_mm_i = 1\{\alpha Z_i + \varepsilon_i > 0\} \quad \textbf{3. 2}$$

$p_i = \Pr\left(account_{mm_i} = 1 \middle| Z\right) = \Lambda({Z_i}'\alpha)$ and $\Lambda(.)$is the cumulative density function (cdf) of the logistic distribution.

The likelihood of adoption equals to $\Lambda(Z'\alpha) = \frac{e^{(Z'\alpha)}}{1+e^{(Z'\alpha)}}$ **3. 3**

The marginal effect of the Logit model is $\Lambda(Z'\alpha)[1- \Lambda(Z'\alpha)]\ \alpha_j$ **3.4**

For the sake of robustness of the results, a cluster specific fixed effect (CSFE) model is estimated. This is a method that is well fitted for data with countries. In our model countries are defined as « clusters » (e.g. Cameron and Trivedi, 2005). We assume that the country characteristics are fixed and constants. The concern is that some aspects of the population regression model vary by cluster. Suppose the *ith* household in the overall sample is the *jth* household in the *cth* sampled cluster. A quite general model for clustered data is:

$$account\_mm_{jc} = 1\{{Z_{jc}}'\alpha_c + \eta_c + \varepsilon_{jc} > 0\} \quad \textbf{3. 5}$$

Here just the regression intercept η_c varies across clusters, whereas the slope coefficients are assumed to be constant across clusters. However, the intercept may possibly be correlated with the regressors

To examine the suitability of the logistic regression model, a number of tests are conducted. The Wald test is conducted to examine the contribution of each predictor variable to the model. We also performed the Lagrange multiplier (LM) test (Stukel, 1988).The McFadden's Pseudo-R2 and the Omnibus's "goodness-of-fit" test of Model Coefficients gives an overall indication of how well the model performs (Hosmer & Lemeshow, 2000; Cameron and Trivedi, 2009; Pallant, 2011). The Hosmer-Lemeshow test provides a validation of the

Logit model and is appropriate when the significance value is greater than 0.05 (Pallant, 2011). To diagnose the presence of multicollinearity in the Logit model, the tolerance test is performed. It shows how much of the variability of the specified independent variable is not explained by the other independent variables in the model (Pallant, 2011).

3.4.3. Data and descriptive statistics

In the cluster analysis, countries are grouped according to their rate of Mobile Money Adoption and the number of years spent since the first MMU was launched. Structural data on Mobile Money adoption is provided by the Financial Access Survey (FAS). The number of years spent is obtained in the GSMA Mobile Money Tracker Database. The macroeconomic variables about country characteristics are provided by the World Development indicators (2017). Our individual level data come from the World Bank's 2017 Global Findex database. The database is obtained thanks to surveys realized in 143 countries and covering almost 150,000 individuals worldwide. The target population is the entire civilian, non-institutionalized population aged 15 and above. The Global Findex database provides a large number of indicators on financial inclusion enabling to assess the amount of account penetration, the use of financial services, the purposes and motivations, the alternatives to formal finance, etc. It also provides micro-level information such as gender, age, income and education that will be used in our estimations. Our sample consists of 8000 adults from the 08 WAEMU countries because of their particular characteristics and their common monetary and financial policies.

Table 3.1 below displays the descriptive statistics for the individual level analysis of mobile money adoption in WAEMU. From the table, $account\_mm_i$ is a dummy variable, which takes 1 with probability *p* if individual *i* has a mobile money and 0 with probability *1-p* otherwise. Z_i is a vector of Controls variables including *account_fi, debitcard, Creditcard, phone, employed*; sex, *age, income and level of education* (Oumar et al., 2017). Indeed, *account_fi* is a dummy variable equal to one if the individual has an account at a financial institution and zero elsewhere. *Sex* is a dummy variable equal to one if the individual is a man and zero elsewhere. The age of the individual is represented with two measures: one with the number of years (*Age*) and the second with its square (*Age square*) in order to control for a possible nonlinear relation between age and mobile money adoption. Five dummy variables (1st poorest 20%, second poorest 20%, third poorest 20%, fourth poorest 20% and fifth poorest 20%) have been used to measure the relationship between income and mobile money adoption.

The First poorest 20% is a dummy variable equal to one if income is in the first income quintile, zero elsewise, and so on for the other dummies.

Concerning education, we use three dummy variables: Primary education and less, secondary education and completed Tertiary education. Primary education is equal to one if the individual has completed à to 8 years of education and 0 elsewhere. Secondary education is equal to one if the individual has achieved 9 to 15 years of education and zero elsewise. Tertiary education is equal to one if the individual has completed more than 15 years of education and zero elsewise. The base category dummy variable is primary school or less. ε_i is the error term.

Table 3.1: *Descriptive statistics*

Variable	**Definition**	**Obs**	**Percent**
Categorical variables			
Account_mm	=1 if the individual possesses a mobile money account	7000	28.67
Account_ FI	=1 if the individual possesses an account at a financial institution.	7000	25.63
Debit card	=1 if the individual possesses a debit card, 0 otherwise	6,925	12.10
Credit card	=1 if the individual possesses a credit card, 0 otherwise	6,887	4.05
Saved	=1 if the individual has saved during the last 12 months, 0 otherwise	7000	48.51
Borrowed	=1 if the individual has borrowed during the last 12 months, 0 otherwise	7000	46.50
Remittance received	=1 if the individual has received remittance during the last 12 months, 0 otherwise	6,946	34.12
Gender (Female)	=1 if the individual is a man, 0 otherwise	7000	58.54
Phone	=1 if the individual possesses a mobile phone, 0 otherwise	6,976	73.10
Employed	=1 if the individual is employed, 0 otherwise	6,000	67.73
Education		6,936	
Primary education	=1 if the individual has primary education, 0 otherwise		60.91
Secondary education	=1 if the individual has secondary education, 0 otherwise		36.38
University education	=1 if the individual has university education, 0 otherwise		2.71
Income quintile		7000	
First quintile)	=1 if the individual belongs to the category of the 20% poorest, 0 otherwise		32.51
Second quintile	=1 if the individual belongs to the category of the 40% poorest, 0 otherwise		15.77
Third quintile	=1 if the individual belongs to the category of the 60% poorest, 0 otherwise		16.74
Fourth quintile	=1 if the individual belongs to the category of the 80% poorest, 0 otherwise		18.40
Fifth quintile	=1 if the individual belongs to the category of the richest, 0 otherwise		21.19

Continuous variable	**Definition**	**Obs**	***Mean***	***Std.dev.***	***Min***	***Max***
Age	Is the age of the individual	6,944	32.725	14.16	15	99

Source: Author, 2019

In light of the descriptive statistic, although 73.03% of the adult population in WAEMU possesses a mobile phone, only 27.15% of them have a mobile money account as of 2017 data compared to about 7.9% in 2014. At the meantime, 24.60% of adults in WAEMU have an account at a financial institution showing the huge financial gap that mobile money should fill. Despite the positive trend of the mobile money adoption, the statistics support the fact that in WAEMU countries, people are still risk averse vis-à-vis the utilization of digital financial services. One reason for that may be the lack of financial education of poor people and the distance between mobile money services points in rural area as well as the high cost of mobile money services. Looking at the socioeconomic side, the Table 3.1 shows that on average 57.75 % of mobile money owners are female and they are on average 33 years old. Moreover, the literature has pointed out the important role of education in the adoption process. Indeed, 34.33% of individuals in the sample have a secondary level of education while only 3.68 % have completed the tertiary level. However, the sample consists mainly of uneducated and individuals with primary education level (61.14%). This may indicate that formal financial exclusion from either demand side or supply side is mainly present among this category of population and then mobile money should fill the gap by providing its services to them. Furthermore, our sample is dominated in the Fourth and fifth poorest 20% which respectively count 21.11% and 27.87% of the sample.

3.5. Results and Discussion

This section presents respectively the macroeconomic and microeconomic driving factors of mobile money adoption in WAEMU countries.

3.5.1. Macroeconomic driving factors of Mobile Money adoption in WAEMU

We ran a cluster analysis to regroup countries with similar mobile money adoption rate and number of years since the first Mobile Money for Unbanked (MMU) is implemented. A dendrogram helps to distinguish the groups formed by the cluster analysis (Figure 2.2), where the heights of the links of the dendrogram inform about the level of proximity between groups which are derived by observation of the dendrogram and the Duda and Hart index (Table 3.2).

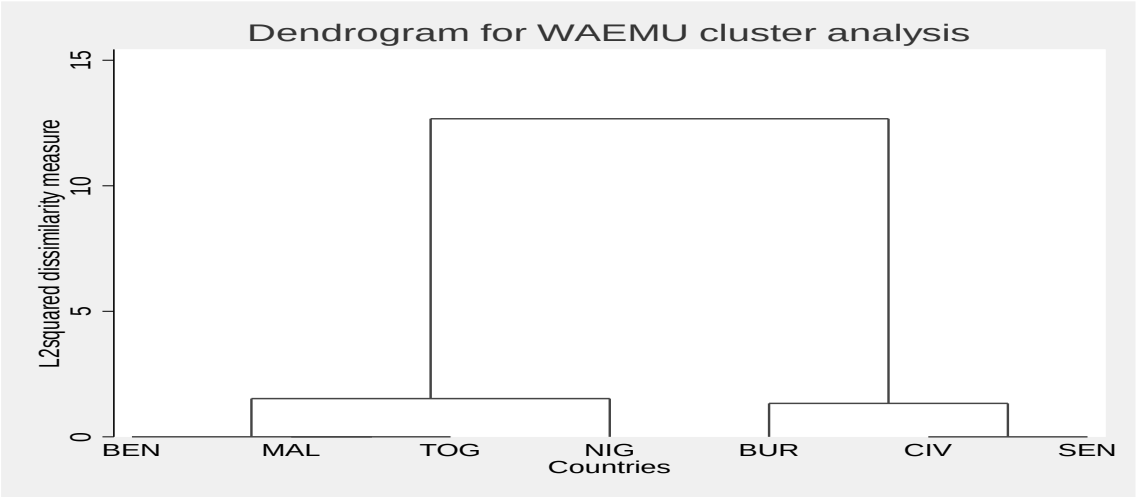

Figure 3. 2 Dendrogram for cluster analysis,WAEMU

Source: *Author, 2019*

Table 3. 2: *Duda and Hart Index*

Number of clusters	Duda and Hart	
	Je(2)/Je(1)	Pseudo T-square
1	0.184	22.14
2	0.002	766.31
3	0.000	2520.48
4	**0.211**	**3.73**
5	0.000	-

Source: *Author, 2019*

From the dendrogram and the Dado and hart Index, we observe four groups of countries. Two of them being composed by only one country, Niger and Burkina Faso. However, Niger is close to the cluster composed by Benin, Mali and Togo and Burkina is close to the cluster composed by Côte d'Ivoire and Senegal. In respect to the Mobile Money adoption rate, we construct two clusters which consist of the group of countries with low Mobile Money adoption rate and the group of countries with high Mobile Money adoption rate. A comparison of countries characteristics between the two clusters is made to identify which factors could explain the difference in Mobile Money adoption rate (Table 3.3). Indeed, the first difference is observed in terms of literacy rate where cluster1 has a literacy rate of 0.35 and cluster 2 has 0.40. It fits with the need for residents of cluster2 to have a good level of education to avoid

volitional control factors (Ajzen,1985, 1991). In fact, potential adopters must have the necessary abilities to adopt Mobile Money, mainly literacy skills and a sufficient perceived self efficacy (Khraim et al., 2011). This finding is confirmed by the customer readness with 0.27 for cluster 1 and 0.33 for cluster 2. Moreover, many studies have shown that early adopters are more educated (Chia et al., 2006; Tobin and Adjei, 2012).

Besides, cluster2 presents a higher mobile penetration (0.9899) than cluster1 (0.7916). People from cluster2 countries are more familiar with mobile phone technology which reduces the complexity of using fianancial mobile services (Rogers, 1983; Bosire, 2012). Moreover, Cluster2 presents a higher labour force which could confirm the need for residents of this cluster to send a part of their earning to their family. In addition, the existence of a good mobile infrastructure as well as the affordability of the mobile services is very important in the adoption proccess of Mobile money services. Indeed, cluster2 has on average 0.251 as mobile infastructure score while cluster1 has 0.179. This means that the existence of mobile infrastructure is a key issue for bridging the banking infrastructure gap. Similarly, the affordability of mobile phone services leads to an access of financial services at low cost.

Unlikely to some studies such as the one of Peruta (2015), our study found that country with high mobile money adoption rate are less endowned in banking infrastructure than country with very low mobile money adoption rate. In fact, there are 4.46 bank branches per 100000 inhabitants in cluster1 and 4.05 bank branches per 100000 inhabitants in country with high adoption rate. This may be explained by the fact that the lack of banking infrastructure compel people to opt for an innovation tool to bridge this gap. Similarly, Beck et al. (2007) found that higher branch and ATM intensity were interpreted as higher possibilities for households and enterprises to have access to financial services and opportunity to use them. Reversely to our findings, Jack and Suri (2011) reveal that early adopters of Mobile money services are principally banked people. This means that Mobile Money services could not be considered independentely from the existing banking system. It is a “banking beyond branches” solution according to Alexandre et al.(2010). We also noticed that the adoption of a new technology depends on the income status. Indeed, countries from cluster2 in which the Mobile money adoption rate is high , have on average USD 1030 of Gross National Income per capita while the low adopting countries have on average USD 636 of Gross National Income per capita.

Table 3. 3: *Mean vectors of the clusters analysis*

Country characteristics	Cluster1	Cluster2	Mean Dif
MM adoption rate	0.173	0.329	0.156**
Years spent since first implementation	7.800	9.666	1.866**
Literacy rate	0.354	0.404	0.049*
Mobile phone subscribers per 100	0.791	0.989	0.198**
Internet adoption rate	0.097	0.220	12.340*
Consumer readiness	0.277	0.332	0.054*
Urban growth	0.043	0.044	0.000
Urban population	0.368	0.440	0.072*
Mobile Infrastructure	0.179	0.251	0.071*
Affordability of mobile services	0.350	0.433	0.083**
Bank Branch per 100000	4.460	4.050	- 0.410***
ATM per 100000	5.038	5.220	0.182**
GNI per Capita	636	1030	394***
Labor force	5632612.4	6728508.67	1095896*

*(10%). ** (5%) *** (1%).
Cluster1: Benin, Mali, Niger and Togo
Cluster2: Burkina Faso, Ivory Coast and Senegal

Source: Author, 2019

3.5.2. Microeconomic driving factors of Mobile Money adoption in WAEMU

Table 3.4 provides the estimation of Logit model and its marginal effects outcomes as well as the Cluster Specific Fixed Effect Logit (Soumare et al., 2016; Cameron and Trivedi, 2005) for robustness check. The Logit model was retained preferably to probit model after the Hausman test. In addition, all the validation tests confirm that the Logit model fits well for this analysis. Indeed, the Wald test and the Likelihood-ratio test indicated support the inclusion of age square in the model. The Omnibus goodness-of-fit test is highly significant. Hence, the relationship between the combination of the independent variables and the dependent variable is verified and validated. The significance value of the Hosmer-Lemeshow test is greater than 0.05 confirming the fact that the Logit model is valid and appropriate. Moreover, we estimated a fixed effect Logit with the same data and found that the Logit model is appropriate and robust for this analysis. The coefficients of the fixed effect estimations are almost the same as those of the standard Logit estimation.

Table 3.4: *Estimation results and Robustness check*

	Logit Estimation		**Cluster Specific Fixed effect (Robustness check)**	
VARIABLES	Mobile Money	Marg Effect	Mobile Money	Cond Marg Effect
	(1)	(2)	(3)	(4)
Sex (Female)	0.220***	0.037***	0.220***	0.018***
	(0.064)	(0.010)	(0.070)	(0.005)
Age	0.032***	0.005***	0.0320***	0.002***
	(0.011)	(0.001)	(0.008)	(0.000)
Age square	-0.000445***	-7.52e-05***	-0.000***	-3.80e-05***
	(0.000)	(2.41e-05)	(0.000)	(9.12e-06)
Education (Primary and less as base category)				
Secondary	0.691***	0.122***	0.691***	0.054***
	(0.067)	(0.012)	(0.055)	(0.006)
Tertiary	0.930***	0.169***	0.929***	0.066***
	(0.173)	(0.034)	(0.136)	(0.013)
Income Statuts (First quintile)				
Second quintile	0.380***	0.061***	0.379***	0.035***
	(0.114)	(0.018)	(0.106)	(0.010)
Third quintile	0.361***	0.058***	0.360***	0.034***
	(0.112)	(0.017)	(0.088)	(0.006)
Fourth quintile	0.356***	0.057***	0.355**	0.033***
	(0.107)	(0.017)	(0.142)	(0.012)
Fifth quintile	0.547***	0.090***	0.546***	0.049***
	(0.103)	(0.016)	(0.119)	(0.010)
Account at a FI	0.501***	0.084***	0.500***	0.042***
	(0.0836)	(0.014)	(0.121)	(0.010)
Debitcard	0.016	0.002	0.016	0.001
	(0.108)	(0.018)	(0.095)	(0.008)
Creditcard	0.674***	0.114***	0.673***	0.057***
	(0.155)	(0.026)	(0.101)	(0.012)
Mobile phone	0.922***	0.156***	0.921***	0.078***
	(0.086)	(0.014)	(0.115)	(0.011)
Employed	0.578***	0.097***	0.577***	0.049***
	(0.070)	(0.011)	(0.055)	(0.007)
Country specific effect (Togo as base category)				
Benin	-0.129	-0.021		
	(0.114)	(0.019)		
Niger	-0.732***	-0.124***		
	(0.148)	(0.025)		
Mali	0.482***	0.081***		
	(0.116)	(0.019)		
Senegal	0.858***	0.145***		
	(0.112)	(0.018)		
Burkina	0.951***	0.161***		
	(0.110)	(0.018)		
Ivory Coast	0.993***	0.168***		
	(0.109)	(0.018)		
Constant	-3.979***			
	(0.243)			
Pseudo R2	0.1561			0.1105
Wald	971.95			
Log likelihood	-3412.9115			-3388.8356
Observations	6,721	6,721	6,721	6,721

*(10%). ** (5%) *** (1%). z - stat (.). The average marginal effect dy/dx for factor levels is the discrete change from the base level.

Source: *Author, 2019*

The results from the second column of the Table 3.4 show that all the individual characteristics are significant at 1% level. In addition, apart from the low performing countries including Benin and Togo, the other country variables are significant at 1% level. The variable Age has a nonlinear relationship with the indicator of mobile money adoption. This effect is significantly positive and negative respectively for Age and Age square with an optimal age of 34. These results are consistent with the literature at some extent. However, Age is often regarded in the literature as relating negatively with the possibility of innovation adoption, because the youth are often more adventurous and more fascinated by technology than the old (AbuShanab and Pearson, 2007; Schiffman and Kanuk, 2009; Mbiti and Weil, 2011 and Fall et al 2015). Hence younger people are more likely to have mobile money account, but after a certain age, the probability of having such an account decrease. Besides, consistently with Laforet and Li (2005), Zin and Weill (2016) we find that being a man increases the probability of having a mobile money account. Indeed, Laforet and Li (2005), investigating the determinant of mobile banking and internet banking adoption in China found that the adoption rate is higher for man than for women.

Hove and Dubus (2019) as well as Zin and Weill (2016) found that being a woman decreases the probability of having an account. In contrast, Riqueline and Ries (2010) found in Singapore that the convenience and the social norms are the key driving factors, which influence the women's adoption of a technology such as mobile banking. Besides, all categories of income (income status) significantly and gradually influence the mobile money account ownership in WAEMU. Greater income is therefore associated with the likelihood of adopting mobile money. According to AbuShanab and Pearson (2007), income level is positively and significantly related to adoption of innovation in financial sector. This because those with high income are willing to rapidly adopt e-banking to access their funds. Similarly, Kolodinsky et al. (2000) found that the likelihood of adopting e-banking innovations increases amongst people with higher financial assets and higher levels of education. So, education is positively and significantly associated with the likelihood of having a mobile money account. Like Rogers (1995), Allen et al. (2016) worldwide, Zin and Weill (2016) worldwide, Fungácová and Weill (2015) in China, Soumaré et al. (2016) in WAEMU and CAEMC, we find that more educated adults are more likely to access digital financial services and by this way to be financially included. Our findings concur with those of Domeher et al. (2014) that indicate the likelihood of educated customers to understand the risks and benefits pertaining to an innovative financial

product. In addition, the ownership of an account at a financial institution; a debit card as well as a credit card positively affect the likelihood of adopting mobile money in WAEMU.

Moreover, the ownership of a mobile phone as well as being employed are key to adopting mobile money in the WAEMU countries. Since we cannot directly interpret the result from Logit estimation, we compute marginal effect based on the outcome and the same variables of the Logit estimation. The third column of table 3.4 then presents the marginal effect outcomes of the Logit estimations for the main indicators of digital financial services adoption in WAEMU. Thanks to the calculation of the marginal effects, we can conclude that age, gender, education, high income and the country of residence are the most important factors explaining the ownership of a mobile money account. Being a man increases the probability of having a mobile money account by 3.72%. This probability is about 0.54% if the individual got old up to a certain threshold (34 years) from where it starts decreasing.

For an individual who has a secondary level of education, the probability of having a mobile money account increase by 12.20 % whereas the one of tertiary education increases by 16.90 % compared to individuals with primary and less education. This gap from the group of primary and less is due to the fact that the proportion of uneducated people in the base category is high and they are generally uncomfortable even with the usage of SMS on their mobile phone. This gap is very impressive as regards to the tertiary educated people. In fact, these impressive findings can be justified by the fact that those who adopt and use a mobile money for their transactions are very comfortable with its services because of the delicateness of the operation they used to make at their bank or microfinance. Explicitly, in WAEMU, it is very difficult to make an operation at bank or at a microfinance institution without spending long moment in the waiting line. For that reason, the very educated people often prefer having the ubiquitous tools which is the mobile money to save their time and even to support their relatives in the remote area (Chogo and Sedoyeka, 2014). However, it is worth noting that authors are not all unanimous about the role of education on the mobile money adoption. But it is obvious that in the context of WAEMU, as generally in sub–Saharan African countries, education is a key-driving factor in the process of adoption of an innovative product in the financial sector. However, the experience gained from using financial account is driven by other factors for mobile money adoption.

In accordance with the literature, the results pointed out that the probability to adopt mobile money increases by 8.47% and 11.4% respectively when the individual has already an account at a financial institution and a credit card. For instance, Jack and Suri (2011) reveal that

early adopters of Mobile money services are principally banked people. The key role of income in the process of adoption of digital finance and mobile money specifically is also stood out by the results. Indeed, the probability of adopting mobile money service increase respectively with the category of income. The effect is higher with the fifth quintile than it is with the fourth, third and second quintile. Being therefore in the category of the richest increases the likelihood of adopting the mobile money of 9.08% as regard to the first quintile category. This difference is respectively about 5.72%, 5.81%, 6.14% when the individual belongs to the fourth, third and the second quintile category. As a result, income is very crucial in the process of adoption and effective usage of a new technology in the domain of finance. This is because poor people are constrained by sufficient financial resources that might allow them to face their immediate needs and looking then for an innovative product to adopt. Another key driving factor of mobile money is the detention of mobile phone.

With this ubiquitous tool, people are willing to access financial services even in remote area. For instance, the results show that the ownership of a mobile phone increases the probability of mobile money adoption by 15.60%. However, the employed individuals are more willing to adopt mobile money than the unemployed people. This is because they need to save and even make remittance to their family via mobile money. In fact, being employed increased the probability of mobile money adoption by 9.77%. This result is confirmed by the high correlation between employment status and remittance in the correlation table in appendix II.

Last but not the least, our findings confirm the fact that each WAEMU country displays different dynamics and responses diversely to digital finance. For instance, apart from Benin, Niger and Togo, which are the poorest digital financial market in WAEMU, all other WAEMU countries have a significant dynamics of mobile money adoption. Being in Côte d'Ivoire, Burkina Faso, Senegal and Mali increases the likelihood of adopting mobile money of respectively 16.80%, 16.1%, 14.5% and 8.16%. However, being in the remaining countries reduce the probability of mobile money adoption. This result can be explained regarding the feeble revenue as well as the heavy sociocultural consideration in those poorly performing countries.

3.6. Concluding remarks

WAEMU region consists of countries with low rate of digital financial inclusion compared to their counterpart of east Africa especially Kenya. At the same time, these countries are among those that are witnessing rapid expansion of mobile phone penetration in the world.

It is then conceivable to pursuit the financial inclusion goal by developing financial services on mobile phone. In other words, the digital finance services might be a key-driving factor of expanding financial inclusion in WAEMU. This paper aimed then to investigate the driving factors of digital finance and particularly mobile money adoption in WAEMU. For that purpose, using both a country level data and a sample of 8000 adults in WAEMU from the World Bank Global Findex (2017) database, we made first, a cluster analysis to investigate the macroeconomic driving factors of mobile money adoption.

We found that country characteristic such as literacy rate, labor force, mobile infrastructure and even banking infrastructure in terms of numbers of ATM per 100000 people are the main macroeconomic determinants of mobile money adoption. We estimate thereafter a logistic regression to examine the microeconomic factors affecting the adoption of mobile money in the WAEMU countries. The study pointed out very interesting results for policy implications. It finds that being young, man, educated, relatively richer and even banked increases the likelihood of adopting mobile money in WAEMU. The findings also reveal that some countries such as Côte d'Ivoire, Mali, Senegal and Burkina Faso are performing well as far as digital financial inclusion is concerned due to their policy implemented and some structural factors.

These findings support the view that policies favoring mobile money adoption may boost financial inclusion and alleviate poverty in developing countries especially in WAEMU area. Moreover, all the WAEMU countries should follow the example of Kenya where the government made flexible the regulation in the sector of digital finance leading the M-PESA as a success story in Africa. The central Bank of the WAEMU (BCEAO) in collaboration with governments of WAEMU countries should take steps toward innovative financial inclusion strategy including, financial education, telecommunication infrastructure development across remote areas. However, considering the risk pertaining to digital technologies, regulatory policy ensuring data protection and trust in the usage of digital technologies are key to a mass adoption of digital finance leading to the reduction of poverty in that region.

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Appendix II

A.2.1. Logit estimation

```
.  logit mm sex age age2 i.educ i.inc_q account_fin debitcard creditcard phone employed benin bur
> kina civ mali niger senegal togo

note: togo omitted because of collinearity
Iteration 0:   log likelihood = -4044.2913
Iteration 1:   log likelihood = -3450.3152
Iteration 2:   log likelihood = -3413.2561
Iteration 3:   log likelihood = -3412.9116
Iteration 4:   log likelihood = -3412.9115

Logistic regression                             Number of obs     =      6,721
                                                LR chi2(20)       =    1262.76
                                                Prob > chi2       =     0.0000
Log likelihood = -3412.9115                     Pseudo R2         =     0.1561
```

mm	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.2200349	.0638843	3.44	0.001	.094824	.3452458
age	.03208	.0110845	2.89	0.004	.0103549	.0538052
age2	-.0004447	.0001382	-3.22	0.001	-.0007155	-.0001739
educ						
secondary	.6914672	.0674367	10.25	0.000	.5592937	.8236406
completed tertiary or more	.9300898	.1717389	5.42	0.000	.5934878	1.266692
inc_q						
Second 20%	.3798487	.1135037	3.35	0.001	.1573856	.6023118
Middle 20%	.3606345	.1107349	3.26	0.001	.1435981	.577671
Fourth 20%	.3555315	.1072916	3.31	0.001	.1452439	.5658191
Richest 20%	.5469441	.1037815	5.27	0.000	.3435361	.7503521
account_fin	.5010941	.0817464	6.13	0.000	.3408741	.6613142
debitcard	.0163863	.1056492	0.16	0.877	-.1906823	.223455
creditcard	.6739193	.1468934	4.59	0.000	.3860135	.9618252
phone	.9217365	.0875054	10.53	0.000	.7502291	1.093244
employed	.5778306	.0703838	8.21	0.000	.4398808	.7157803
benin	-.1285994	.1142052	-1.13	0.260	-.3524374	.0952386
burkina	.9507916	.1088049	8.74	0.000	.737538	1.164045
civ	.9925995	.108495	9.15	0.000	.7799532	1.205246
mali	.4823759	.1133317	4.26	0.000	.2602499	.7045019
niger	-.7322287	.1469276	-4.98	0.000	-1.020202	-.4442559
senegal	.8576946	.110077	7.79	0.000	.6419476	1.073442
togo	0	(omitted)				
_cons	-3.979	.2369463	-16.79	0.000	-4.443406	-3.514594

A.2.2. Probit estimation

```
. probit mm sex age age2 i.educ i.inc_q account_fin debitcard creditcard phone employed benin bur
> kina civ mali niger senegal togo

note: togo omitted because of collinearity
Iteration 0:   log likelihood = -4044.2913
Iteration 1:   log likelihood = -3422.6798
Iteration 2:   log likelihood = -3410.2122
Iteration 3:   log likelihood = -3410.1769
Iteration 4:   log likelihood = -3410.1769

Probit regression                               Number of obs     =      6,721
                                                LR chi2(20)       =    1268.23
                                                Prob > chi2       =     0.0000
Log likelihood = -3410.1769                     Pseudo R2         =     0.1568
```

mm	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.1324407	.0374447	3.54	0.000	.0590504	.2058311
age	.0176167	.0062633	2.81	0.005	.0053408	.0298925
age2	-.0002415	.0000771	-3.13	0.002	-.0003926	-.0000904
educ						
secondary	.4110272	.0401495	10.24	0.000	.3323356	.4897188
completed tertiary or more	.5569088	.1045601	5.33	0.000	.3519748	.7618429
inc_q						
Second 20%	.2222721	.0653144	3.40	0.001	.0942582	.3502861
Middle 20%	.2134346	.0637273	3.35	0.001	.0885314	.3383378
Fourth 20%	.2039213	.0619836	3.29	0.001	.0824356	.325407
Richest 20%	.3173945	.0602253	5.27	0.000	.1993551	.435434
account_fin	.3057161	.0487436	6.27	0.000	.2101804	.4012519
debitcard	.0158562	.0637548	0.25	0.804	-.1091008	.1408133
creditcard	.3989428	.0876054	4.55	0.000	.2272394	.5706462
phone	.5253508	.0482492	10.89	0.000	.4307841	.6199174
employed	.3409245	.0407263	8.37	0.000	.2611025	.4207466
benin	-.0861461	.0666606	-1.29	0.196	-.2167985	.0445063
burkina	.5593364	.0641999	8.71	0.000	.4335069	.6851659
civ	.5873602	.0641414	9.16	0.000	.4616453	.7130751
mali	.279889	.0661213	4.23	0.000	.1502937	.4094844
niger	-.3963203	.0798331	-4.96	0.000	-.5527902	-.2398504
senegal	.5056258	.064572	7.83	0.000	.3790671	.6321846
togo	0	(omitted)				
_cons	-2.324721	.1335148	-17.41	0.000	-2.586405	-2.063037

A.2.3. Hausman test

.

	Coefficients			
	(b) log	(B) pro	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
sex	.2200349	.1324407	.0875942	.05176
age	.03208	.0176167	.0144634	.0091453
age2	-.0004447	-.0002415	-.0002031	.0001147
educ				
2	.6914672	.4110272	.28044	.0541823
3	.9300898	.5569088	.373181	.1362403
inc_q				
2	.3798487	.2222721	.1575766	.0928284
3	.3606345	.2134346	.1471999	.0905597
4	.3555315	.2039213	.1516102	.0875758
5	.5469441	.3173945	.2295496	.0845193
account_fin	.5010941	.3057161	.195378	.0656242
debitcard	.0163863	.0158562	.0005301	.0842442
creditcard	.6739193	.3989428	.2749765	.1179109
phone	.9217365	.5253508	.3963857	.0730014
employed	.5778306	.3409245	.236906	.0574042
benin	-.1285994	-.0861461	-.0424533	.0927318
burkina	.9507916	.5593364	.3914551	.0878457
civ	.9925995	.5873602	.4052394	.0875046
mali	.4823759	.279889	.2024868	.0920437
niger	-.7322287	-.3963203	-.3359084	.1233467
senegal	.8576946	.5056258	.3520688	.0891482

b = consistent under Ho and Ha; obtained from logit
B = inconsistent under Ha, efficient under Ho; obtained from probit

Test: Ho: difference in coefficients not systematic

chi2(19) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 226.26
Prob>chi2 = 0.0000

A.2.4. Logit robust standard errors

```
. logit mm sex age age2 i.educ i.inc_q account_fin debitcard creditcard phone employed benin burk
> ina civ mali niger senegal togo, robust

note: togo omitted because of collinearity
Iteration 0:   log pseudolikelihood = -4044.2913
Iteration 1:   log pseudolikelihood = -3450.3152
Iteration 2:   log pseudolikelihood = -3413.2561
Iteration 3:   log pseudolikelihood = -3412.9116
Iteration 4:   log pseudolikelihood = -3412.9115

Logistic regression                             Number of obs     =      6,721
                                                Wald chi2(20)     =     971.95
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -3412.9115               Pseudo R2         =     0.1561
```

mm	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.2200349	.0640155	3.44	0.001	.0945668	.3455029
age	.03208	.0113196	2.83	0.005	.009894	.0542661
age2	-.0004447	.000143	-3.11	0.002	-.000725	-.0001644
educ						
secondary	.6914672	.0669963	10.32	0.000	.5601568	.8227776
completed tertiary or more	.9300898	.1730756	5.37	0.000	.5908678	1.269312
inc_q						
Second 20%	.3798487	.1138225	3.34	0.001	.1567607	.6029367
Middle 20%	.3606345	.111567	3.23	0.001	.1419672	.5793018
Fourth 20%	.3555315	.1073704	3.31	0.001	.1450894	.5659737
Richest 20%	.5469441	.1033302	5.29	0.000	.3444205	.7494676
account_fin	.5010941	.0835569	6.00	0.000	.3373256	.6648626
debitcard	.0163863	.1079607	0.15	0.879	-.1952127	.2279854
creditcard	.6739193	.1545522	4.36	0.000	.3710026	.976836
phone	.9217365	.0864347	10.66	0.000	.7523277	1.091145
employed	.5778306	.0704183	8.21	0.000	.4398132	.7158479
benin	-.1285994	.1137735	-1.13	0.258	-.3515915	.0943927
burkina	.9507916	.11025	8.62	0.000	.7347055	1.166878
civ	.9925995	.1091097	9.10	0.000	.7787485	1.206451
mali	.4823759	.115741	4.17	0.000	.2555277	.7092241
niger	-.7322287	.1477131	-4.96	0.000	-1.021741	-.4427165
senegal	.8576946	.1121659	7.65	0.000	.6378535	1.077536
togo	0	(omitted)				
_cons	-3.979	.2426503	-16.40	0.000	-4.454586	-3.503414

A.2.5. Marginal effect

```
Average marginal effects                        Number of obs     =      6,721
Model VCE    : Robust

Expression   : Pr(mm), predict()
dy/dx w.r.t. : sex age age2 2.educ 3.educ 2.inc_q 3.inc_q 4.inc_q 5.inc_q account_fin debitcard
               creditcard phone employed benin burkina civ mali niger senegal togo
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.0372052	.0108031	3.44	0.001	.0160316	.0583787
age	.0054243	.0019075	2.84	0.004	.0016857	.009163
age2	-.0000752	.0000241	-3.12	0.002	-.0001224	-.000028
educ						
secondary	.1220007	.0120481	10.13	0.000	.0983869	.1456145
completed tertiary or more	.1690167	.0343378	4.92	0.000	.1017159	.2363175
inc_q						
Second 20%	.061383	.0182405	3.37	0.001	.0256322	.0971338
Middle 20%	.0580909	.0177776	3.27	0.001	.0232475	.0929343
Fourth 20%	.0572197	.0169974	3.37	0.001	.0239054	.0905339
Richest 20%	.0907611	.0166134	5.46	0.000	.0581995	.1233228
account_fin	.0847288	.0140209	6.04	0.000	.0572484	.1122091
debitcard	.0027707	.0182541	0.15	0.879	-.0330066	.0385481
creditcard	.1139513	.0259883	4.38	0.000	.0630152	.1648875
phone	.1558541	.0143809	10.84	0.000	.1276681	.1840402
employed	.0977039	.0117271	8.33	0.000	.0747191	.1206887
benin	-.0217446	.0192456	-1.13	0.259	-.0594653	.0159762
burkina	.160767	.0181984	8.83	0.000	.1250988	.1964351
civ	.1678362	.0179733	9.34	0.000	.1326091	.2030633
mali	.0815637	.019466	4.19	0.000	.0434111	.1197164
niger	-.1238107	.0249591	-4.96	0.000	-.1727297	-.0748918
senegal	.1450254	.0186566	7.77	0.000	.1084591	.1815918
togo	0	(omitted)				

Note: dy/dx for factor levels is the discrete change from the base level.

A.2.6. Robustness Check: Fixed effect Logit estimation

```
. clogit mm sex age age2 i.educ i.inc_q account_fin debitcard creditcard phone employed, group(co
> untry) robust
note: multiple positive outcomes within groups encountered.

Iteration 0:   log pseudolikelihood =  -3393.363
Iteration 1:   log pseudolikelihood = -3388.8367
Iteration 2:   log pseudolikelihood = -3388.8356
Iteration 3:   log pseudolikelihood = -3388.8356

Conditional (fixed-effects) logistic regression

                                                Number of obs     =      6,721
                                                Wald chi2(6)      =          .
                                                Prob > chi2       =          .
Log pseudolikelihood = -3388.8356               Pseudo R2         =     0.1105

                                              (Std. Err. adjusted for clustering on country)
------------------------------------------------------------------------------
             |               Robust
          mm |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         sex |   .2197923   .0702474     3.13   0.002     .0821099    .3574747
         age |   .0320445   .0087595     3.66   0.000     .0148762    .0492127
        age2 |  -.0004442   .0001159    -3.83   0.000    -.0006713   -.0002171
             |
        educ |
   secondary |   .6906342   .0555441    12.43   0.000     .5817697    .7994987
completed t~y |    .928877   .1359747     6.83   0.000     .6623715    1.195383
             |
       inc_q |
  Second 20% |   .3794669   .1061563     3.57   0.000     .1714044    .5875295
  Middle 20% |   .3602732   .0887101     4.06   0.000     .1864046    .5341418
  Fourth 20% |   .3551794     .14182     2.50   0.012     .0772173    .6331415
 Richest 20% |   .5463365   .1189658     4.59   0.000     .3131678    .7795052
             |
  account_fin |   .5004597   .1212493     4.13   0.000     .2628154    .7381041
    debitcard |   .0163326   .0954916     0.17   0.864    -.1708276    .2034928
   creditcard |   .6730693    .100624     6.69   0.000       .47585    .8702887
        phone |   .9208647   .1147633     8.02   0.000     .6959327    1.145797
     employed |   .5771886   .0559173    10.32   0.000     .4675926    .6867845
------------------------------------------------------------------------------
```

A.2.7. Conditional marginal effect

```
.  margins, dydx(_all)post

Average marginal effects                        Number of obs     =      6,721
Model VCE    : Robust

Expression   : Pr(mm|fixed effect is 0), predict(pu0)
dy/dx w.r.t. : sex age age2 2.educ 3.educ 2.inc_q 3.inc_q 4.inc_q 5.inc_q account_fin debitcard
               creditcard phone employed
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.0188045	.0057485	3.27	0.001	.0075376	.0300715
age	.0027416	.0005731	4.78	0.000	.0016184	.0038648
age2	-.000038	9.12e-06	-4.17	0.000	-.0000559	-.0000201
educ						
secondary	.0540013	.006623	8.15	0.000	.0410204	.0669821
completed tertiary or more	.0669046	.0129507	5.17	0.000	.0415217	.0922875
inc_q						
Second 20%	.0358979	.0108962	3.29	0.001	.0145418	.057254
Middle 20%	.0342929	.0067493	5.08	0.000	.0210645	.0475213
Fourth 20%	.0338634	.0125709	2.69	0.007	.0092248	.0585019
Richest 20%	.0489696	.0105208	4.65	0.000	.0283492	.0695899
account_fin	.0428173	.0105287	4.07	0.000	.0221813	.0634532
debitcard	.0013973	.0082805	0.17	0.866	-.0148321	.0176268
creditcard	.057585	.0129196	4.46	0.000	.032263	.0829071
phone	.0787854	.0115922	6.80	0.000	.0560651	.1015057
employed	.0493819	.0071859	6.87	0.000	.0352977	.063466

A.2.8. Logit post estimation test

○ *Goodness of fit test*

```
. estat gof, group(10)

Logistic model for mm, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =      7615
             number of groups =        10
     Hosmer-Lemeshow chi2(8) =         6.86
                 Prob > chi2 =         0.5513
```

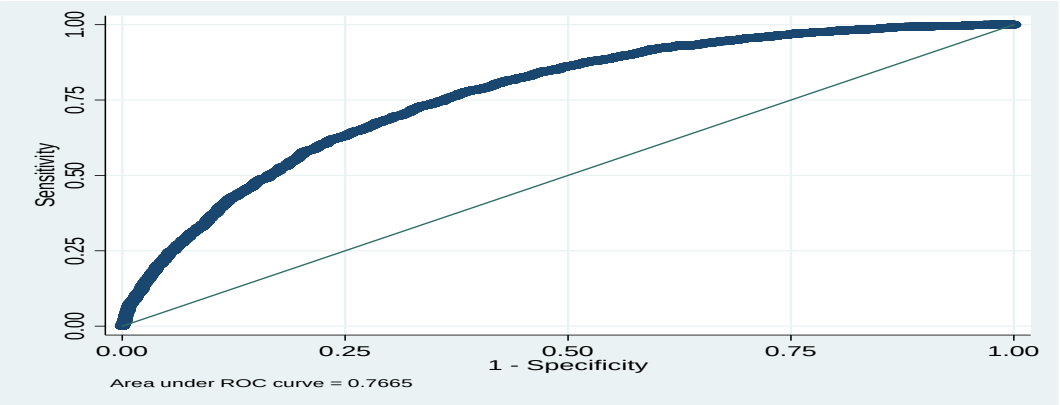
○ Wald test of no interaction

```
. test age2

 ( 1)  [mm]age2 = 0

           chi2(  1) =    9.67
         Prob > chi2 =    0.0019
```

○ Likelihood-ratio test

```
. lrtest B

Likelihood-ratio test                           LR chi2(1)  =     11.04
(Assumption: . nested in B)                     Prob > chi2 =    0.0009
```

Lroc curve


Sensitivity
0.00
0.25
0.50
0.75
1.00
0.00
0.25
0.50
0.75
1.00
1 - Specificity
Area under ROC curve = 0.7665

t

A.2.8. Correlation table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
age	1	1.0000																	
saved	2	0.0032	1.0000																
borrowed	3	0.0108	0.2758	1.0000															
mm	4	-0.0315	0.2575	0.1418	1.0000														
sex	5	0.0564	0.0591	0.0423		1.0000													
Primary_edu	6	0.2265	-0.1406	-0.0480	-0.2362	-0.1637	1.0000												
Secondary_edu	7	-0.2316	0.1064	0.0283	0.2031	0.1311	-0.9230	1.0000											
Tertiary_educ	8	0.0011	0.0935	0.0520	0.0956	0.0719	-0.2465	-0.1455	1.0000										
firstincom~t	9	0.0361	-0.1061	-0.0477	-0.0957	-0.0682	0.1380	-0.1181	-0.0572	1.0000									
secincomep~t	10	0.0213	-0.0468	0.0004	-0.0325	-0.0218	0.1187	-0.0964	-0.0623	-0.1918	1.0000								
thirdincom~t	11	0.0139	-0.0309	-0.0057	-0.0307	-0.0165	0.0686	-0.0507	-0.0488	-0.2034	-0.2135	1.0000							
fourthinco~t	12	-0.0222	0.0176	0.0123	0.0009	0.0083	-0.0301	0.0321	-0.0034	-0.2222	-0.2333	-0.2473	1.0000						
fifthincom~t	13	-0.0386	0.1349	0.0317	0.1296	0.0796	-0.2415	0.1898	0.1430	-0.2669	-0.2802	-0.2971	-0.3246	1.0000					
fi_account	14	0.0629	0.3005	0.1758	0.2136	0.1297	-0.2487	0.1721	0.2061	-0.1075	-0.0734	-0.0580	0.0117	0.1870	1.0000				
phone	15	0.0117	0.1837	0.0669	0.2277	0.1545	-0.2278	0.1902	0.1066	-0.0608	-0.0580	-0.0453	0.0091	0.1279	0.2050	1.0000			
employed	16	0.0109	0.2004	0.1189	0.1402	0.1430	-0.0129	-0.0067	0.0500	-0.0404	-0.0014	-0.0032	-0.0008	0.0372	0.1362	0.1483	1.0000		
debitcard	17	0.0595	0.2338	0.1255	0.1771	0.0954	-0.2098	0.1314	0.2084	-0.0817	-0.0686	-0.0438	-0.0222	0.1808	0.5871	0.1473	0.0841	1.0000	
Creditcard	18	0.0362	0.1324	0.1566	0.1138	0.0199	-0.0597	0.0426	0.0461	-0.0076	-0.0017	-0.0053	-0.0173	0.0279	0.2699	0.0484	0.0503	0.3387	1.0000

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ESSAY III

From Expanding Financial Services to Tackling Poverty: The Accelerating Role of Digital Finances in WAEMU

Abstract

This essay aims at assessing the accelerating role of digital technology in fighting poverty through financial inclusion in the WAEMU countries. Based on a sample of WAEMU's adult population from the World Bank's Findex database, we estimate a recursive bivariate probit that addresses the endogeneity issues. Findings show that both mobile led financial inclusion and bank led financial inclusion are essential for sustainable poverty alleviation in WAEMU. In addition, the change in poverty status can be indirectly due to certain driving factors of mobile money adoption including the ownership of mobile phones and education achievements which are conducive to digital financial inclusion. It stood out as the key role of governments to accompany both Mobile Network Operators (MNOs) and Financial Institutions to deliver financial services through technologies to last miles. This requires then a flexible regulation toward the digital finance business in WAEMU.

Keywords: Digital Financial Inclusion, Poverty, Recursive Bivariate probit, WAEMU

JEL Code: D14-I32-O33

Résumé

Cet essai vise à évaluer l'effet de l'inclusion financière digitale sur la réduction de la pauvreté dans les pays de l'UEMOA. Sur la base d'un échantillon de la population adulte des pays de l'UEMOA tiré de la base de données de la Findex de la banque mondiale nous estimons un probit bivarié récursif qui permet de tenir compte de l'endogénéité. Il ressort de nos résultats que l'adoption du mobile money affecte significativement, positivement et diversement la probabilité de sortir de la pauvreté dans les pays de l'UEMOA selon leur niveau d'inclusion financière. L'inclusion financière bancaire ainsi que l'inclusion financière digitale sont toutes autant importantes pour la réduction de la pauvreté dans l'UEMOA. De plus, cette réduction de la pauvreté est aussi due indirectement à certains facteurs déterminant l'adoption du mobile money dont la détention du téléphone portable et son utilisation pour accéder aux services financiers. Il urge alors pour les décideurs de politique économique de favoriser les Opérateurs de téléphonie Mobile ainsi que les institutions financières dans leurs efforts pour l'inclusion financière dans l'UEMOA en rendant plus flexible la régulation concernant la finance digitale.

Mots clés : Inclusion Financière Digitale, Pauvreté, Bivariate probit, UEMOA

JEL Code: D14-I32-O33

4.1. Introduction

Numerous studies on the financial inclusion-poverty nexus have investigated factors that influence financial inclusion and assessed the impact of such inclusion on poverty and income inequality in the world (Park and Mercado, 2018; Dawood et al., 2019; Inoue, 2019; Mushtaq and Bruneau, 2019; World Bank, 2020; Bukari et al.,2020; Churchill and Marisetty, 2020). Most of these studies are in line with the theoretical framework of Schumpeter (1911). Indeed, Schumpeter (1911) highlight the importance of finance for economic growth and indirectly for poverty reduction. However, the achievement of the Sustainable Development Goals (SDGs) including the poverty issues, is undeniably a major challenge for national, regional and even international organizations. In addition, the eradication of the extreme poverty is the first and the most important point in the 2030 Sustainable Development agenda (UN, 2017). According to the World Bank, poverty refers to the inability to find shelter, to afford health care, to find decent employment and even to obtain drinking water (World Bank, 2014).

However, while the number of poor people worldwide declines considerably from 1.9 billion to 836 million between 1990 and 2015, many people still live-in precarious conditions in developing countries and particularly in Sub-Saharan Africa (Asongu and Kodila-Tedika, 2017). Besides, the number of people who have been involuntary excluded from formal financial services has barely decreased from 2 billion in 2014 to about 1.7 billion in 2017 (Demirguc-Kant et al., 2017). In fact, this exclusion is caused by the high costs, distance and many other barriers related to the access to formal financial services. Those excluded households rely indeed on informal financial services including money transfer by bus or taxi (Kikulwe et al., 2014) as well as the rotating savings and credit association (ROSCA), which might be very risky and therefore keeps them in a persistent poverty. However, if financial services are available to the poor, it may provide them with a means to save. In less developed countries (LDCs), cases exist where money is stored under a mattress, which may be problematic and hamper a household's ability to move up the social ladder. This amount of money is vulnerable to theft, and keeping track of where all the money is hidden within a household is challenging.

In WAEMU, despite all the effort deployed by the central Bank of the West African States to achieve high level of financial inclusion, poverty rates are still very high in WAEMU countries. This requires then to design and implement new packages of financial inclusion's strategies (BCEAO, 2016, 2017). Indeed, WAEMU countries are among the poorest in Sub Saharan Africa. WAEMU is an economic area consisting of 8 countries out of the 15 in West Africa with 43% of

the population below the international USD 1.90 per day line in 2013 (AfDB, 2018). For this purpose, governments in WAEMU have designed and implemented policies conducive to poverty alleviation. In fact, the analysis of the WAEMU's poverty profile indicates that the poverty rate varies depending on countries. Indeed, according to the World Bank (World Bank, 2018), from 51.5% in 2011, the poverty has significantly dropped to 46.3% in Ivory Coast. This is the same in Burkina Faso with a 7% decrease of the poverty rate that is from 47% to 40.1% over the same period. However, it is worth noting that 92% of the poor live in rural area in that country where access to financial services is challenging. Besides, after a decade of modest growth, Senegal has designed a National Development Plan including financial inclusion program that has impacted its economic growth with more than 6% growth rate from 2014 to date. This has decreased the poverty level from 47% in 2011 to nearly 40% in 2015. Likewise, due to its national plan, including financial Inclusion plan, Togo has witnessed a declining poverty rate with about 1.6 points between 2015 and 2017.

However, studies have shown that the availability of new financial tools improves savings (Karlan et al., 2014), consumption and even productive investment (Dupas and Robinson, 2013). These studies agree that access and use of appropriate financial services for savings, remittances and credit is very important for poverty alleviation in developing countries where financial institutions are severely absent (CGAP, 2019; UNCDF, 2015; Dupas and Robinson, 2013). Financial inclusion through digital development appears then as a very important tool to fight against extreme poverty and vulnerability in the world (UNCDF, 2015; World Bank, 2014; Donovan, 2012). In fact, according to ITU (2016), smartphone users are estimated at 7.2 million in 2013 compared to 525 million by 2020 (ITU, 2016). This boosts the trend of mobile money market from USD 655.8 million in 2014 to reach an estimated value of USD 1.3 billion in 2019 (Caulderwood, 2015; Asongu and Nwachukwu, 2018).

GSM operators appear as a complete infrastructure that African countries have ever known. This is because mobile phone is used by more than 80% of the population and leads Africa as a leader in terms of mobile money, mobile banking and mobile payment (ITU, 2016). In West Africa, for example, the introduction of digital money including mobile money by the central bank (BCEAO) has allowed the disadvantaged people to access affordably the same financial services such as credit and other financial transactions proposed costly by financial institutions (BCEAO, 2016; Beck and Demirguc-Kunt, 2008). Mobile money not only reduces transaction costs and promotes financial inclusion but also increases individuals' savings, particularly for health emergencies (Ky et al., 2018; Ky et al., 2021) and agricultural investment in fertilizer (Batista &

Vicente, 2020), and even reduces poverty with a more pronounced outcome for female-headed households (N'dri and Kakinaka, 2020; Suri & Jack, 2016).

Yet, several studies have been interested on the effect of mobile financial services adoption on households' well-being in developing countries (Kikulwe et al., 2014; Jack and Suri, 2014; Munyegera and Matsumoto, 2014). Almost these studies agreed on the positive effect of mobile financial services on the households' wellbeing. Indeed, Kikulwe et al. (2014) found a positive relationship between mobile money and household income in Kenya. Access to financial services through mobile money including remittances reduces transaction cost and increases household income. It thereby affects the well-being of the household and helps them escape the vicious cycle of poverty (Kikulwe et al., 2014). Similarly, Munyegera and Matsumoto (2014) find that mobile money adoption increases per capita household consumption in Uganda. In addition, although very few studies have been devoted to the effect of mobile money on food security, mobile money also has the potential to increase food security through the reduction of transaction costs and availability of payment methods (Murendo, 2016).

The adoption and the effective use of mobile money contributes therefore to poverty alleviation. For example, Gupta et al. (2009) have pointed out the importance of remittances through mobile money in poverty reduction in Africa. Indeed, access to basic financial services such as savings, micro insurance, credit, through the expansion of mobile phone and Internet can improve the standard of living of poor people and reduce their vulnerability to shocks (Asongu and Odhiambo, 2018; CGAP, 2016; Dupas and Robinson, 2013; Beck and Demirguc Kunt, 2008). In other words, digital financial inclusion boosts savings, credit, and investment and allows consumption smoothing, risk management, assets and income increasing as well as provides a good living condition to poor people. It helps generate income, create jobs and use efficiently resources for the sake of poverty and vulnerabilities reduction, whether at the individual or national level. Fitting into that line, this study aims then at assessing the effect of digital financial inclusion on poverty reduction in WAEMU. Our findings indicate that several key factors drive the probability of lifting out of poverty, but the most important are directly or indirectly related to the mobile money adoption.

The rest of this chapter is organized as follows. Section 4.2 summarizes the literature review. Section 4.3 presents the methodology as well as the data. Results and discussions are presented in the Section 4.4. Section 4.5 concludes the paper with some policy recommendations.

4.2. Literature Review

In this section, we theoretically and empirically analyze the finance-poverty nexus in emphasizing the role of digital finance in increasing financial inclusion and alleviating poverty. Indeed, the economic theory supports the fact that a well-functioning financial system is favorable to economic growth. Moreover, several scholars argue that innovation is favorable to growth as well as to poverty reduction. So, some studies in emphasizing the importance of innovation in financial sector, evidenced the positive role of financial development including digital financial inclusion for growth and poverty. Most of those studies indicate that the advent of mobile money as an innovative tool for financial inclusion is very important in increasing remittance, saving, income for both farmers and non-farmers household leading to poverty alleviation.

4.2.1. A theoretical analysis of the poverty – finance nexus

The theoretical debate relating poverty to finance is not new in the economic literature (Levine, 2008; Jalilian and Kirkpatrick, 2005; Rajan and Zingales, 2003; Dollar and Kraay 2002; Schumpeter, 1911). Schumpeter (1911) highlights the importance of finance for economic growth and indirectly for poverty reduction. Dollar and Kray (2002) argue that growth is good for the poor implying that growth enhancing policies including financial development, should then be encouraged for the sake of poverty reduction. For Rajan and Zingales (2003), as financial market imperfections have led to the persistent of poverty, financial development will help correct those imperfections and alleviate poverty. In addition, they suggest that a healthy financial system allows for competition to emerge which may undermine the strength of powerful incumbents.

So, moving away from a limited and uncompetitive financial system that is full of cliques, may allow poor households and small businesses to prosper. Jalilian and Kirkpatrick (2005) in this line argue that the best way of delivering financial services to the poor is by eliminating market imperfections which lead to market failure and high transaction cost. In the same vein, Levine (2008) provides a theoretical hypothesis of how finance may alleviate poverty and lower inequality through intergenerational mobility. Levine (2008) argues that the broad access to finance will help poor people finance their education as well as investment opportunities and then lift them out of poverty. The financial development may help poor household smooth their consumption and prevent them from failing below poverty during crises.

There are many empirical evidences supporting the key role of financial development in the reduction of poverty. They also evidenced many channels by which financial development may

induce poverty alleviation through its growth increased effect (Songa et al., 2020; Dollar and Kray, 2002; Levine, 2008). Most of them pointed out the positive role of the development of the financial sector in emphasizing the constraints pertaining to it. In fact, they show that by the supply side, that is the financial institutions, the lack of financial infrastructures may impede the financial system to play well efficiently its role. In the demand side, some authors found that the feeble income in developing countries is due to the imperfection of the financial system that impede households to benefit from the opportunities and get out of poverty. Indeed, due to the issues related to asymmetric information and collateral, the usual channel can no longer adequately help poor lift out of poverty. The advent of mobile money as a digital financial tool that has already been accepted by most of people in developing countries may bridge the infrastructural deficit and collateral constraint and provide financial services to the last miles. Besides, a number of empirical studies in Africa found that digital finance including mobile money has the promise to improve financial access among the poor because of its affordability and reduced distance between households and service point (Jack and Suri, 2014; Adrianaivo and Kpodar, 2011; Aker et al., 2011).

4.2.2. An empirical analysis of the finance –poverty nexus

Empirically, many studies have found that broadly financial development and more specifically financial inclusion can contribute either directly or indirectly to poverty reduction and inclusive development (Gutiérrez-Romero and Ahamed 2020; Churchill and Marisetty, 2020; Songa et al.,2020; CGAP, 2019; UNCTD, 2014, 2015; Adrianaivo and Kpodar, 2011; Beck et al., 2007). For example, Gutiérrez-Romero and Ahamed (2020) show using cross-country data across 79 low and lower middle- income countries that financial inclusion, particularly financial outreach, is a key driver of poverty reduction in these countries. This effect is not direct, but indirect, by mitigating the detrimental effect that inequality has on poverty. Using household survey data, Churchill and Marisetty (2020) examines the effect of financial inclusion on poverty in India. The authors first construct an Indicator for financial inclusion and test it on several measures of poverty. They find evidence of positive effect of financial inclusion on poverty and income inequality. Songa et al. (2020) present evidence that both access to formal finance and digital finance significantly promote households' consumption and reduce poverty. Beck et al. (2007) complementing the study of Dollar and Kraay (2002) with a stricter focus on the impact of financial development on poverty, specifically examining the Gini coefficient, the income shares of the poor, and the percentage of people living on less than USD 1.92 a day conclude that financial development is poverty reducing. Furthermore, they find that 40% of income growth from the

poorest quintile is a result of reductions in inequality, but 60% due to the impact of financial development on aggregate growth.

Recent quasi-experimental and case studies in developing countries such as in China, India, Nigeria and Ghana also suggest that increasing financial inclusion, in the form of increasing outreach and usage, can help to reduce household vulnerability to poverty, particularly in those with financial services in distant places (Bukari et al.,2020; Churchill & Marisetty, 2020; Dimova & Adebowale, 2018; Koomson, et al., 2020; Li, 2018). However, Goksu et al., (2017), using a micro-data set across 140 countries, found a non-linear relationship between financial inclusion and inequality. Their findings suggest that in lower stages of development, only a small group, the wealthy, benefit from financial inclusion progress, but with a broader level of financial inclusion gradually all other groups benefit Park and Mercado (2018) show that financial inclusion is positively associated with lower levels of poverty in high- and upper-middle-income economies, but not in middle-low and low-income economies.

For the World Bank, the development of financial services through the diffusion of technology is conducive to fight against chronic poverty and induce inclusive and sustainable development (World Bank, 2014, 2020). This is also echoed by Fadun (2014) who found that a reduction in the financially excluded people help alleviate poverty. Inclusive finance allows the poor to smooth their consumption, create jobs and protect themselves against potential socio-economic vulnerabilities (Okoye et al., 2017). In addition, the development of financial services can directly contribute to poverty reduction in various ways (Odhiambo, 2009, 2010). First, it can improve opportunities for poor people to access financial services by solving financial market imperfections problems (Barret, 2016; Jalilian and Kirkpatrick, 2005). Second, access to financial credit services will allow the poor to engage in high-yield activities and reduce their vulnerability to shocks (Ellis et al. 2010). The effective access to financial services would allow the poor to smooth their consumption, reduce vulnerability, and build the physical and human capital they need to break out of the vicious circle of poverty (Barrett et al., 2016; Honoran, 2006).

4.2.3. Impact of mobile based financial services on poverty

Only few empirical studies have focused on the direct impact of mobile money adoption on poverty in developing countries. Yet, most of these studies consider mobile money as a key element of financial inclusion and thus assess the impact of financial inclusion either directly or indirectly on poverty. In fact, most of those studies pointed out the positive effect of mobile financial services to wellbeing through the increase of remittance, savings, income, health as well

as education of children. According to the CGAP (2019), digital technologies reduce transaction cost and unlock business models as well as product innovation that impact the lives of poor people. Furthermore, Sahay et al. (2015) for example, investigating the relationship between financial inclusion and economic growth, find that financial inclusion has a positive effect on economic growth but must be associated with financial development.

In the same vein, Sharma (2016) shows using a VAR and a Granger causality test that the various dimensions of financial inclusion positively impact economic growth and therefore contribute to poverty reduction. In addition, Odhiambo (2009) shows that financial services development does not necessarily improve savings but leads to poverty reduction. Ogunniyi and Ojebuyi (2016) by investigating the mobile phones adoption by Nigerian farmers find that the use of this technology induces an increase in household income. This finding is confirmed by the study of Danquah and Iddrisu (2018) who find that the adoption of mobile phones induces an increase in non-farm household incomes in Ghana. Similarly, Sekabira and Qaim (2017) by investigating the role of mobile money on off-farm income on a panel of coffee producers in Uganda find that the adoption of mobile money has positively affected remittances received but also has increased the off-farm income as well as the consumption of Ugandan households. This is because mobile money helps these farmers reduce liquidity constraints and facilitates transactions with foreign buyers.

Moreover, some others authors pointed out that remittances received through mobile money directly increase household income and indirectly constitute an insurance for poor people (Jack and Suri, 2014; Munyegera and Matsumoto, 2016). In the same vein, Kikulwe et al. (2014) show that farmers who have adopted mobile money use more fertilizers, pesticides and more labor for their activities. The mobile money is then conducive to jobs creation, incomes raising and then poverty alleviation (Kikulwe et al., 2014). Similarly, Cull et al. (2018) indicate that mobile banking services positively impact the well-being of households. These authors find that in developing countries, those who have accounts at mobile bankers are more able to become financially active than those who are forced to open it at bank. Jack and Sury (2014; 2016) also find a long-term positive effect of mobile money on consumption and poverty reduction in Kenya. By examining the impact of transaction associated to the adoption of mobile money on risk sharing in Kenya, they show that M-Pesa users were able to fully absorb large negative income shocks without any reduction in their consumption. By contrary, the consumption of households without access to M-Pesa declines by 7% in response to the same shock. Honohan, and King (2012) on the contrary shows that more financial services development is detrimental to national poverty reduction.

4.3. Methodology and data

Theories and policies related to pro poor growth and finance indicate a strong relationship between innovation and poverty alleviation. Using different econometrics approaches, some empirical studies have moved forward on the key place of financial innovation in inclusive development and poverty alleviation (Dollar and Kraay, 2002; Becker et al., 2007; Asongu and De Moor, 2015). In considering the direct and indirect benefit individuals may reap from the adoption of a technology in terms of well-being improvement and poverty alleviation (Asongu et al, 2018) we follow the Levine (2008) theoretical analysis to model the relationship between financial inclusion and poverty in emphasizing the accelerating role of digital finance including mobile money.

4.3.1. Estimation strategy

The econometric approach adopted in this study passes through three steps. First, we assume that the probability of lifting out of poverty depends significantly on the adoption of Mobile Money. We therefore use a Probit model by estimating the probability of lifting out of poverty as a function of the mobile money adoption and some control variables. The univariate probit model is presented as follows:

$$Pov_i = 1\{\alpha_1 Z_1 + \beta_1 MM_i + \varepsilon_{1i} > 0\} \quad \textbf{4. 1}$$

However, it is possible that less poor individuals are more likely to adopt mobile money than the poorest. This means that if we are not careful, we could wrongly attribute the change in the poverty status only to the adopters of mobile Money. In opposite, it may be because the individual was already rich that he adopted this technology. This is the endogeneity problem that often appears in these kinds of analyses. Thus, we model the decision of mobile money adoption and poverty status simultaneously. Considering that Mobile money (*MM)* and the poverty status (*Pov*) are all dichotomous variables, and referring to Maddala (1983) and Green (2003), we specify the following simultaneous latent equations models:

$$Pov_i = 1\{\alpha_1 Z_1 + \beta_1 MM_i + \varepsilon_{1i} > 0\} \quad \textbf{4. 2a}$$

$$MM_i = 1\{\alpha_2 Z_2 + \beta_2 Pov_i + \varepsilon_{2i} > 0\} \quad \textbf{4. 2b}$$

Where $\begin{pmatrix}\varepsilon_1\\ \varepsilon_2\end{pmatrix} \rightarrow \aleph\left[\begin{pmatrix}0\\0\end{pmatrix}\ \begin{pmatrix}1\ \rho\\ \rho\ 1\end{pmatrix}\right]$; the two errors are jointly correlated with a null mean, a constant variance and a correlation term ρ. Z_1 and Z_2 contain all exogenous variables.

The mobile money adoption (*MM*) is a binary variable that takes the value 1 for adoption and 0 otherwise. The poverty status (*Pov*), on the other hand, takes the value of 0 for the individual belonging to the 40% poorest income quintile and 1 if he belongs 60% income quintile. Z is a matrix of socio-economic determinants of both mobile money adoption and/or poverty status. It includes gender, education, age and age square as well as employment status. In addition, Z includes binary variables of financial inclusion such as the ownership of a financial account, of a credit and/or debit card as well as the dummies of savings, credit and remittances behavior. We also take into account the country specific effect to assess how the relationship between digital financial inclusion and poverty reduction differ from one country to another in WAEMU.

However, since equations (***4. 2a***) and ***4. 2b***) contain endogenous regressors, we cannot use the usual probit model to derive unbiased estimators. For this purpose, we estimate these equations by the SURE probit procedure. This procedure is based on the fact that the decision of adopting mobile money depends on the poverty status and vice versa. The SURE probit estimation procedure gives unbiased estimators by addressing the problems of unobserved heterogeneity, endogeneity and correlation. Equations (***4. 2a***) and (***4. 2a***) can also be estimated directly by the two-step method, but the interpretation of the estimated coefficients may be tedious (Maddala, 1983). Consequently, we decide to follow alternative methods.

The first is to estimate the reduced forms of equations (***4. 2a***) and (***4. 2a).***

In replacing equation 1 in equation 2 we get:

$$Pov_i = \alpha_1{}'Z_1 + \beta_1[\alpha_2{}'Z_2 + \beta_2 Pov_i + \varepsilon_{2i}] + \varepsilon_{1i} \qquad \textbf{4. 2a'}$$

$$MM_i = \alpha_2{}'Z_2 + \beta_2[\alpha_1{}'Z_1 + \beta_1 MM_i + \varepsilon_{1i}] + \varepsilon_{2i} \qquad \textbf{4. 2b'}$$

$$Pov_i = \alpha_1{}'Z_1 + \beta_1\alpha_2{}'Z_2 + \beta_1\beta_2 Pov_i + \beta_1\varepsilon_{2i} + \varepsilon_{1i} \qquad \textbf{4. 2a''}$$

$$MM_i = \alpha_2 Z_2 + \beta_2\alpha_1{}'Z_1 + \beta_2\beta_1 MM_i + \beta_2\varepsilon_{1i} + \varepsilon_{2i} \qquad \textbf{4. 2b''}$$

$$Pov_i - \beta_1\beta_2 Pov_i = \alpha_1{}'Z_1 + \beta_1\alpha_2{}'Z_2 + \beta_1\varepsilon_{2i} + \varepsilon_{1i} \qquad \textbf{4. 2a'''}$$

$$MM_i - \beta_2\beta_1 MM_i = \alpha_2{}'Z_2 + \beta_2\alpha_1{}'Z_1 + \beta_2\varepsilon_1 + \varepsilon_{2i} \qquad \textbf{4. 2b'''}$$

$$(1-\beta_1\beta_2)Pov_i = \alpha_1{}'Z_1 + \beta_1\alpha_2{}'Z_2 + \beta_1\varepsilon_{2i} + \varepsilon_{1i} \qquad \textbf{4. 2a'''}$$

$$(1-\beta_2\beta_1)MM_i = \alpha_2{}'Z_2 + \beta_2\alpha_1{}'Z_1 + \beta_2\varepsilon_{1i} + \varepsilon_{2i} \qquad \textbf{4. 2b'''}$$

$$Pov_i = \alpha_1'Z_1/(1-\beta_1\beta_2) + \beta_1\alpha_2'Z_2/(1-\beta_1\beta_2) + (\beta_1\varepsilon_{2i} + \varepsilon_{1i})/(1-\beta_1\beta_2) \quad \textbf{4. 2a''''}$$

$$MM_i = \alpha_2'Z_2/(1-\beta_2\beta_1) + \beta_2\alpha_1'Z_1/(1-\beta_2\beta_1) + (\beta_2\varepsilon_{1i} + \varepsilon_{2i})/(1-\beta_2\beta_1) \quad \textbf{4. 2b''''}$$

The reduced forms of equations (***4. 2a***) and (***4. 2a)*** yield:

$$Pov_i = \pi_{11}'Z_1 + \pi_{12}'Z_2 + \mu_{1i} \quad \textbf{4. 3a}$$

$$MM_i = \pi_{21}'Z_2 + \pi_{22}'Z_1 + \mu_{2i} \quad \textbf{4. 3b}$$

Where $Pov_i = 1$ if the individual is not poor and 0 otherwise; $MM_i = 1$ if the individual has adopted Mobile Money and 0 otherwise; Z_1 and Z_2 contain all exogenous variables. π_{11}, π_{12} are the parameters of the reduced form of equation 4.2a and π_{21} and π_{22} the parameters of the reduced form of equation 4.2b.

We estimate the equations $(\mathbf{4.3a})$ and $(\mathbf{4.3b})$ with the bivariate probit procedure which is specified as follows:

$$Pov_i = \begin{cases} 1 \; if \; Pov_i^* > 0 \\ 0 \; if \; Pov_i^* < 0 \end{cases} \text{ and } MM_i = \begin{cases} 1 \; if \; MM_i^* > 0 \\ 0 \; if \; MM_i^* < 0 \end{cases} \quad \textbf{4. 4}$$

The covariance of the reduced form is $cov(\mu_{1i}, \mu_{2i}) \neq 0$. In order to check for correlation between dependent variables, we test the significance of Rho (ρ) which represents the correlation between the errors of the two probit models. If $\rho = 0$ the estimation of each of the equations by the standard probit method would give the same result as the simultaneous estimation. In the case $\rho \neq 0$ simultaneous estimation by the bivariate probit procedure is required.

The second alternative strategy is to consider the two equations in which MM appears as endogenous variables among the explanatory variables in the Poverty Equation (*Pov*) while *Pov* variable does not appear in the Mobile Money adoption (MM) equation. This procedure is known as the recursive bivariate probit model (Maddala, 1983; Green, 2003). In this case, the MM equation is considered in a reduced form while the *Pov* equation is in the structural form with MM as an explanatory variable. The recursive bivariate probit model is presented as follow:

$$Pov_i = 1\{\alpha_1 Z_1 + \beta_1 MM_i + \varepsilon_{1i} > 0\} \quad \textbf{4. 5a}$$

$$MM_i = 1\{\alpha_2 Z_2 + \varepsilon_{2i} > 0\} \quad \textbf{4. 5b}$$

The parameter of interest (β_1) is called the average treatment effect and is derived as follow:

$$E_x[P(\varepsilon_{1i} > -\alpha_1 Z_1 - \beta_1) - P(\varepsilon_{1i} > -\alpha_1 Z_1)] \quad \textbf{4. 6}$$

The joint probability distribution of Pov_i and MM_i (conditionally to Z_1 and Z_2) contains four elements:

$$P(Pov_i = 0, MM_i = 0|Z_1, Z_2) = P(\varepsilon_{1i} \leq -\alpha_1 Z_1, \varepsilon_{2i} \leq -\alpha_2 Z_2) \quad \textbf{4. 7a}$$

$$P(Pov_i = 1, MM_i = 0|Z_1, Z_2) = P(\varepsilon_{1i} > -\alpha_1 Z_1, \varepsilon_{2i} \leq -\alpha_2 Z_2) \quad \textbf{4. 7b}$$

$$P(Pov_i = 0, MM_i = 1|Z_1, Z_2) = P(\varepsilon_{1i} \leq -\alpha_1 Z_1 - \beta_1, \varepsilon_{2i} > \alpha_2 Z_2) \quad \textbf{4. 7c}$$

$$P(Pov_i = 1, MM_i = 1|Z_1, Z_2) = P(\varepsilon_{1i} > -\alpha_1 Z_1 - \beta_1, \varepsilon_{2i} > \alpha_2 Z_2) \quad \textbf{4. 7d}$$

This distribution is completely determined if the joint probability distribution of ε_{1i} and ε_{2i} are known. In the bivariate probit model, it is assumed that errors terms have the following joint distribution function: $F(\varepsilon_{1i}, \varepsilon_{2i}) = \Phi(\varepsilon_{1i}, \varepsilon_{2i}\ \rho)$ where Φ denotes the cumulative density function of the standard bivariate distribution and ρ the correlation coefficient. In this case, the joint probability function $f(Pov_i, MM_i|Z_1, Z_2)$ may be written as follows.

$$f(Pov_i, MM_i|Z_1, Z_2) = \Phi[s_1(\alpha_1 Z_1 + \beta_1 MM_i), s_2(\alpha_2 Z_2), s_1 s_2\, \rho] \quad \textbf{4. 8}$$

Where $s_1 = 2Pov_i - 1$ and $s_2 = 2MM_i - 1$

Since the above model is completely determined, it can be estimated by the Full Information Maximum Likelihood (FIML) and treated as a bivariate probit model ignoring the simultaneity (Greene, 2003). The equations to be estimated are as follows:

$$Pov_i = 1\,\{\alpha_1 Z_1 + \beta_1 MM_i + \varepsilon_{1i} > 0\} \quad \textbf{4. 9a}$$

$$MM_i = 1\,\{\pi_2 Z_2 + \mu_{2i} > 0\} \quad \textbf{4. 9b}$$

However, the estimation of a recursive bivariate probit model requires a number of restrictions to identify the parameters of the model. Maddala (1983) suggests to exclude at least one exogenous variable of the reduced form model from the structural model. Wilde (2000) shows that Maddala focused on a specific case where constant term is the only exogenous regressor. For this author, parameters of the model are identified if there is at least one non constant explanatory variable. Consequently, following Maddala (1983) we impose an exclusion restriction in the model. It's first made by including the variables in the two equations and subsequently omitting them from the equations in which they are not significant. To this end, we include the "phone" variable in the MM Adoption Equation and exclude it from the Poverty Equation (*Pov*). This exclusion is justified by the fact that the ownership of a mobile phone ideally precedes the adoption of the mobile money.

4.3.2. Marginal Effects

The next step after the estimation of the parameters is to consider the marginal effects of the covariates on the conditional distribution (Greene, 1996). We compute therefore the marginal

effects of the explanatory variables on the probability of lifting out of poverty as well as the one from the probability of adopting mobile money. It is worth noting that the marginal effect measures the change in the probability of lifting out of poverty given a one-unit change in the explanatory variable. Due to the fact that the decision of mobile money adoption and the probability of lifting out of poverty are jointly determined, the marginal effects in the poverty equation can be decomposed into direct effects from the explanatory variables in the poverty equation and indirect effects, or cross-effects, from the explanatory variables in the mobile money adoption equation. Following Green (1996), it is presented as follows:

$$P(Pov_i = 1|Z_1, Z_2) = P(Pov_i = 1, MM_i = 1|Z_1, Z_2)\, P(Pov_i = 1|Z_1, Z_2) + P(Pov_i = 1, MM_i = 0|Z_1, Z_2)\, P(MM_i = 0|Z_1, Z_2) \quad \textbf{4. 10}$$

$$P(Pov_i = 1|Z_1, Z_2) = \Phi_{[Pov_i=1/MM_i=1]} \times \Phi_{[Pov_i=1]} + \Phi_{[Pov_i=1/MM_i=0]} \times \Phi_{[MM_i=0]} \quad \textbf{4. 11}$$

Where Φ denotes the cumulative density function of the standard bivariate distribution, and

$$\Phi_{[Pov_i=1/MM_i=1]} = \Phi\left(\frac{\alpha' Z_1 - \rho\beta' Z_2}{\sqrt{1-\rho^2}}\right); \quad \Phi_{[Pov_i=1]} = \Phi(\alpha' Z_1); \quad \Phi_{[Pov_i=1/MM_i=0]} = \Phi\left(\frac{\alpha' Z_1 + \rho\beta' Z_2}{\sqrt{1-\rho^2}}\right)$$

$$\Phi_{[Pov_i=1]} = \Phi(-\beta' Z_2).$$

Note that Z_1, and Z_2 are respectively the vector of explanatories variables of equation 1 and 2 and α', β' are also in vectoral form.

The marginal probability of lifting out of poverty with respect to an explanatory variable Z_k is obtained by differentiating equation (4.11) and given as follows:

$$\frac{\partial(Pov_i = 1|Z_{1i}, Z_{2i})}{\partial Z_k} = \alpha_k \phi_{[Pov_i=1]} \Phi_{[Pov_i=1/MM_i=1]} + \alpha_k \phi_{[Pov_i=1]} \Phi_{[Pov_i=1/MM_i=0]} + \beta_k \phi_{[MM_i=1]} \Phi_{[Pov_i=1/MM_i=1]} - \beta_k \phi_{[MM_i=0]} \Phi_{[Pov_i=1/MM_i=0]} \quad \textbf{4. 12}$$

$$= \alpha_k \phi_{[Pov_i=1)} (\Phi_{[Pov_i=1/MM_i=1]} + \Phi_{[Pov_i=1/MM_i=0]}) + \beta_k (\phi_{[MM_i=1]} \Phi_{[Pov_i=1/MM_i=1]} - \phi_{[MM_i=0]} \Phi_{[Pov_i=1/MM_i=0]}) \quad \textbf{4. 13}$$

$$\frac{\partial(Pov_i = 1|Z_{1i}, Z_{2i})}{\partial Z_k} = \alpha_k \phi_{[Pov_i=1]} + \beta_k (\phi_{[MM_i=1]} \Phi_{[Pov_i=1/MM_i=1]} - \phi_{[MM_i=0]} \Phi_{[Pov_i=1/MM_i=0]}) \quad \textbf{4. 14}$$

Since $\Phi_{[Pov_i=1/MM_i=1]} + \Phi_{[Pov_i=1/MM_i=0]} = 1$ and where ϕ is the density function.

The first term ($\alpha_k \phi_{(Pov_i=1)}$) in equation (***4. 14***) is the direct marginal effect of a variable Z_k on the probability of lifting out of poverty in WAEMU. This is analogous to the marginal effect of Z_k in the univariate probit model ***(equation* 4. 3**).

The second term $\beta_k(\phi_{[MM_i=1]}\Phi_{[Pov_i=1/MM_i=1]} - \phi_{[MM_i=0]}\Phi_{[Pov_i=1/MM_i=0]})$ is the indirect effect, or cross-effect, from the mobile money adoption in the poverty equation. This term reduces to the single-equation probit marginal effect when $\rho = 0$.

However, the effect of mobile money adoption on the probability of lifting out of poverty is given as follows:

$$P(Pov_i = 1, MM_i = 1|Z_1, Z_2) - P(Pov_i = 1, MM_i = 0|Z_1, Z_2) \quad \textbf{4. 15}$$

4.3.3. Data and descriptive statistics

Data are drawn from the Global Financial Development (2017) database of the World Bank. This is a survey conducted in 143 countries with nearly 140 languages and covering nearly 150,000 individuals. Approximately 1,000 adult civilians are interviewed in each country. However, our sample is constituted by the eight WAEMU countries grouped in two clusters for the interest of comparison. The choice of the WAEMU countries relies on their homogeneity as far as monetary union is concerned. Although this is a strong assumption, we suppose that grouping these countries in two clusters includes in the analysis of the role of structural factors in poverty alleviation pertaining to each group of countries. Considering the similarity within each group of countries results in more accurate estimators for the robustness check. In fact, clusters are constructed based on the digital financial inclusion level in terms of the mobile money adoption rate and the year since when the first mobile money for the unbanked is launched in each country. As a result, we have a cluster of countries with low digital financial inclusion rate and the cluster of countries with relatively high digital financial inclusion rate. The first group comprises Benin, Bissau Guinea, Mali, Niger and Togo, while the second group includes Burkina Faso, Ivory Coast and Senegal.

The poverty status is a binary variable that takes the value 0 if the individual is poor and 1 if he is not poor. Ideally, recent analyses of poverty consider its multi-dimensional approaches rather than only its monetary dimension. But given the data constraints, we use the successive income quintile group as proxy for poverty. We follow the approach of Gallup World Poll, which interviews people across the world on their perception not only of their income but also of their well-being. The Gallup World Poll therefore pointed out that living in poor countries implies a

poor perception of people's well-being. This correlation between level of income and self-satisfaction of well-being shows the rational of income quintiles group in the analysis of multidimensional poverty. For example, the Findex (2017) data shows 5 income quintiles. Assuming that from one quintile to another, the level of education, income as well as the level of health improve, it results then that this indicator can effectively use as for the multidimensional poverty level of an individual. The level of education and health for an individual belonging to the fifth 20 percent richest is obviously greater than the one belonging to the first 20 percent poorest. This approach then leads us to dichotomize the poverty status by considering individuals who belong to the quintiles of the 40 percent poorest as below the poverty line and then poor and those belonging to the quintiles of the 60 percent richest as above the poverty line and then non-poor.

Digital financial inclusion is measured in this study by two proxies: mobile phone led financial inclusion and bank led financial inclusion. Indeed, we approximate the first measure by the mobile money adoption rate. Consequently, the mobile money adoption is a dummy which takes the value 1 for the individual who owns an active mobile money account during the past 12 months and 0 otherwise. As the variable of interest of our study, we hope that the adoption of mobile money would be positively correlated with the likelihood of lifting out of poverty in WAEMU. The second measure of digital financial inclusion is the one that considers financial inclusion led by financial institutions. For example, the ownership of an account in a financial institution, of a credit or debit card, as well as savings, credit and remittances behavior are proxies of digital financial inclusion led by financial institutions. These variables take the value 1 if the individuals own an account, possesses a debit or a credit card as well as saved, borrowed and made remittances during the 12 last months and 0 otherwise.

Table 4. 1: *Descriptive statistics*

Variable	**Definition**	**Obs**	**Percent**
Categorical variables			
Account_mm	=1 if the individual possesses a mobile money account	7000	28.67
Account_ FI	=1 if the individual possesses an account at a financial institution.	7000	25.63
Debit card	=1 if the individual possesses a debit card, 0 otherwise	6,925	12.10
Credit card	=1 if the individual possesses a credit card, 0 otherwise	6,887	4.05
Saved	=1 if the individual has saved during the last 12 months, 0 otherwise	7000	48.51
Borrowed	=1 if the individual has borrowed during the last 12 months, 0 otherwise	7000	46.50
Remittance received	=1 if the individual has received remittance during the last 12 months, 0 otherwise	6,946	34.12
Gender (Female)	=1 if the individual is a man, 0 otherwise	7000	58.54

	=1 if the individual possesses a mobile phone, 0 otherwise	6,976	
Phone			73.10
Employed	=1 if the individual is employed, 0 otherwise	6,000	
			67.73
Education		6,936	
Primary education	=1 if the individual has primary education, 0 otherwise		60.91
Secondary education	=1 if the individual has secondary education, 0 otherwise		36.38
University education	=1 if the individual has university education, 0 otherwise		2.71
Poverty (40%poorest)	=1 if the individual belongs to the category of the 40% poorest, 0 otherwise	7000	32.51

Continuous variable	**Definition**	**Obs**	***Mean***	***Std.dev.***	***Min***	***Max***
Age	Is the age of the individual	6,944	32.725	14.16	15	99

Source: Author, 2019

Table 4.1 indicates that 32.51% of the individuals surveyed in this study are poor, compared with 67.49% of the non-poor. In addition, while 73.10% of the individuals surveyed have a mobile phone, only 28.67% have a mobile money account that they use to make their savings transactions, credit as well as money transfers that is becoming increasingly a key element in poverty reduction (Munyegera and Matsumoto, 2016). In addition, holding an account at a financial institution as well as electronic means of payment are a vehicle for poverty reduction in developing countries. Indeed, 25.63% of adults aged 15 and over have an account at the bank or at a microfinance institution in the WAEMU. In addition, 12.10% of adults use their debit cards while 4.05% hold credit cards. These statistics reveal that in the WAEMU, individuals still do not have a culture of using second and third generation digital financial instruments. In addition, several authors have shown that women, youth and the unemployed are at greater risk of poverty, necessitating wide-ranging policies on the part of economic decision makers (World Bank, 2014). 58.57% of respondents are women, 67.73% are employed with an average age of about 33. Education, a major factor in the formation of human capital, is a major determinant of poverty in developing countries. The level of education increases the probability of finding a job descends to get out of poverty. Educated individuals also have the ability to self-employ and innovate, which leads to economic growth and poverty reduction. In addition, education ensures good health, controls births to ensure demography and human capital in line with economic development objectives. Descriptive statistics show that 60.91% have a primary level of education, 36.38% a secondary level and 2.68% a higher level of education, effectively indicating the importance of basic education for the population. In order to impose restrictions on exclusion, the binary variable “phone” with a percentage of 73.10% detention is chosen to indirectly explain poverty. Indeed, we believe that

not everyone who holds a mobile phone is likely to get out of poverty. However, using the mobile phone for financial purposes allows the cellular to lift out of poverty.

4.4. Results and discussion

Literature has argued that the adoption of technology improves the way individuals operate and thus contributes to improving their well-being (Asongu et al., 2018). The advent of mobile technology, like mobile phones, bridges the financial infrastructure gap and allows those excluded from formal finance to access financial services at a lower cost, which in turn allows them to exit poverty in all its forms (Jack and Suri, 2014). From the empirical literature, there are a number of variables that explain the probability of lifting out of poverty. These variables include gender, education, work status, living environment, technology adoption and the use of payment methods. They are categorical variables except age, which is a continuous variable. Table 4.2 displays the estimates results including the Probit, bivariate probit and the recursive bivariate probit estimations. From the Table 4.2, we determine the probability so that an individual lift out of poverty through three models.

First, we estimate the probability of lifting out of poverty (column1) with a simple univariate probit model regardless of correlation and simultaneity issues. The marginal effects of the probit model are presented in Column 2 of table 2. Subsequently, due to the endogeneity of mobile money in the poverty model, we estimate the reduced form of both poverty and mobile money adoption equations (Column 3 and 5) with a bivariate probit. The conditional marginal effects deriving from the bivariate probit estimation are presented in columns 4 and 5 of the same table. Finally, as suggested by Maddala (1983), the use of bivariate probit must respect a number of considerations including the condition of consistency. This condition requires that the product of the coefficients associated to the two endogenous variables from structural form models is zero. To this end, we assume equal to zero the coefficient related to poverty status in the equation of mobile money adoption to facilitate analyses. As a result, we estimate a model with recursive simultaneous equations using the recursive bivariate probit model (column 7 and 10). The direct and indirect marginal effects of the Poverty status Equation are presented in columns 8 and 9 of Table 4.2 and those derived from the Mobile Money adoption Equation are presented in column 11 of the same table.

Table 4.2: Results (Probit, Bivariate probit and Recursive Bivariate probit)

	Probit		Bivariate probit				Recursive Bivariate probit				
	Pov Poverty Status	Marg Eff	Pov Poverty Status	Marg Effect Pr (Pov=1|mm=1)	MM Mobile Money	Marg Effect Pr (mm=1|Pov=1)	Pov Poverty Status	Marginal Effect: Direct	Marginal Effect: Indirect	MM Mobile Money	Marginal Effect
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mobile Money	0.088**	0.029**					0.658***	0.219***			
	(0.042)	(0.014)					(0.208)	(0.068)	(0.068)		
Sex (Male)	0.069**	0.023**	0.073**	0.025**	0.169***	0.051***	0.048	0.016	0.031***	0.159***	0.042***
	(0.034)	(0.011)	(0.034)	(0.012)	(0.038)	(0.011)	(0.036)	(0.012)	(0.011)	(0.038)	(0.010)
Age	0.004	0.001	0.004	0.001	0.018***	0.005***	0.002	0.000	0.002	0.020***	0.005***
	(0.005)	(0.001)	(0.005)	(0.001)	(0.006)	(0.002)	(0.005)	(0.001)	(0.001)	(0.006)	(0.001)
Age square	-6.52e-05	-2.19e-05	-7.03e-05	-2.47e-05	-0.000***	-7.59e-05***	-3.55e-05	-1.18e-05	-3.73e-05*	-0.000***	-7.37e-05***
	(6.27e-05)	(2.11e-05)	(6.24e-05)	(2.19e-05)	(8.09e-05)	(2.48e-05)	(6.42e-05)	(2.14e-05)	(2.21e-05)	(8.19e-05)	(2.18e-05)
Education (Primary and less as base category)											
Secondary	0.450***	0.152***	0.460***	0.158***	0.375***	0.118***	0.377***	0.126***	0.176***	0.377***	0.104***
	(0.039)	(0.012)	(0.039)	(0.012)	(0.040)	(0.013)	(0.054)	(0.018)	(0.014)	(0.040)	(0.011)
Higher	0.911***	0.264***	0.925***	0.270***	0.517***	0.169***	0.786***	0.234***	0.325***	0.518***	0.147***
	(0.148)	(0.029)	(0.147)	(0.028)	(0.106)	(0.039)	(0.157)	(0.036)	(0.043)	(0.106)	(0.032)
Account at FI	0.195***	0.065***	0.199***	0.070***	0.160***	0.049***	0.164***	0.054***	0.072***	0.157***	0.041***
	(0.050)	(0.017)	(0.050)	(0.017)	(0.050)	(0.015)	(0.052)	(0.017)	(0.017)	(0.050)	(0.013)
Remittance received	0.069*	0.023*	0.086**	0.030**	0.637***	0.195***	-0.043	-0.014	0.041***	0.635***	0.170***
	(0.037)	(0.012)	(0.037)	(0.013)	(0.037)	(0.011)	(0.059)	(0.019)	(0.013)	(0.037)	(0.009)
Saved	0.203***	0.068***	0.211***	0.074***	0.341***	0.105***	0.145***	0.048***	0.081***	0.341***	0.091***
	(0.037)	(0.012)	(0.036)	(0.013)	(0.039)	(0.012)	(0.044)	(0.015)	(0.012)	(0.039)	(0.010)
Borrowed	-0.045	-0.015	-0.042	-0.015	0.119***	0.036***	-0.061*	-0.020*	-0.011	0.116***	0.030***
	(0.035)	(0.011)	(0.035)	(0.012)	(0.038)	(0.011)	(0.035)	(0.011)	(0.012)	(0.038)	(0.010)
Debitcard	0.250***	0.084***	0.252***	0.088***	0.040	0.012	0.226***	0.075***	0.083***	0.034	0.009
	(0.071)	(0.023)	(0.072)	(0.025)	(0.065)	(0.020)	(0.072)	(0.024)	(0.025)	(0.065)	(0.017)
Creditcard	-0.414***	-0.139***	-0.405***	-0.142***	0.326***	0.099***	-0.461***	-0.154***	-0.134***	0.325***	0.086***
	(0.091)	(0.030)	(0.091)	(0.032)	(0.090)	(0.027)	(0.091)	(0.030)	(0.033)	(0.090)	(0.024)
Mobile phone	0.098**	0.033**	0.106***	0.037***	0.456***	0.140***			0.041***	0.461***	0.123***
	(0.039)	(0.013)	(0.039)	(0.013)	(0.050)	(0.015)			(0.014)	(0.049)	(0.013)
Employed	-0.022	-0.007	-0.016	-0.005	0.273***	0.083***	-0.057	-0.019	0.004	0.278***	0.074***
	(0.037)	(0.012)	(0.036)	(0.012)	(0.042)	(0.013)	(0.039)	(0.013)	(0.013)	(0.042)	(0.011)
Country specific eff	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-0.097		-0.112		-2.428***		0.0152			-2.457***	
	(0.108)		(0.108)		(0.134)		(0.114)			(0.134)	
Wald	459.63		1737.12				2020.67				
Pseudo R^2	0.058										
Rho			0467939 Prob > chi2 = 0.134				-.339734 ** Prob > chi2 = 0.013				
LL	-3950.776		-7124.958				-7124.5875				
Obs	6,684	6,684	6,819	6,819	6,819	6,819	6,819	6,819	6,819	6,819	6,819

Source: Author, 2019

The estimated values of Rho (ρ) indicate that only the recursive model allow the simultaneous estimation of the probability of lifting out of poverty and the decision to adopt mobile money. The non-significance of Rho (ρ) in the reduced form equations suggests that it is preferable to estimate the probability of lifting out of poverty separately from the decision to adopt mobile money. This does not allow us to correct the possible endogeneity appearing in the univariate probit model. For this purpose, we consider for this analysis, the recursive bivariate probit model for which the coefficient of Rho (ρ) is significant. To verify the robustness of our results, we exclude from the recursive model the variable *fi_account*, which we believe explains poverty significantly and can be correlated with the adoption of mobile money. In addition, we group our sample into two clusters including the cluster of countries with low digital financial Inclusion rate (Cluster1) and the cluster of countries with high digital financial inclusion rate (Cluster2). The results from the robustness check confirm those found with the initial recursive model, but the marginal effects are greater than those initially found.

However, the negative value of ρ (-0.339) in the recursive model may appear counter intuitive at first glance regarding the positive sign of the mobile money adoption coefficient in the Poverty status equation. This sign is normal because once adoption is controlled in the poverty model, the unobserved characteristics that are likely to lift the individual out of poverty also make him less likely to adopt mobile money. For instance, an individual who has a poor experience of using debit/credit cards may not be tempted to adopt mobile money. Consistent with World Bank (2016) findings concerning the profile of the world's poor, the output of the recursive bivariate probit model shows that variables such as mobile money, education (secondary and higher), saved during the past 12 months, remittance received, ownership of a debit cards, ownership of an account at a financial institution positively and significantly affect the likelihood of lifting out of poverty at 1% level. In opposite, owning a credit card affects negatively and significantly at 1% level the probability of lifting out of poverty in WAEMU.

These results are consistent with those displayed by the univariate probit model but with diverse degrees of significance. However, apart from the above-mentioned variables, it results from the univariate probit model that mobile phone ownership affects positively and respectively at 5% level the probability of lifting out of poverty. It should be noted that the low significance of the coefficient related to the mobile money adoption in the simple probit model may mean that this variable is strongly correlated with the ownership of mobile phone.

Consequently, the univariate probit model yield biased estimation due to the correlation and the endogeneity problem (Greene; 2003). Nevertheless, this problem of endogeneity, is addressed by the recursive bivariate probit model and its marginal effects are then interpreted.

In examining the poverty status equation, it come out at first glance that the adoption of mobile money affects directly and significantly the probability of lifting out of poverty. Indeed, the adoption of such a technology increases by 21.9% the probability that a poor individual becomes non poor owing to the utility and several financial services mobile money provides to him. This result confirms those obtained by Jack and Suri (2014) and Munyegera and Matsumoto (2016) who show that mobile money is a vehicle for financial inclusion and inclusive development. In addition to the adoption of mobile money, findings show that mobile phone is very crucial for poverty reduction in developing countries in general and WAEMU in particular. Indeed, its effect on poverty passes through its utilization to access financial services. Therefore, having a mobile phone affects the mobile money adoption by 12.3% and induces a positive and very significant effect of 4.13% on the probability of lifting out of poverty in WAEMU countries. Thus, the expansion of the mobile phone by making it more affordable allows the poorest to access financial services and thereby improve their well-being. This result also confirms the findings of Danquah and Iddrisu (2018) in Ghana that indicate that the possession of a mobile phone improves the likelihood to lift out of poverty the non-farm households in Ghana. As indicated by Abor et al. (2018), developing countries like WAEMU can benefit from mobile technology by ensuring its affordability and have unlimited access to mobile technology networks to access financial services.

Consistently with the literature, the results suggest that the use of innovative tools in banking sector to access financial services leads to poverty reduction. Indeed, owning an account at a financial institution and having a debit card is quite essential for poverty reduction in the WAEMU countries. The ownership of an account and a debit card increases respectively the probability of lifting people out of poverty by 5.47% and 7.52%. By contrast, the possession of a credit card reduces the probability of lifting out of poverty by 15.4%. This may confirm the detrimental impact of credit card on individual's well-being which may be due to the high interest rates applied to the loan and the negative consequences of the accumulation of loans on the ability to smooth consumption and constitute capital for small businesses. Moreover, in accordance with theories of savings, the results show that having saved over the last 12 months positively affects the likelihood of lifting out of poverty by 4.82%. In addition, having received remittances increases indirectly the probability of lifting out of poverty by 4.14%. These results

are in line with the empirical literature including Munyegera and Matsumoto (2016) who indicated the key role of remittances in households' welfare in Uganda.

Besides, consistently with Eryong and Xiuping (2018) and Zeng (2016), we found that education has both direct and indirect significant effect on the probability of lifting out of poverty. An individual with a secondary school achievement is likely to lift out of poverty directly by 12.6% and indirectly by 17.6% more than an individual who achieves only primary school or less. This gap is even greater with the individual of higher education level. Higher education directly improves the probability of lifting out of poverty by 23.4% and indirectly through its influence on the adoption of mobile money by 32.5%. However, it is worth noting that the indirect effect of education through the adoption of mobile money is more consequent than the direct effect on poverty. This finding supports the view that volitional control factors and the self-efficacy perception depend on the level of education of individuals, which in turn, induced inclusive development including poverty reduction (Afawubo et al., 2017). Similarly, according to World Bank (2016), the level of education is inversely linked to poverty and confirms that individuals at the primary level have a high propensity to be below the poverty line than more educated people.

However, the non-significance of the variable "sex" appears counter-intuitive but suggests that the probability of lifting out of poverty does not depend directly on gender, but rather indirectly on the propensity of men to use mobile money to develop their small businesses. In fact, being a man, improves the probability of lifting out of poverty by 3.14% through the adoption of mobile money. Moreover, although not significant in the poverty model, the variable "age" indirectly affects poverty status through its non-linear effect on mobile money adoption. Accordingly, the World Bank (2016) indicates that young people are more likely to be poor compared to adult.

4.4.1. Robustness check

In so far, we have considered some homogeneity among WAEMU countries because of their monetary union. Thus, in order to check the robustness of our results, we assume some heterogeneity among those countries. As a result, we consider two groups of countries consisting of countries with high digital financial inclusion on the one hand and countries with low digital financial inclusion on the other. The last group includes Benin, Mali, Niger and Togo whereas the first group consisting of countries with strong digital financial inclusion with more than 80 percent of mobile money transactions in WAEMU are Côte d'Ivoire, Burkina Faso and Senegal (BCEAO, 2017). Although this is a strong assumption, this study considers that regarding the structural characteristic and the legislation that are similar within each group of countries, the effect of digital financial inclusion and especially the adoption of mobile money on poverty will vary from one group of countries to another. In addition, we remove from the determinants of poverty the variable "fi_account" which denotes the ownership of an account at a financial institution. This will help derive with precision the direct effect of financial inclusion via mobile money on poverty.

Table A.3.1 and Table A.3.2 in Appendix III present the estimate results of the bivariate recursive probit models for robustness check. The estimate results show that the exclusion of the formal financial inclusion variable from the structural equation as well as the grouping of countries improve the magnitude of the impact of mobile money adoption on poverty reduction. The adoption of mobile financial services contributes more to poverty reduction in countries with high digital financial inclusion (34.9%) than in countries with low digital financial inclusion (28.1%). As a result, the importance of technology and communication infrastructure in Côte d'Ivoire and Senegal implies the propensity of the population in these countries to adopt digital financial services. In addition, education achievements in countries with low financial inclusion contributes more to poverty reduction than in the countries with high digital financial inclusion. Moreover, formal financial inclusion almost equally affects poverty reduction in both groups of countries. Likewise, holding a mobile phone similarly affects the probability of lifting out of poverty in both groups. These results confirm those initially found, but the marginal effects are larger regarding the heterogeneity among these countries.

4.5. Concluding remarks

This study aimed at assessing the impact of digital financial inclusion on poverty in WAEMU. Based on a sample of 8,000 adults from the eight countries in the region, we estimate a recursive bivariate probit model. From the estimate results, the results reveal that several key factors drive the probability of lifting out of poverty, but the most important are directly or indirectly related to the adoption of mobile money. Besides, digital financial inclusion can be led by mobile phone operators (MNOs) through mobile money and financial institutions (FI) through credit and debit cards. In fact, the effect through the channel of mobile money is greater than the one through banking credit and debit card. This is due to the comparative advantage concerning the accessibility and the affordability of mobile money even in remote area. Mobile money services appear to fill this absence of formal financial structures accessibility to poor people in remote areas of the WAEMU countries. In addition, education is key in the sustainable poverty reduction strategies. It affects either directly the probability of lifting people out of poverty or indirectly through its effect on the adoption of a mobile financial service. Since the mobile financial services are almost SMS based services, the most educated people are more comfortable with mobile money and are likely to understand the importance of those technologies on their well-being. Furthermore, the study indicates that the ownership of a mobile phone per se does not lift people out of poverty, but its use for financials' sake is critical to changing poverty status.

The study suggests therefore to governments in WAEMU area to facilitate access to mobile financial services through the affordability of mobile money services, the education of the population including the financial education. It furthermore appeals to policy makers to design and implement flexible legislation to incentivize collaboration between Mobile Network Operators and financial institutions to offer effective financial services. In addition, awareness of the use of second and third generation of mobile money services including online payment, bill payment would significantly increase financial inclusion and induce inclusive development and sustainable poverty reduction in the WAEMU countries. Moreover, policy makers in that region should have special care on policies towards leveraging domestic and international remittances enabled by digital technologies.

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Appendix III

A.3.1.: Table A.3.1. Recursive Bivariate Probit (Cluster1)

	(1)	(2)	(3)	(4)	(5)
	Poverty	Marginal Effect		Mobile	Marginal Effect
VARIABLES	Status	Direct	Indirect	Money	
mm	0.828***	0.281***			
	(0.191)	(0.0641)			
sex	0.0223	0.00756	0.0268*	0.143***	0.0349***
	(0.0409)	(0.0139)	(0.0137)	(0.0465)	(0.0113)
age	-0.00324	-0.00110	-0.00107	0.000463	0.000113
	(0.00497)	(0.00168)	(0.00176)	(0.00696)	(0.00169)
age2	2.88e-05	9.76e-06	5.16e-06	-3.67e-05	-8.91e-06
	(5.62e-05)	(1.90e-05)	(2.03e-05)	(8.47e-05)	(2.06e-05)
Education (Primary as base category)					
Secondary	0.359***	0.122***	0.196***	0.416***	0.106***
	(0.0670)	(0.0226)	(0.0217)	(0.0507)	(0.0135)
Tertiary	0.615***	0.195***	0.325***	0.624***	0.170***
	(0.142)	(0.0387)	(0.0431)	(0.0939)	(0.0296)
Remittance rec	0.0864**	0.0293**	0.0301*		
	(0.0433)	(0.0147)	(0.0154)		
Saved	0.163***	0.0552***	0.0567***		
	(0.0411)	(0.0139)	(0.0157)		
Borrowed	-0.0252	-0.00853	-0.00876		
	(0.0384)	(0.0130)	(0.0133)		
Employed	-0.0869*	-0.0294*	0.0185	0.368***	0.0895***
	(0.0463)	(0.0157)	(0.0154)	(0.0533)	(0.0128)
fi_account			0.0574***	0.433***	0.105***
			(0.0115)	(0.0490)	(0.0117)
phone			0.0670***	0.506***	0.123***
			(0.0124)	(0.0580)	(0.0139)
Country Spec Eff	YES	YES	YES	YES	YES
Constant	0.104			-1.853***	
	(0.111)			(0.144)	
Observations	3,859	3,859	3,859	3,859	3,859

Cluster1 consists of: *Benin, Mali, Niger and Togo*

A.3.2.: Table A.3.2. Recursive Bivariate Probit (Cluster2)

	(1)	(2)	(3)	(4)	(5)
	Poverty	Marginal Effect			
VARIABLES	Status	Direct	Indirect	Mobile Money	Marginal Effect
mm	1.098***	0.349***			
	(0.177)	(0.0499)	(0.0331)		
sex	0.0503	0.0160	0.0300*	0.102*	0.0348*
	(0.0527)	(0.0168)	(0.0160)	(0.0529)	(0.0179)
age	0.00780	0.00248	0.00635**	0.0286***	0.00973***
	(0.00892)	(0.00285)	(0.00257)	(0.00930)	(0.00314)
age2	-0.000102	-3.23e-05	-8.01e-05***	-0.000353***	-0.000120***
	(0.000108)	(3.44e-05)	(3.06e-05)	(0.000117)	(3.95e-05)
Secondary	0.188**	0.0602**	0.135***	0.497***	0.176***
	(0.0842)	(0.0279)	(0.0245)	(0.0535)	(0.0191)
Tertiary	0.540**	0.162**	0.262***	0.524***	0.186***
	(0.267)	(0.0717)	(0.0847)	(0.192)	(0.0705)
Remittance Rec.	0.0567	0.0180	0.0184		
	(0.0480)	(0.0153)	(0.0157)		
saved	0.215***	0.0682***	0.0695***		
	(0.0523)	(0.0170)	(0.0191)		
borrowed	-0.0442	-0.0141	-0.0143		
	(0.0473)	(0.0150)	(0.0154)		
Employed	-0.105*	-0.0334*	0.0117	0.343***	0.116***
	(0.0595)	(0.0186)	(0.0160)	(0.0542)	(0.0181)
fi_account			0.0558***	0.418***	0.142***
			(0.0109)	(0.0558)	(0.0185)
Phone			0.0654***	0.490***	0.166***
			(0.00904)	(0.0729)	(0.0242)
Country Spec Eff	YES	YES	YES	YES	YES
Constant	-0.255			-1.834***	
	(0.162)			(0.177)	
Observations	2,922	2,922		2,922	2,922

Cluster2 consists of: *Burkina Faso, Cote d'Ivoire and Senegal*

A.3.3.: TableA3: Correlations table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
age	1	1.0000															
saved	2	0.0032	1.0000														
borrowed	3	0.0108	0.2758	1.0000													
mm	4	-0.0315	0.2575	0.1418	1.0000												
sex	5	0.0564	0.0591	0.0423	0.1311	1.0000											
Primary_edu	6	0.2265	-0.1406	-0.0480	-0.2362	-0.1637	1.0000										
Secondary_edu	7	-0.2316	0.1064	0.0283	0.2031	0.1386	-0.9230	1.0000									
Tertiary_educ	8	0.0011	0.0935	0.0520	0.0956	0.0719	-0.2465	-0.1455	1.0000								
fi_account	9	0.0629	0.3005	0.1758	0.2136	0.1297	-0.2487	0.1721	0.2061	1.0000							
pov	10	-0.0450	0.1194	0.0365	0.0999	0.0701	-0.2016	0.1685	0.0940	0.1418	1.0000						
rem_send	11	0.0157	0.3415	0.1619	0.3247	0.1255	-0.2191	0.1654	0.1468	0.3410	0.1398	1.0000					
rem_rec	12	-0.0151	0.2258	0.1531	0.3119	0.0368	-0.1798	0.1486	0.0879	0.1549	0.0873	0.2866	1.0000				
phone	13	0.0117	0.1837	0.0669	0.2277	0.1545	-0.2278	0.1902	0.1066	0.2050	0.0934	0.2240	0.1743	1.0000			
employed	14	0.0109	0.2004	0.1189	0.1402	0.1430	-0.0129	-0.0067	0.0500	0.1362	0.0324	0.1549	0.0545	0.1483	1.0000		
debitcard	15	0.0595	0.2338	0.1255	0.1771	0.0954	-0.2098	0.1314	0.2084	0.5871	0.1180	0.2825	0.1017	0.1473	0.0841	1.0000	
creditcard	16	0.0362	0.1324	0.1566	0.1138	0.0199	-0.0597	0.0426	0.0461	0.2699	0.0073	0.1224	0.0376	0.0484	0.0503	0.3387	1.0000

y

A.3.4. Table A.3.4. Probit estimation results and Marginal effects

```
.  probit pov mm sex age age2 i.educ fi_account rem_rec saved borrowed debitcard creditcard phone
>  employed benin burkina civ mali niger senegal togo,robust

note: togo omitted because of collinearity
Iteration 0:   log pseudolikelihood = -4197.5884
Iteration 1:   log pseudolikelihood =  -3953.104
Iteration 2:   log pseudolikelihood = -3950.7799
Iteration 3:   log pseudolikelihood = -3950.7763
Iteration 4:   log pseudolikelihood = -3950.7763

Probit regression                               Number of obs     =      6,684
                                                Wald chi2(20)     =     459.63
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -3950.7763               Pseudo R2         =     0.0588
```

pov	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
mm	.0887588	.0419652	2.12	0.034	.0065085	.1710091
sex	.0698198	.0345159	2.02	0.043	.0021697	.1374698
age	.0043352	.0052546	0.83	0.409	-.0059636	.0146339
age2	-.0000652	.0000627	-1.04	0.299	-.0001881	.0000578
educ						
secondary	.4499793	.03915	11.49	0.000	.3732468	.5267118
completed tertiary or more	.9105732	.1482624	6.14	0.000	.6199843	1.201162
fi_account	.1950387	.0508006	3.84	0.000	.0954714	.2946059
rem_rec	.0695244	.0379143	1.83	0.067	-.0047863	.143835
saved	.2025084	.0370388	5.47	0.000	.1299137	.2751031
borrowed	-.0454086	.0350853	-1.29	0.196	-.1141745	.0233574
debitcard	.2500451	.0711038	3.52	0.000	.1106843	.389406
creditcard	-.41429	.091312	-4.54	0.000	-.5932582	-.2353219
phone	.0985182	.0394111	2.50	0.012	.0212739	.1757625
employed	-.0225725	.0371814	-0.61	0.544	-.0954466	.0503017
benin	.0057826	.0620525	0.09	0.926	-.1158381	.1274033
burkina	.0765888	.0630922	1.21	0.225	-.0470696	.2002472
civ	-.0320398	.0628551	-0.51	0.610	-.1552335	.0911538
mali	.1017152	.0629595	1.62	0.106	-.0216833	.2251136
niger	.2670147	.0634024	4.21	0.000	.1427483	.3912812
senegal	.0170394	.0627191	0.27	0.786	-.1058878	.1399666
togo	0	(omitted)				
_cons	-.0969812	.1084754	-0.89	0.371	-.309589	.1156266

A.3.5. Table A.3.5. Marginal Effect

```
.  margins,dydx(*)post

Average marginal effects                        Number of obs     =      6,684
Model VCE    : Robust

Expression   : Pr(pov), predict()
dy/dx w.r.t. : mm sex age age2 2.educ 3.educ fi_account rem_rec saved borrowed debitcard
               creditcard phone employed benin burkina civ mali niger senegal togo
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
mm	.0298276	.01409	2.12	0.034	.0022118	.0574435
sex	.0234631	.0115857	2.03	0.043	.0007556	.0461706
age	.0014568	.0017657	0.83	0.409	-.0020038	.0049175
age2	-.0000219	.0000211	-1.04	0.299	-.0000632	.0000194
educ						
secondary	.1516875	.0127715	11.88	0.000	.1266559	.1767192
completed tertiary or more	.2640207	.0294583	8.96	0.000	.2062835	.321758
fi_account	.0655433	.0170259	3.85	0.000	.0321732	.0989134
rem_rec	.0233639	.0127272	1.84	0.066	-.0015809	.0483086
saved	.0680535	.0123753	5.50	0.000	.0437983	.0923087
borrowed	-.0152597	.0117854	-1.29	0.195	-.0383586	.0078392
debitcard	.0840283	.0238523	3.52	0.000	.0372786	.130778
creditcard	-.1392233	.0305738	-4.55	0.000	-.1991468	-.0792998
phone	.0331073	.0132267	2.50	0.012	.0071835	.0590311
employed	-.0075855	.0124934	-0.61	0.544	-.0320722	.0169011
benin	.0019433	.0208528	0.09	0.926	-.0389274	.042814
burkina	.0257379	.0212005	1.21	0.225	-.0158143	.0672901
civ	-.0107671	.0211212	-0.51	0.610	-.0521639	.0306298
mali	.0341817	.0211435	1.62	0.106	-.0072589	.0756222
niger	.089731	.0212375	4.23	0.000	.0481063	.1313557
senegal	.0057261	.0210764	0.27	0.786	-.0355828	.0470351
togo	0	(omitted)				

A.3.6.: Table A.3.6.: Bivariate probit estimation results and marginal effects

```
.  biprobit (pov= sex age age2 i.educ fi_account rem_rec saved borrowed debitcard creditcard empl
> oyed phone benin burkina civ mali niger senegal togo) (mm= sex age age2 i.educ fi_account rem_r
> ec saved borrowed debitcard creditcard employed phone benin burkina civ mali niger senegal togo
> ), nolog
note: togo omitted because of collinearity
note: togo omitted because of collinearity

Seemingly unrelated bivariate probit            Number of obs     =      6,684
                                                Wald chi2(38)     =    1737.12
Log likelihood =  -7124.958                     Prob > chi2       =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
pov						
sex	.0733473	.0345125	2.13	0.034	.0057041	.1409904
age	.0047182	.0052052	0.91	0.365	-.0054839	.0149202
age2	-.0000703	.0000624	-1.13	0.260	-.0001926	.000052
educ						
secondary	.4596574	.0391174	11.75	0.000	.3829886	.5363262
completed tertiary or more	.9254843	.1466872	6.31	0.000	.6379826	1.212986
fi_account	.1993323	.0506011	3.94	0.000	.1001561	.2985086
rem_rec	.0869395	.0370028	2.35	0.019	.0144152	.1594637
saved	.2105089	.0368839	5.71	0.000	.1382178	.2828001
borrowed	-.042842	.0351262	-1.22	0.223	-.111688	.026004
debitcard	.2523457	.0723965	3.49	0.000	.1104511	.3942402
creditcard	-.40461	.0919078	-4.40	0.000	-.584746	-.2244739
employed	-.0167377	.0367616	-0.46	0.649	-.0887891	.0553138
phone	.1063974	.0389612	2.73	0.006	.0300349	.1827599
benin	.0044237	.0619432	0.07	0.943	-.1169827	.1258301
burkina	.0888393	.0636158	1.40	0.163	-.0358454	.2135241
civ	-.0185903	.0625174	-0.30	0.766	-.1411222	.1039416
mali	.1068875	.062874	1.70	0.089	-.0163433	.2301183
niger	.2638434	.0642256	4.11	0.000	.1379636	.3897233
senegal	.0275537	.0624464	0.44	0.659	-.0948389	.1499463
togo	0	(omitted)				
_cons	-.1116784	.1080068	-1.03	0.301	-.323368	.1000111
mm						
sex	.1694624	.0388212	4.37	0.000	.0933743	.2455505
age	.0182145	.0065696	2.77	0.006	.0053384	.0310907
age2	-.0002477	.0000809	-3.06	0.002	-.0004063	-.000089
educ						
secondary	.375115	.0406469	9.23	0.000	.2954485	.4547814
completed tertiary or more	.5166879	.1060956	4.87	0.000	.3087444	.7246315
fi_account	.1598213	.0506991	3.15	0.002	.060453	.2591896
rem_rec	.6373791	.0373754	17.05	0.000	.5641247	.7106335
saved	.3412632	.0398242	8.57	0.000	.2632091	.4193172
borrowed	.1190594	.0383434	3.11	0.002	.0439078	.194211
debitcard	.0405177	.0651886	0.62	0.534	-.0872496	.1682851
creditcard	.3259877	.0901756	3.62	0.000	.1492468	.5027286
employed	.2732085	.0427024	6.40	0.000	.1895133	.3569036
phone	.4562326	.0502785	9.07	0.000	.3576886	.5547766
benin	-.1032392	.0687887	-1.50	0.133	-.2380625	.0315842
burkina	.4562498	.0661813	6.89	0.000	.3265367	.5859628
civ	.4804791	.0662734	7.25	0.000	.3505857	.6103726
mali	.2095318	.0682872	3.07	0.002	.0756913	.3433722
niger	-.4403977	.0837067	-5.26	0.000	-.6044599	-.2763355
senegal	.4151798	.0667727	6.22	0.000	.2843078	.5460518
togo	0	(omitted)				
_cons	-2.42793	.1336555	-18.17	0.000	-2.68989	-2.165971
/athrho	.0468281	.0246684	1.90	0.058	-.0015211	.0951772
rho	.0467939	.0246144			-.0015211	.0948909

```
Wald test of rho=0: chi2(1) = 3.60355                  Prob > chi2 = 0.0577
```

A.3.7. Table A.3.7: Conditional Marginal Effect

```
.  margins, predict(pmarg1) dydx(*) atmeans force post

Conditional marginal effects                    Number of obs     =      6,684
Model VCE    : OIM

Expression   : Pr(pov=1), predict(pmarg1)
dy/dx w.r.t. : sex age age2 2.educ 3.educ fi_account rem_rec saved borrowed debitcard
               creditcard employed phone benin burkina civ mali niger senegal togo
at           : sex             =    .5888689 (mean)
               age             =    32.70826 (mean)
               age2            =    1270.288 (mean)
               1.educ          =    .6053262 (mean)
               2.educ          =    .3674446 (mean)
               3.educ          =    .0272292 (mean)
               fi_account      =    .2582286 (mean)
               rem_rec         =     .345751 (mean)
               saved           =    .4866846 (mean)
               borrowed        =    .4655895 (mean)
               debitcard       =    .1204369 (mean)
               creditcard      =    .0399461 (mean)
               employed        =    .6796828 (mean)
               phone           =    .7360862 (mean)
               benin           =    .1439258 (mean)
               burkina         =    .1400359 (mean)
               civ             =    .1451227 (mean)
               mali            =    .1443746 (mean)
               niger           =    .1398863 (mean)
               senegal         =    .1424297 (mean)
               togo            =     .144225 (mean)
```

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.0257908	.0121362	2.13	0.034	.0020043	.0495773
age	.001659	.0018302	0.91	0.365	-.0019282	.0052462
age2	-.0000247	.0000219	-1.13	0.260	-.0000677	.0000183
educ						
secondary	.1576631	.0128247	12.29	0.000	.132527	.1827991
completed tertiary or more	.2702674	.0284458	9.50	0.000	.2145146	.3260202
fi_account	.0700904	.017783	3.94	0.000	.0352364	.1049444
rem_rec	.0305702	.0130108	2.35	0.019	.0050694	.0560709
saved	.0740204	.0129605	5.71	0.000	.0486182	.0994226
borrowed	-.0150644	.0123511	-1.22	0.223	-.039272	.0091433
debitcard	.0887313	.0254273	3.49	0.000	.0388947	.1385678
creditcard	-.1422713	.0322852	-4.41	0.000	-.2055491	-.0789935
employed	-.0058854	.0129263	-0.46	0.649	-.0312205	.0194497
phone	.0374121	.0137004	2.73	0.006	.0105597	.0642645
benin	.0015555	.0217808	0.07	0.943	-.0411341	.0442451
burkina	.0312382	.0223667	1.40	0.163	-.0125997	.0750761
civ	-.0065368	.0219828	-0.30	0.766	-.0496224	.0365487
mali	.0375844	.0221073	1.70	0.089	-.0057451	.0809139
niger	.0927742	.0225749	4.11	0.000	.0485282	.1370201
senegal	.0096886	.0219576	0.44	0.659	-.0333476	.0527248
togo	0	(omitted)				

```
. margins, predict(pmarg2) dydx(*) atmeans force post

Conditional marginal effects                    Number of obs     =      6,684
Model VCE    : OIM

Expression   : Pr(mm=1), predict(pmarg2)
dy/dx w.r.t. : sex age age2 2.educ 3.educ fi_account rem_rec saved borrowed debitcard
               creditcard employed phone benin burkina civ mali niger senegal togo
at           : sex             =     .5888689 (mean)
               age             =     32.70826 (mean)
               age2            =     1270.288 (mean)
               1.educ          =     .6053262 (mean)
               2.educ          =     .3674446 (mean)
               3.educ          =     .0272292 (mean)
               fi_account      =     .2582286 (mean)
               rem_rec         =      .345751 (mean)
               saved           =     .4866846 (mean)
               borrowed        =     .4655895 (mean)
               debitcard       =     .1204369 (mean)
               creditcard      =     .0399461 (mean)
               employed        =     .6796828 (mean)
               phone           =     .7360862 (mean)
               benin           =     .1439258 (mean)
               burkina         =     .1400359 (mean)
               civ             =     .1451227 (mean)
               mali            =     .1443746 (mean)
               niger           =     .1398863 (mean)
               senegal         =     .1424297 (mean)
               togo            =      .144225 (mean)
```

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.0519455	.0118846	4.37	0.000	.0286521	.0752388
age	.0055833	.0020131	2.77	0.006	.0016378	.0095289
age2	-.0000759	.0000248	-3.06	0.002	-.0001245	-.0000273
educ						
secondary	.1175629	.0130276	9.02	0.000	.0920292	.1430965
completed tertiary or more	.1689768	.0390497	4.33	0.000	.0924408	.2455127
fi_account	.0489902	.0155425	3.15	0.002	.0185275	.0794528
rem_rec	.1953764	.0114584	17.05	0.000	.1729182	.2178345
saved	.1046077	.0121552	8.61	0.000	.080784	.1284314
borrowed	.0364954	.0117452	3.11	0.002	.0134752	.0595155
debitcard	.0124199	.0199865	0.62	0.534	-.0267528	.0515927
creditcard	.0999253	.0276588	3.61	0.000	.0457151	.1541355
employed	.0837468	.0130554	6.41	0.000	.0581587	.1093349
phone	.1398494	.0151856	9.21	0.000	.1100861	.1696126
benin	-.031646	.0210761	-1.50	0.133	-.0729545	.0096625
burkina	.1398546	.0203151	6.88	0.000	.1000378	.1796715
civ	.1472817	.0203575	7.23	0.000	.1073817	.1871816
mali	.0642279	.0209305	3.07	0.002	.0232048	.105251
niger	-.1349955	.0253923	-5.32	0.000	-.1847634	-.0852276
senegal	.1272654	.0204708	6.22	0.000	.0871434	.1673875
togo	0	(omitted)				

Note: dy/dx for factor levels is the discrete change from the base level.

dd

A.3.8.: Table A3.8: Recursive bivariate probit estimation results

```
.  biprobit (pov= mm sex age age2 i.educ fi_account rem_rec saved borrowed debitcard creditcard e
> mployed benin burkina civ mali niger senegal togo) (mm= sex age age2 i.educ fi_account rem_rec
> saved borrowed debitcard creditcard employed phone benin burkina civ mali niger senegal togo),
> nolog
note: togo omitted because of collinearity
note: togo omitted because of collinearity

Seemingly unrelated bivariate probit            Number of obs     =      6,684
                                                Wald chi2(38)     =    2020.67
Log likelihood = -7124.5875                     Prob > chi2       =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
pov						
mm	.6575161	.2083168	3.16	0.002	.2492227	1.065809
sex	.0485404	.0360379	1.35	0.178	-.0220926	.1191735
age	.0022324	.0053138	0.42	0.674	-.0081825	.0126472
age2	-.0000355	.0000642	-0.55	0.580	-.0001613	.0000903
educ						
secondary	.37672	.0542125	6.95	0.000	.2704655	.4829745
completed tertiary or more	.7862561	.1573345	5.00	0.000	.4778862	1.094626
fi_account	.1643948	.052906	3.11	0.002	.060701	.2680886
rem_rec	-.0436017	.0595644	-0.73	0.464	-.1603457	.0731423
saved	.1446343	.0448016	3.23	0.001	.0568248	.2324439
borrowed	-.0619275	.0351391	-1.76	0.078	-.1307989	.006944
debitcard	.2258318	.0722672	3.12	0.002	.0841908	.3674729
creditcard	-.4613824	.0914014	-5.05	0.000	-.6405258	-.282239
employed	-.0574709	.0397939	-1.44	0.149	-.1354654	.0205237
benin	.0189601	.0610492	0.31	0.756	-.1006942	.1386145
burkina	-.0027034	.0717064	-0.04	0.970	-.1432454	.1378386
civ	-.1131875	.0713239	-1.59	0.113	-.2529798	.0266049
mali	.0676175	.0643253	1.05	0.293	-.0584577	.1936928
niger	.2824659	.0637182	4.43	0.000	.1575804	.4073513
senegal	-.0495139	.0677581	-0.73	0.465	-.1823174	.0832895
togo	0	(omitted)				
_cons	.0152041	.1139343	0.13	0.894	-.2081031	.2385113
mm						
sex	.1589779	.0388566	4.09	0.000	.0828204	.2351355
age	.0204372	.0066251	3.08	0.002	.0074522	.0334222
age2	-.0002761	.0000819	-3.37	0.001	-.0004367	-.0001156
educ						
secondary	.3765455	.0405833	9.28	0.000	.2970038	.4560873
completed tertiary or more	.5178885	.1060655	4.88	0.000	.3100039	.7257731
fi_account	.1569821	.0506673	3.10	0.002	.057676	.2562882
rem_rec	.6354808	.0373468	17.02	0.000	.5622824	.7086792
saved	.3413384	.0397359	8.59	0.000	.2634575	.4192194
borrowed	.1158403	.0382497	3.03	0.002	.0408722	.1908083
debitcard	.0347612	.0651821	0.53	0.594	-.0929934	.1625158
creditcard	.3250062	.0903716	3.60	0.000	.1478811	.5021312
employed	.278111	.0425255	6.54	0.000	.1947625	.3614595
phone	.4611562	.0495568	9.31	0.000	.3640266	.5582858
benin	-.1108016	.0686527	-1.61	0.107	-.2453584	.0237551
burkina	.4589241	.0659217	6.96	0.000	.32972	.5881282
civ	.4696183	.0662275	7.09	0.000	.3398148	.5994218
mali	.2038648	.0682249	2.99	0.003	.0701464	.3375832
niger	-.4405668	.0832884	-5.29	0.000	-.6038091	-.2773245
senegal	.4109851	.0667044	6.16	0.000	.2802469	.5417234
togo	0	(omitted)				
_cons	-2.457335	.1338918	-18.35	0.000	-2.719758	-2.194912
/athrho	-.3537917	.142862	-2.48	0.013	-.6337962	-.0737873
rho	-.339734	.126373			-.5606607	-.0736537

```
Wald test of rho=0: chi2(1) = 6.13284                  Prob > chi2 = 0.0133
```

A.3.9.: Table A3.9: Marginal effects

```
. margins, predict(pmarg1) dydx(*) force post
(note: prediction is a function of possibly stochastic quantities other than e(b))

Average marginal effects                        Number of obs     =      6,684
Model VCE    : OIM

Expression   : Pr(pov=1), predict(pmarg1)
dy/dx w.r.t. : mm sex age age2 2.educ 3.educ fi_account rem_rec saved borrowed debitcard
               creditcard employed benin burkina civ mali niger senegal togo phone
```

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
mm	.218959	.0681884	3.21	0.001	.0853122	.3526058
sex	.0161644	.0120237	1.34	0.179	-.0074015	.0397304
age	.0007434	.0017704	0.42	0.675	-.0027265	.0042133
age2	-.0000118	.0000214	-0.55	0.580	-.0000537	.0000301
educ						
secondary	.1261001	.0183172	6.88	0.000	.0901991	.1620011
completed tertiary or more	.2335324	.0360437	6.48	0.000	.1628881	.3041766
fi_account	.054745	.0176797	3.10	0.002	.0200934	.0893966
rem_rec	-.0145198	.019777	-0.73	0.463	-.0532819	.0242423
saved	.0481646	.0150279	3.21	0.001	.0187104	.0776188
borrowed	-.0206224	.0116781	-1.77	0.077	-.043511	.0022662
debitcard	.0752041	.0240911	3.12	0.002	.0279864	.1224218
creditcard	-.1536447	.0302157	-5.08	0.000	-.2128663	-.0944231
employed	-.0191383	.0132076	-1.45	0.147	-.0450247	.0067481
benin	.0063139	.0203293	0.31	0.756	-.0335307	.0461585
burkina	-.0009003	.0238768	-0.04	0.970	-.0476979	.0458973
civ	-.0376925	.0236465	-1.59	0.111	-.0840388	.0086538
mali	.0225173	.0214465	1.05	0.294	-.019517	.0645516
niger	.0940638	.0210886	4.46	0.000	.052731	.1353966
senegal	-.0164886	.0225279	-0.73	0.464	-.0606425	.0276653
togo	0	(omitted)				
phone	0	(omitted)				

Note: dy/dx for factor levels is the discrete change from the base level.

```
.         margins, predict(pcond1) dydx(*) force post
(note: prediction is a function of possibly stochastic quantities other than e(b))

Average marginal effects                        Number of obs     =      6,684
Model VCE    : OIM

Expression   : Pr(pov=1|mm=1), predict(pcond1)
dy/dx w.r.t. : mm sex age age2 2.educ 3.educ fi_account rem_rec saved borrowed debitcard
               creditcard employed benin burkina civ mali niger senegal togo phone
```

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
mm	.2329348	.0680126	3.42	0.001	.0996326	.3662371
sex	.031419	.0119273	2.63	0.008	.008042	.054796
age	.0026192	.0018308	1.43	0.153	-.0009691	.0062076
age2	-.0000373	.0000221	-1.69	0.091	-.0000805	5.98e-06
educ						
secondary	.1758564	.0144161	12.20	0.000	.1476014	.2041114
completed tertiary or more	.3249424	.0436252	7.45	0.000	.2394386	.4104462
fi_account	.0722836	.0175821	4.11	0.000	.0378233	.1067439
rem_rec	.0414064	.0133931	3.09	0.002	.0151564	.0676563
saved	.0817765	.0126684	6.46	0.000	.056947	.106606
borrowed	-.0115751	.0123519	-0.94	0.349	-.0357845	.0126342
debitcard	.0831142	.0254211	3.27	0.001	.0332897	.1329386
creditcard	-.1343751	.0331126	-4.06	0.000	-.1992745	-.0694757
employed	.0045211	.0132165	0.34	0.732	-.0213826	.0304249
benin	-.0031959	.0217256	-0.15	0.883	-.0457772	.0393854
burkina	.0400997	.0221014	1.81	0.070	-.0032183	.0834176
civ	.0019158	.0217668	0.09	0.930	-.0407463	.0445779
mali	.0421932	.0217677	1.94	0.053	-.0004707	.0848571
niger	.0606527	.0264758	2.29	0.022	.0087611	.1125443
senegal	.0192275	.0218715	0.88	0.379	-.0236399	.0620949
togo	0	(omitted)				
phone	.0412571	.0144069	2.86	0.004	.01302	.0694941

Note: dy/dx for factor levels is the discrete change from the base level.

gg

```
. margins, predict(pmarg2) dydx(*) force post

Average marginal effects                        Number of obs     =      6,684
Model VCE    : OIM

Expression   : Pr(mm=1), predict(pmarg2)
dy/dx w.r.t. : mm sex age age2 2.educ 3.educ fi_account rem_rec saved borrowed debitcard
               creditcard employed benin burkina civ mali niger senegal togo phone
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
mm	0	(omitted)				
sex	.042454	.0103379	4.11	0.000	.0221921	.0627158
age	.0054576	.0017663	3.09	0.002	.0019957	.0089196
age2	-.0000737	.0000218	-3.38	0.001	-.0001165	-.0000309
educ						
secondary	.1044567	.0115236	9.06	0.000	.0818709	.1270425
completed tertiary or more	.1473831	.0325854	4.52	0.000	.0835169	.2112492
fi_account	.041921	.0135016	3.10	0.002	.0154583	.0683837
rem_rec	.1697008	.0093191	18.21	0.000	.1514358	.1879659
saved	.0911521	.0104472	8.73	0.000	.070676	.1116282
borrowed	.0309344	.0101947	3.03	0.002	.0109531	.0509156
debitcard	.0092827	.0174043	0.53	0.594	-.0248291	.0433946
creditcard	.0867907	.0240661	3.61	0.000	.039622	.1339594
employed	.0742676	.0112572	6.60	0.000	.052204	.0963313
benin	-.0295888	.0183249	-1.61	0.106	-.0655049	.0063273
burkina	.1225526	.017425	7.03	0.000	.0884002	.156705
civ	.1254084	.0174931	7.17	0.000	.0911226	.1596942
mali	.0544407	.0181872	2.99	0.003	.0187944	.0900871
niger	-.1176504	.0221534	-5.31	0.000	-.1610702	-.0742305
senegal	.1097508	.0176716	6.21	0.000	.075115	.1443866
togo	0	(omitted)				
phone	.1231486	.0130373	9.45	0.000	.097596	.1487013

Note: dy/dx for factor levels is the discrete change from the base level.

hh

A.3.10. Theoretical framework of Levine

Levine (2008) provides a theoretical hypothesis of how finance may alleviate poverty and lower inequality through intergenerational mobility. He argues that the broad access to finance will help poor people finance their education as well as investment opportunities and then lift them out of poverty. The financial development may help poor household smooth their consumption and prevent them from failing below poverty during crises. His model includes dynasties *i* and generations *t*, and shows how the income of a dynasty $Y(i,t)$ may be affected by financial development.

$$Y(i,t) = K_h(i,t) * r_w(i,t) + A(i,t) * r_A(i,t) \quad \textbf{4. 1}$$

Where $Y(i,t)$ is the income of a dynasty and is affected by its human capital $K_h(i,t)$ at the wage rate $r_w(i,t)$ as well as its initial assets $A(i,t)$ at its return rate $r_A(i,t)$. Considering a bequest motive, where savings from generation t to t+1 is a convex function of wealth ($A' > A''$), wealth differences will persist in the long term and the long-term distribution of wealth will depend on its initial distribution.

However, the human capital is a function of ability *b* and schooling *s*, where both are complimentary inputs in human capital production as follows:

$$K_h(i,t) = K_h[b(i,t), s(i,t)] \quad \textbf{4. 2}$$

With $[K_h]'_b > 0$, $[K_h]'_s > 0$ and $[K_h]''_{bs} > 0$.

There may be two cases with one assuming financial underdevelopment and the other assuming perfect financial development.

With financial market friction or underdevelopment, human capital accumulation is no longer socially efficient and hinders then poverty alleviation. This is due to the fact that schooling becomes a joint function of both ability and parental wealth $A(i,t-1)$: $s(i,t) = S[b(i,t), A(i,t-1)]$ and the human capital becomes:

$$K_h(i,t) = K_h\{b(i,t), S[b(i,t), A(i,t-1)]\} \quad \textbf{4. 3}$$

Hence, poor smart children receive too little education and less intelligent rich children receive too much education. In imperfect capital market, lenders may require collateral before given credit to borrowers. Thus, accumulated assets will play a critical role in securing funding. The rate of return on assets $r_A(i,t)$ becomes:

$$r_A(i,t) = R[e(i,t), A(i,t-1)] \quad \textbf{4. 4}$$

Where $e(i,t)$ is the borrower's effort in terms of talent and which varies between individuals and the generations of dynasty and $[R]'_e > 0$ and $[R]'_A < 0$.

Thus, the initial distribution of wealth determines which dynasties may obtain external finance. Poor individuals with great ideas do not receive funding while rich individuals, with average ideas have their project funded and remain rich. With inefficient innovations, growth is hindered and this prevents the whole income from increasing. With perfect financial market, the $A(i,t-1)$ term is no longer present in the equations. This means that schooling purely depends on ability or intelligence, $s(i,t) = S[b(i,t)]$ and economic opportunity no longer depends on dynastic wealth. With no dynasties cut off from external finance due to greater financial development, the rate of return on savings is purely determined by the borrower's ability. So, $r_A(i,t) = R[e(i,t)]$ where $[R]'_e > 0$ and society's resources are provided to the most talented and not just the wealthiest. This reduces income inequality and the prevalence of poverty. In addition, society benefits as higher rates of economic growth are achieved. Consequently, the development of financial system through the adoption of digital finance is key to directing the society's resources to the most talented without any initial asset.

GENERAL CONCLUSION

General Conclusion

In this thesis, we empirically investigated the accelerating role of digital finance in reducing poverty through financial inclusion. Indeed, evidences show that persistent poverty is due to financial exclusion that is the fact of the multiple financial market failure. The advent of digital technologies including mobile money platform, Distributed Ledger Technology, Blockchain as well as Internet of Things through mobile and computing platforms in the financial sector is a promise for delivering affordable financial services to the disadvantaged people that are usually excluded from the formal financial system. In this dissertation, we focused on the particular case of mobile money because most of the excluded people are poor but own a mobile phone as asset. We find from the three essays, interesting and interrelated results that have important policy implications.

In the first essay, we investigate the accelerating role of digital technology in the dynamic of financial inclusion in WAEMU using data from the BCEAO and the ITU databases to estimate both static and dynamic panel data models. We find that the dynamics of financial inclusion differ from one country to another and the effect of mobile phone and Internet on financial inclusion is perceived differently across countries in the WAEMU region. In addition, the results show that the simultaneous use of Internet and mobile phone is more conducive to financial inclusion than the separate use of these technologies. This is because, beyond mobile money, the digital inclusion of an economy through the adoption of second and third generations' mobile money services is becoming increasingly a major issue in the WAEMU countries. Moreover, payments and other online transactions require strong internet connectivity. This is because the online banking services are made possible by the use of the internet on smartphones and take a large part of digital finance in developing countries

In the second essay, we aimed to investigate the driving factors of digital finance and particularly mobile money adoption in WAEMU. For that purpose, using both a country level data and a sample of 8000 adults in WAEMU from the World Bank Global Findex (2017) database, we made first, a cluster analysis and then a logistic analysis to investigate both the macroeconomic and microeconomics driven factors of mobile money adoption in that region. We found that country characteristic such as literacy rate; labor force, mobile infrastructure and even banking infrastructure in terms of numbers of ATM per 100000 people are the main macroeconomic determinants of mobile money adoption. In addition, being young, man,

educated, relatively richer and even banked increases the likelihood of adopting mobile money in WAEMU. The findings also reveal that some countries such as Côte d'Ivoire, Mali, Senegal and Burkina Faso are performing well as far as digital financial inclusion is concerned due to their policy implemented and some structural factors.

Last but not the least, the third essay evidenced the effect of the digital financial inclusion on the reduction of poverty in WAEMU. We thereby pointed out the accelerating role of digital finance including the mobile money to tackling poverty. We therefore used the World Bank Global Findex (2017) database to estimate a probit and a recursive bivariate probit model and found that several key factors drive the probability of lifting out of poverty, but the most important ones are directly or indirectly related to the adoption of mobile money. However, digital financial inclusion can be led by mobile phone operators (MNOs) through mobile money and financial institutions (FI) through credit and debit cards. In fact, the effect through the channel of mobile money is greater than the one through banking credit and debit card. In addition, education is key in the sustainable poverty reduction strategies. It affects either directly the probability of lifting people out of poverty or indirectly through its effect on the adoption of a mobile financial service. Since the mobile financial services are almost SMS based services, the most educated people are more comfortable with mobile money and are likely to understand the importance of those technologies on their well-being.

As a matter of fact, some policy implications come out from this dissertation. Generally, policies favoring mobile money adoption may boost financial inclusion and alleviate poverty in developing countries especially in WAEMU area. Moreover, all the WAEMU countries may follow the example of Kenya where the government had made flexible the regulation in the sector of digital finance leading to the M-PESA as a success story in Africa. The States as well as the Central Bank, must design appropriate flexible regulation governing digital financial services flexible in order to encourage new players to enter into the digital finance market. In other words, the central Bank of the WAEMU (BCEAO) in collaboration with governments of WAEMU countries should take steps toward innovative financial inclusion strategy including, financial education, telecommunication infrastructure development over remote areas. However, considering the risk pertaining to digital technologies, regulatory policy ensuring data protection and trust in the usage of digital technologies are key to a mass adoption of digital finance. Furthermore, that policies may emphasize the security of transactions and data protection for clients so that to ensure the security of domestic and international remittances by

migrant and favors financial inclusion. It also urges to provide with each people good education including financial education and literacy program for adult population.

In addition, it urges for policymakers to promote the use of digital technologies by making them affordable, available and accessible even in the remote areas. Furthermore, the extension of communication networks in rural areas remains a big challenge. This may pass by the development of infrastructure conducive to innovation. Moreover, public awareness of adopting second and third generation mobile money services is very critical to a digital inclusion of all WAEMU economies. Given the comparative advantage in terms of infrastructures of mobile telephone operators, it would also be advantageous for banks and microfinance institutions to change their business model by collaborating more with Mobile Network Operators. In addition, that regulation may consider security of transaction and data protection for clients.

There are some limitations that future attempts may consider to advance the field. First of all, the study is done on a panel of countries that are at first glance homogenous because they belong to the same monetary union. In fact, it would sound better to consider a single country in order to make an in-depth cross-sectional analysis of the accelerating role of digital finance in poverty alleviation. This may be done as an impact evaluation study that will compare included individuals to the excluded counterpart. Second, it would sound better to make an in-depth analysis of cross enterprises digital financial inclusion in order to investigate the potential effect of the advent of mobile based financial services on the development of micro, small and medium enterprise in developing countries. Last but not least, the regulatory framework needs to be more aggressive so as to point out the state of the new generations of mobile financial services in the WAEMU countries.

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