Network Effects and Payment Innovations: Microfoundations and Macroeconomic Implications of Mobile Money and Cashlessness in Botswana

A thesis submitted for the degree of

Doctor of Philosophy
in Economics

by

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April 2025

Dedicated to my mother, my father, my wife, and my daughter whose unconditional support, sacrifices, and endless encouragement have made this PhD journey possible.

Declaration

I declare that this thesis submission represents my ideas in my own words and where others' ideas or words have been included. I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity in my submission. I understand that any violation of the above will cause disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been appropriately cited or from whom proper permission has not been taken when needed.

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Acknowledgements

All the glory goes to Our Heavenly Father for all the blessings, strength and wisdom upon me, and without Him, I could not have made it this far.

My sincere gratitude goes to my supervisor Professor Sheri Markose for her invaluable guidance, support and encouragement over the course of this dissertation. This research was presented at the 11th Warwick Economics PhD Conference in June 2023, Essex Finance Centre (EFiC) Conference in Banking and Corporate Finance in July 2024, and Wits Global Fintech Conference in November 2024, for which I would like to extend my thanks to the conference participants. Special thanks to my employer, Bank of Botswana, for sponsoring my PhD studies and approving my study leave.

Most importantly, my deepest gratitude goes to my family, wife, and daughter for their support throughout my research. Lastly, I acknowledge the support from my colleagues in the Department of Economics at the University of Essex and the Bank of Botswana.

Abstract

This thesis develops the microfoundations of mobile money adoption and its implications for cashless payments and monetary policy in Botswana. Over the past two decades, mobile money, which is low-cost monetary innovation, has significantly extended payment services beyond conventional banking systems, particularly in Africa. However, in Botswana, due to the dominance of bank deposit card payments, there has been a slow uptake of mobile money. This warrants the study of the role of network effects in a new payment media as this underscores the power of incumbency of the dominant payments option. Chapter 2 utilises the game-theoretic framework of Myerson (1998) based on the Binomial probability theory, where potential adopters have to form expectations of how many others will adopt mobile money to quantify network effects as a strategic complementarity in the adoption of new technology. We quantify network effects variable using data from the Global Findex Survey for Botswana, and integrated it into a Logit model alongside demographic variables. Results show that though the expected network effects of mobile money significantly increase its adoption, network effects favouring incumbent cash and bank deposits money are mitigating factors. This leads to slow mobile money adoption despite low switching costs. Chapter 3 extends the theoretical model to examine how pairwise switching to a new payment technology affects the intensive margins across payments media. Findings show that adopting cashless digital payments, such as bank cards and mobile money, allows us to track the falling share of cash transactions. Chapter 4 develops a macroeconomic model linking microfoundations of technology driven changes in payment habits toward digital money via the above intensive margins to monetary base, interest rates and inflation. Results show that cashlessness contributes to a lower inflation rate. This provides valuable insights for policymakers navigating the transition to digital economies with cashless payments.

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Chapter 1

Introduction

The payments technology has undergone significant changes in the past three decades. Several innovative means of payment, such as debit cards, credit cards, online transfers, cryptocurrencies, digital currencies, and mobile money that compete with incumbent cash have entered the payments landscape. These new methods offer convenience and enhanced security, reassuring users of their financial safety (Rogoff, 2016; Schneider, 2017; Fabris, 2019). The global trends show that mobile money services have transformed the financial inclusion landscape in developing and emerging economies. Africa accounts for the largest share of adoption of mobile money services at about 63%, followed by South Asia at 20% (GSMA, 2022). Mobile money is a low-cost innovative cashless media offered by non-bank or mobile network operators, which does not require households to have a bank account. This payment technology allows users to deposit money, transfer funds and purchase goods and services using cell phones. The service also offers a relatively affordable and convenient means of payment, especially in remote areas which lack access to formal financial institutions like banks.

The emergence of mobile money has spurred the debate among scholars seeking to understand the determinants of mobile money adoption (Aron 2018). The empirical research has identified several important drivers and constraints of adoption and usage of mobile money but do not broadly assess the role of network effects and switching costs on mobile money adoption given incumbent bank deposit-based money and cash (Murendo *et al*., 2018). In other words, the literature to date does not develop and operationalize the microfoundations of the adoption of a network good where the utility of adoption increases in the number of adopters.

The main contribution of this dissertation, given in chapter 2, is our model for network effects and switching costs in adoption of a new payments technology such as mobile money. We follow the game theoretic framework of Myerson (1998) and more recently, Sundararajan (2008), and Ioannou and Makris (2018), in modelling the strategic aspects of the utility from expected network effects of adoption when there is uncertainty with regard to how many others will adopt. For this, we use, at the level of a potential adopter in a small sample, his/her assessment of the Binomial Probability of success of yet to adopt agents. As the latter switch, they can 'cannibalize' along the extensive and intensive margins, viz respectively in number of users and the proportion of consumption expenditure that is transacted in one or the other payments media. Our innovation is operationalizing the Binomial probability model to quantify network effects as a strategic complementarity in adopting new technology. We quantify the network effects variable using data from the Global Findex Survey (GFS) for Botswana. This contrasts with papers using experimental data to test similar new technology adoption models like Keser *et al*. (2009) and Ioannou and Makris (2018). These papers have little bearing on how it can be applied to empirically determine adoption rates in the field. This chapter, therefore, fills a crucial gap in the literature on the empirical modelling of payment trends, underscoring the importance and relevance of our research. For the most part, empirical studies on new payment media like mobile money adoption only use demographic factors and do not include network effects of mobile money adoption (Aron, 2018; Coulibaly, 2021). We integrate network effects variables into a Logistic Regression alongside demographic variables. Results show that though the expected network effects of mobile money significantly increase its adoption, network effects favouring incumbent cash and bank deposits money are mitigating factors. This leads to slow mobile money adoption despite low switching costs.

Another major strand of literature seeks to understand the impact of cashlessness, in general, and mobile money, in particular, on the transmission of monetary policy (Adam and Walker (2015); Wiafe *et al*. (2022)). The empirical literature on the impact of payment innovations such as mobile money on the effectiveness and conduct of monetary policy shows inconclusive results. These studies use econometric models and do not explicitly incorporate the microfoundations of changes in payments habits and cashlessness when modelling the impact of mobile money on the conduct of monetary policy.

Chapter 3 extends the theoretical model to examine how pairwise switching to new payment technology affects the intensive margin or portfolio weights across payments media. In this chapter, we consider an interesting property that individuals who switch for the first time to a new payment media have to do so by reducing the portfolio weights from one or the other payments media, viz., along the intensive margin of the extant portfolio weights of payments media. We apply the market equilibrium conditions inspired by CAPM and Arrow (1964) derivations to show that individual portfolio weights for s payment media ,w_{is}, equal the so-called 'market value' weights w_s^A. This chapter quantifies the intensive margin to track the allocation of consumption to cashless payment instruments and how it affects the falling share of cash transactions. Results show that as more households adopt cashless payment media such as bank cards and mobile money, cash usage for consumption declines. Further, the results show that households continue to allocate more of their retail payments to bank cards than mobile money, mainly due to the high network effects of the conventional banking system.

Cashlessness is a global phenomenon driven by innovations in payment technology and the growth of the digital economy and e-commerce. This dissertation focuses on the demand side of mobile money as a source of cashlessness due to changes in payment habits from this low cost payment innovation. The supply side, from a microeconomic perspective, is not examined in detail due to the monopolistic nature of the mobile money market in Botswana, where a single dominant mobile network operator largely controls the provision of mobile money. From a macroeconomic perspective, the monetary model is entirely demand-led, reflecting the micro foundations of cashlessness due to new payment technology adoption. Contemporary monetary policy that targets inflation is based on interest rate setting and not on controlling money supply. Hence, our strategy in Chapter 4 is to incorporate the micro founded demand for cash and card as these are substituted by the new payments media in the form of mobile money. This is done within a Taylor rule interest rate policy setting, with our new contribution which shows how cashlessness leads to lower inflation.

Chapter 4 develops a new macroeconomic model linking micro-founded technology changes in payment habits toward cashlessness to explain the fall in the growth in the monetary base, and the subsequent trends in interest rates and inflation rates. Recently, there has been a lot of interest in modelling the monetary policy implications for the growth of digital money adoption and the dwindling of state supplied cash in retail transactions. With less cash withdrawals for transactions from bank deposits, digital card and mobile money payments enhance commercial bank liquidity. Our model extends macroeconomic models of Marimon *et al*. (1997) and Markose and Loke (2002) that focus on digital cashless payments by incorporating a micro-founded framework based on the Myerson (1998) model of adoption of new digital payments media based on network effects. This chapter identifies the two main factors of optimal deposit interest rates to be: i) the falling ratio of optimal cash transaction balances to monetary base, and ii) the rising share of non-interest bearing deposits to total deposits. These factors proxy for enhanced liquidity in depository institutions due to the switch from cash payments to bank deposit based card payments and mobile money. We also derive inflation rate considering the micro-founded changes in payments habits by households, and find that an increase in cashless retail expenditures, on average, contributes to a lower inflation rate. This macroeconomic model is calibrated and tested against the macroeconomic data for Botswana.

In summary, this thesis makes an in depth and innovative contribution to the microfoundations of new payments technology adoption involving mobile money and analyses the implications of the resulting cashlessness on monetary policy. This study yields valuable insights to policymakers and central banks, ultimately aiming to transition to digital economies with cashless payments. We structure this thesis as follows: Chapter 2 models and quantifies the impact of network effects and switching costs on mobile money adoption. Chapter 3 illustrates how pairwise switching to new payment technology affects extensive and intensive margins, and finally, Chapter 4 analyses the impact of micro-founded technology changes in payment habits toward cashlessness in explaining the growth in the monetary base, interest rate and inflation rate.

Chapter 2

Mobile Money a Low-Cost Monetary Innovation: Strategic Complementarities and Network Effects that Govern Adoption Rates

Abstract

The adoption of mobile money, particularly in Africa, has been a major development of monetary systems. This chapter examines the adoption of this new payment medium in the presence of two incumbent means of payment, namely, cash and bank deposit-based money. We model the critical role of network effects and switching costs in the adoption of mobile money. While switching costs are relatively easy to model, the potential network effects that arise from increasing returns to use from new adopters is problematic. Using an innovative game theoretic approach based on strategic complementarities in coordination games, we model the utility from expected network effects, which entails uncertainty of how many people will adopt mobile money. We utilize a framework by Myerson (1998) based on the Binomial Probability distribution where potential adopters have to form expectations on successful new adopters. To quantify network effects of mobile money a cross-sectional consumer-level data from the 2017 and 2022 Global Findex survey for Botswana is used where different cohorts, such as financially excluded and banked-only individuals, have different utility from expected network effects if evaluated from within each cohort or across the general population. The latter is larger than the more plausible case where expectations are formed within one's cohort. The main contribution of this chapter lies in providing the micro-founded utility of expected network effects and switching cost variables in addition to the demographic variables in the empirical specification of a cross-section Logit Model for mobile money adoption. The Akaike Information Criteria (AIC) for model selection yields superior results with the incorporation of the utility of expected network effects and switching costs. The Logit model shows that general population and cohort network effects have a relatively equal impact of about 3% increase in the probability of mobile money adoption. Results also show that a tipping point for mobile money adoption is not yet reached, and indeed, the rate of adoption is low because, despite the low switching cost to mobile money, the incumbency network effects of cash-only users and bank account holders seem to exert a negative impact. Additionally, the adoption of mobile money is positively affected by individuals' characteristics such as being richer, employed, more educated and having a bank account.

Keywords: Mobile money; financially excluded; bank accounts; network effects; switching costs; strategic complementarities; tipping points; Binomial Probability

2.1. Introduction

Mobile money is a recent innovation that provides financial transaction services to individuals via mobile phones, Aron (2018). Mobile money has extended payments services beyond the traditional commercial bank-based provision. It has also contributed to overcoming problems associated with conventional banking, such as weak institutional infrastructure and the cost structure. Small size, informality, and poor governance place constraints on financial institutions' commercial viability, especially in developing economies, Beck and Cull (2013). Less privileged individuals cannot afford the minimum balance requirements and regular charges of conventional bank accounts. In particular, Markose *et al.* (2020) have shown that when bank accounts for low income and below poverty line customers are rolled out in top-down financial inclusion schemes, insufficient bank balances imply economic unviability for banks, which needs careful design measures to overcome the funding gap.

Further, new low-cost technology associated with mobile money permits *"leapfrogging"* extant provision of formal banking services. **Table 2.1** sets the scene for the global adoption of mobile money which has also transformed the landscape of financial inclusion in developing and emerging economies. Africa accounts for the largest share of adoption of mobile money services, followed by South Asia, and East Asia and Pacific. The proportion of mobile money services is concentrated in the sub-Saharan African region mainly due to the success of the world's popular mobile money service, M-Pesa ("M" for "mobile", "pesa" for "money" in Swahili), which was launched in Kenya in 2007 and operates today in eight countries. However, a small developing economy such as Botswana is not a poster child for mobile money mainly due to its efficient banking system and higher levels of population with bank account than early adopters such as Uganda and Tanzania, which adopted mobile money out of necessity due to poor banking networks. The global map of mobile money adoption shows (**Figure 2.1**) how UK, Europe, and North America with their extensive banking networks has little need for mobile money.

The invention of mobile money has filled a gap and has changed the economics of small or informal cash balances (Kendall *et al.*, 2011). Mobile money technology is expected to bridge the financial services access gap by including the unbanked households especially from rural and poor communities in developing economies. This service allows users to deposit and transfer funds as well as purchase goods and services using their cell phone. The service also offers a relatively affordable and convenient means of payment especially in remote areas with a lack of access to formal financial institutions like banks. The rapid growth in financial innovation particularly in emerging economies has been driven by exponential growth in mobile phone ownership and lack of affordable alternatives (Munyegera and Matsumoto (2016)).

Table 2.1: Distribution of Registered Mobile Money Accounts by Region (Percent)

Regions	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
East Asia and Pacific	23.2	10.5	7.9	8.4	7.4	9.0	10.9	13.0	19.0	22.1	24.4
Europe and Central Asia	1.4	0.8	0.7	0.7	2.3	2.4	2.3	2.0	2.0	1.9	1.6
Latin America and the Caribbean	2.7	2.7	4.6	4.2	3.8	3.3	3.0	2.8	2.8	3.5	3.6
South Asia	2.4	5.7	12.6	17.0	23.3	27.6	30.2	31.8	22.4	22.3	21.0
Middle East	4.1	25.3	17.6	12.1	8.4	6.4	5.0	4.0	3.9	3.6	3.2
Africa	**66.2**	**55.0**	**56.6**	**57.7**	**54.8**	**51.3**	**48.6**	**46.4**	**50.1**	**46.6**	**46.1**
Eastern Africa	55.7	42.6	40.4	36.8	31.6	30.0	26.3	25.0	26.8	22.6	22.0
Central Africa	0.4	2.0	3.6	5.3	4.8	4.2	5.3	4.1	4.6	4.4	4.4
Northern Africa	0.1	0.2	0.4	0.7	1.2	1.3	1.2	1.1	1.1	1.2	1.1
Southern Africa	0.6	0.9	2.2	2.7	2.7	0.9	0.8	0.9	0.9	1.0	0.9
Western Africa	9.5	9.3	10.0	12.3	14.5	14.9	15.0	15.4	16.7	17.4	17.6
Sub-Saharan Africa	66.1	54.9	56.2	57.0	53.6	50.0	47.4	45.4	49.0	45.4	45.0
Global	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

Note: Regional data before 2011 is not available due to confidentiality reasons.
Source: Global System for Mobile Communications Association (GSMA)

Despite the remarkable potential benefits of mobile money to the livelihoods of the poor and for an increase in financial inclusion (Mothobi and Grzybowski (2017)), some of the least-developed economies in Africa still experience a low adoption rate of mobile money. For example, in Botswana, out of 90.8 percent of individuals with a cellphone, only 36.6 percent use mobile money services (Global Findex Survey, 2022). However, since the cell phone penetration is high even amongst unbanked adults, this suggests that there is great potential in mobile money services. Therefore, it is vital to examine factors affecting mobile money adoption in Botswana.

The channels through which mobile money can affect the economy are complex and not well understood. Several studies have examined the economic impact of mobile money usage (see, Jack and Suri (2014); Riley (2018)) and the determinants of mobile money adoption (Aron, 2018; Coulibaly, 2021). The evidence convincingly suggests that mobile money fosters financial inclusion, risk-sharing, and reduce poverty while the impact on welfare and saving is still less conclusive. Furthermore, empirical research has identified several important drivers and constraints to adoption and usage of mobile money but did not broadly assess the role of network effects and switching costs in adopting mobile money given the bank deposit-based money and universally used incumbent cash (Kikulwe *et al*., 2014; Murendo *et al*., 2018; Bongomin *et al*., 2018).

According to Katz and Shapiro (1985, 1986), the adoption of mobile money technology, like other common payments systems, is characterised by network effects, switching costs, and competition with incumbent monies. Once the technology or innovations have been adopted, indirect or direct network effects arise as users' interaction rises (Easley and Kleinberg (2010)). Network effects arise if the value of consuming a particular good or service increases with the total number of consumers who use compatible products or services (Gandal (1994); Farrell and Klemperer (2007)). Switching costs exist if a consumer purchases a product or service repeatedly and find it costly to switch from one operating system to another (Klemperer, 2006). This chapter explicitly factors in switching costs as mobile money accounts do not presuppose bank accounts and hence mobile money adoption can lead to a substitution away from bank accounts, which are more costly to maintain.

Against this background, the main objective of this chapter is to examine the impact of network effects and switching costs on adoption of mobile money, beyond traditional bank deposit-based money and cash. Relative to existing literature, this chapter extends the Baumol (1952) - Tobin (1956) model to directly quantify the network effects and switching costs in explaining the adoption of mobile money.[1] In order to model how a potential new adopter decides whether to adopt a new payments media which has strong strategic complementarities, viz a decision that has payoffs or utility that increase in the similar actions of others, expectations have to be formed about other potential adopters. Hence, the model we adopt to quantify the utility of expected network effects uses the game theoretical approach based on strategic complementarities (see, Bulow *et. al*. (1985); Milgrom and Roberts (1990); Ioannou and Makris (2018)). Players face uncertainty with regard to who will adopt or coordinate on an action at any given time. Binomial distribution that converges to Poisson distribution when

[1] A substantial number of studies have extended the Baumol-Tobin model to analyse dynamics of consumer adoption of financial innovations (Attanasio *et al*. (2002), Markose and Loke (2003), Bauer and Hein (2005), Alvarez and Lippi (2009), and Lippi and Secchi (2009), Yang and Ching (2014)).

number of potential adopters goes to infinity have been used for this. We follow Myerson (1998) in modelling the formation of utility from expected network effects of adoption at the level of a potential adopter that is based on his/her assessment of the Binomial Probability of success of yet to adopt agents.

We are able to relate this payment media adoption model to the well-known S-shaped adoption curve dynamics of Bass (1969) who had seminally brought a probabilistic approach to those that adopt on the basis of the numbers who have adopted to date. The Global Findex Survey data for adoption of mobile money in a country gives the extant numbers, ($k = n_m + n_a$), of those who have adopted from a given sample *N*. This proportion gives the initial probability, p_m, of success, while the Binomial Probability ($Bin\ ({z_m^{Pop}}, p_m, {k_m^{Pop}})$) gives the probability of success for the expected number of yet to adopt agents, ${z_m^{Pop}} = (1 - p_m)N$ with mean given by ${k_m^{Pop}} = p_m z_m^{Pop}$. The Binomial Distribution is shown to be well suited to yield the S-shaped dynamic of the rate of adoption. In the early years of a new technology, the low extant probability of adoption implies that even a small fall in the remaining numbers of those yet to adopt, ${z_m^{Pop}}$, lowers the mean value of new adopters and also their probability of success. This reduces the utility from expected network effects. Only when p_m rises substantially with large proportion of the population having adopted, can strategic complementarities exert the positive acceleration in adoption rates which then peters out as z_m^{Pop} goes to zero with saturation. This framework can also explicitly provide the utility from expected network effects based on the Global Findex Survey Data on the cohorts that potential adopters belong to such as those that are financially excluded and those who have bank accounts and no mobile money accounts.

Our chapter is closely related to Alvarez *et al.* (2023), who extend the Bass (1969) model to incorporate the random diffusion of technology based on a Brownian motion model. Their strategic complementarities benefit flow function includes the increasing impact from the number of those who have adopted but does not include the probability of success based on the expected number of new adopters that a yet to adopt decision maker has to estimate in game theoretic formulations mentioned above. Further, the application of the model is to a new mobile payment App SINPE being rolled out by the Central Bank of Costa Rica to make peer to peer payments from bank account to bank account. Hence, there are no switching costs from other competing payments technology which have considerable benefits of network effects from incumbency.

We implement this innovative approach using cross-sectional data from 2014, 2017 and 2022 Global Findex surveys to quantify the network effects of mobile money and assess its impact on mobile money adoption in Botswana. The empirical results show that despite network effects favour the incumbent cash and bank deposit money more than mobile money, the expected network effects of mobile money significantly increase the adoption of mobile money in 2017 and 2022. Overall, the analysis shows a positive and significant effect of both general population and cohort network effects on mobile money adoption. Further, the chapter establishes that potential adopters, especially financially excluded individuals, tend to be less incentivised to adopt mobile money when considering potential new adopters from their own cohort "local" network compared to when considering an entire population "global" network. Additionally, we argue that regardless of low switching cost to mobile money, consumers find switching from status quo to mobile money unattractive because of incumbency effects, hence the slow adoption of mobile money. The main contribution of this Chapter lies in providing micro-founded utility of expected network effects and switching cost variables in addition to the demographic variables in the empirical specification of a cross section Logit Model for mobile money adoption. The Akaike Information Criteria (AIC) for model selection yields superior results with the incorporation of utility of expected network effects and switching costs.

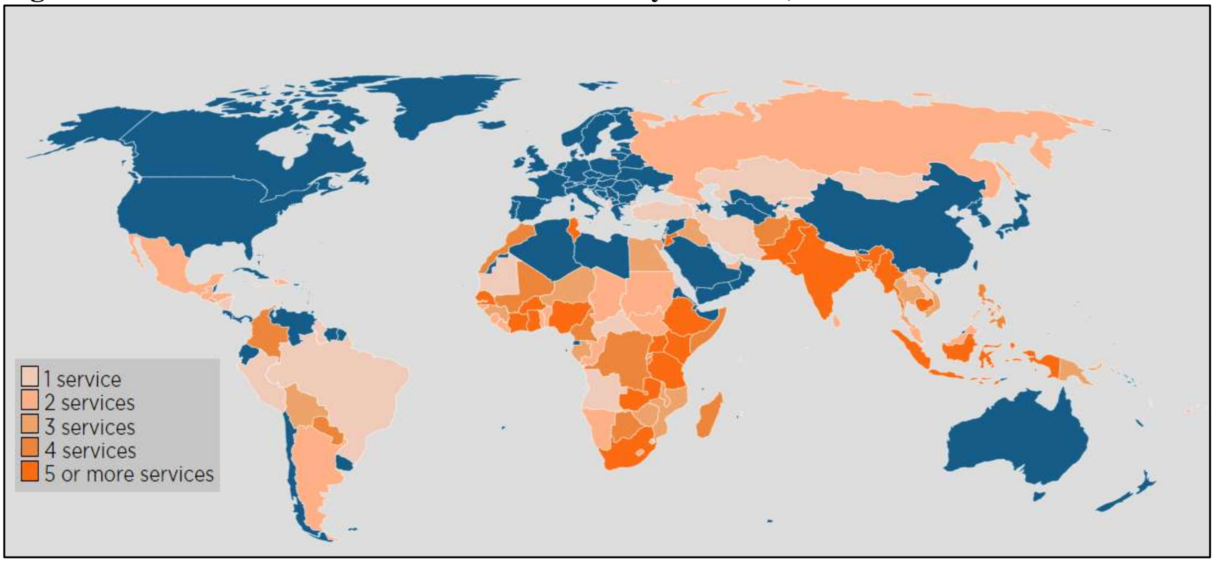
The chapter is structured as follows: Section 2.2 discuss the mobile money status and trends in the specific case of Botswana's economy. Section 2.3 provides theoretical and empirical literature reviews on network effects, switching costs, and other factors affecting the adoption of mobile money services. Section 2.4 presents the methodology, which entails both the theoretical and empirical frameworks. Data sources and variables are described in Section 2.5. The empirical results are discussed in Section 2.6, followed by Section 2.7 which gives the conclusion, limitations of the study, and areas of further research.

2.2. Growth and evolution of mobile money

Mobile money services have evolved considerably in the early 2000s to extend financial services access to the unbanked and banked population, particularly in developing economies. **Figure 2.1** shows the deployment of mobile money services across countries in the world. In

2020, the number of registered mobile money accounts increased by 12.7 percent globally to 1.21 billion accounts.

Figure 2.1: Global Distribution of Mobile Money Services, 2002-2022

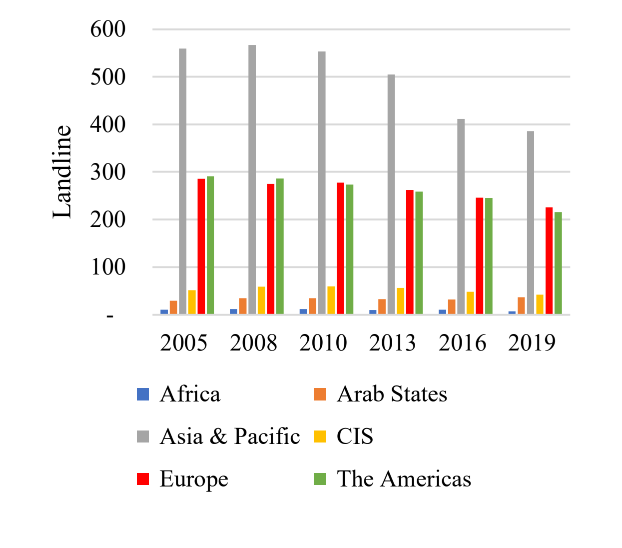


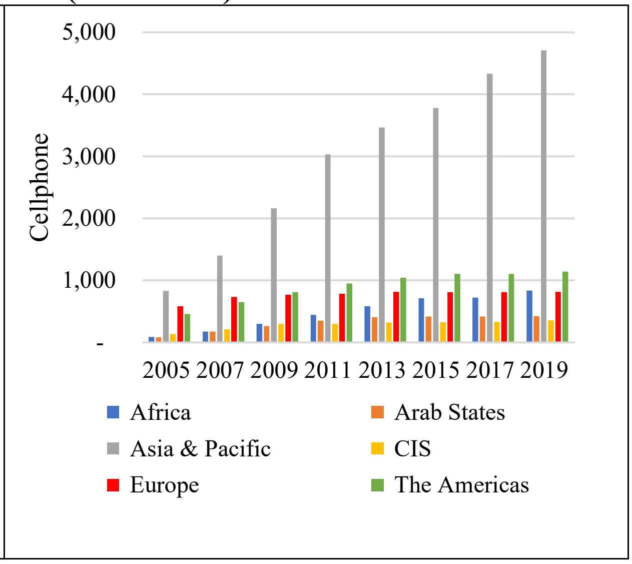
Source: Global System for Mobile Communications Association (GSMA) Note the blue coloured regions do not have mobile money network services.

The service was first adopted by the Philippines through SMART Communications network, which launched SMART-Money in 2000, followed by Globe Telecom, which in 2004 offered G-Cash (Intermedia, 2013). In 2007, Kenya launched M-Pesa, a popular mobile money service offered by a local mobile network operator, Safaricom. M-Pesa provided a cheaper and efficient way to make payments and transfer money, especially for workers who send home remittances. Its large networks of agents make financial services accessible to over 90 percent of Kenya's adult population. Since then, the mobile money industry has expanded significantly to other African economies and South Asia, such as India, Bangladesh, and Pakistan. Therefore, there is no surprise that the body of literature on mobile money is extensive in developing and emerging economies.

Figure 2.2 shows a decreasing trend in fixed telephone subscriptions compared to an increasing trend in mobile phone subscriptions across regions worldwide. The significant growth in mobile phone ownership, especially in developing and emerging economies, has somewhat led to rapid growth in mobile money services. Active mobile money services have increased drastically over the past two decades, indicating that mobile money forms part of the mainstream in most markets where access to financial services is low. Mobile money services are primarily available in developing African and Asian economies where most people have no bank account at a formal financial institution (Demirgüç-Kunt *et al*., 2018).

Figure 2.2: Landline and Cellphone Subscriptions (in Millions)





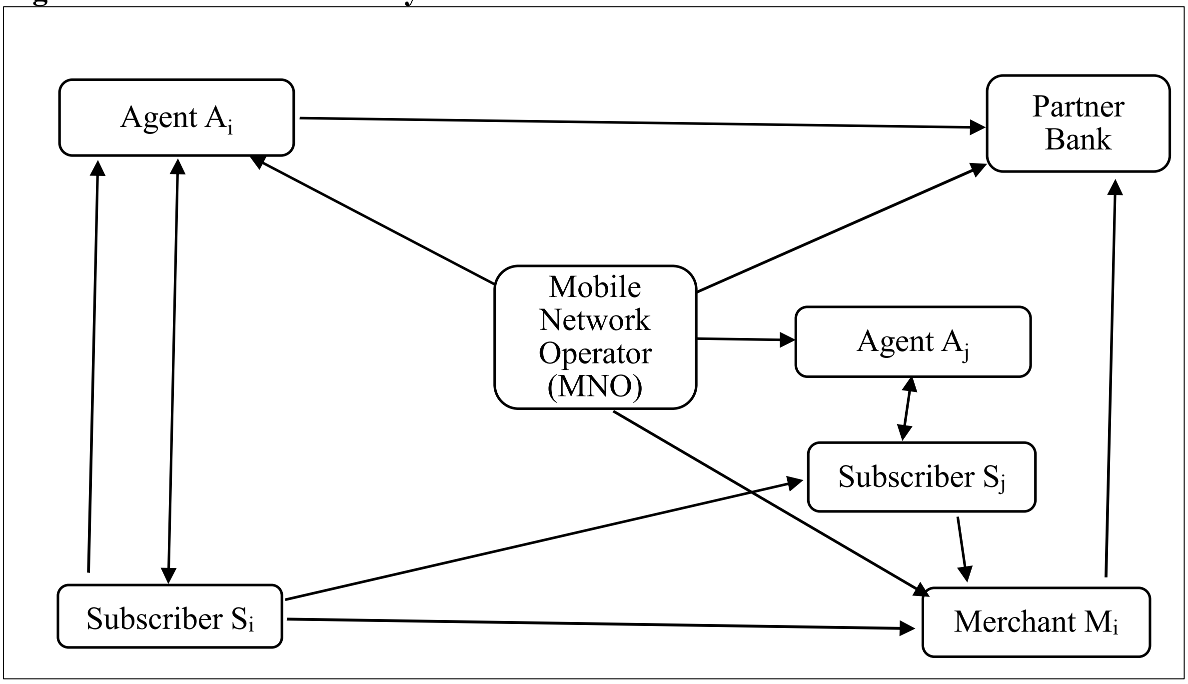
Source: International Telecommunication Union (ITU)

2.2.1. Basic Mobile Money Framework

The mobile money business model consists of key players such as customers or subscribers, mobile network operators (MNO), banks, agents, and merchants. **Figure 2.3** illustrates the channels by which mobile money is created and operated for payments by mobile networks. The MNO provides financial services to the banked and unbanked people through a partnership with a financial intermediary, e.g., a commercial bank. The role of a partner bank is to maintain an efficient payment mechanism by providing secure and trusted payment service and anti-money laundering (AML) requirements. MNO also select and recruit agents for their mobile money network. Mobile money agents are outlets where subscribers or households exchange their conventional money for electronic mobile money (e-MM), and recipients of mobile money transactions substitute their e-MM for traditional money in their transactions.

Consider that MNO has many agents geographically located A_i^{MNO}, $\{A_1, A_2, \ldots, A_A\}$, for convenience superscript MNO is dropped when considering only one MNO. Subscribers S_i, $\{S_1, S_2, S_s, \ldots, S_S\}$, are members of households who can approach an A_i and be registered as a user of a MNO account and mobile network. An agent is given cash by subscriber S_i which the agent converts into the MNO e-MM in the subscriber's account. The agent deposits S_i cash in the agent's MNO partner bank account. Hence, note that the e-MM is fully backed by bank deposit money. Subscriber S_i will send and receive money via person-to-person (P2P) transactions with other subscribers S_j. Subscriber S_j will receive a text message (e.g., P2P transfer SMS) on his phone from the agent of subscriber S_i that e-MM is now in S_j's MNO account. At this point, S_j may perform a cash-out at his MNO account with agent A_j. What is interesting from the perspective of clearing and settlement in a national jurisdiction, typically involving the Real Time Gross Settlement (RTGS), is that mobile P2P payments are facilitated from within a single MNO bank account. In contrast, mobile banking is between the different bank accounts of payor and payee and hence where different banks are involved, the payments will be subject to the RTGS.

Figure 2.3: The Mobile Money Structure



Source: Author's compilation from GSMA

M_i denotes merchants, $\{M_1, M_2, M_m \ldots . M_M\}$. If both S_i and S_j have e-MM in the MNO's account (mobile wallet), it can purchase goods and services from M_i who is registered for MNO's mobile money services. Thus, the mobile money platform offers greater customer convenience of paying using mobile phones. Hence, note that the parties in P2P or person-to-merchant (P2M) cashless payments need not have bank accounts.

2.2.2. Implications of Mobile Money and Mobile Banking on Cash in Circulation

In the absence of cashless e-MM, the implication is that a high cash-based economy will have a high proportion of cash in circulation. As already seen from **Figure 2.1** map of countries with mobile money adoption, e-MM is prominent where neither S_i and S_j have bank accounts. Cash in circulation is economised because the money deposited in an MNO account does not leave that MNO account to facilitate P2P between S_i and S_j. If S_i and S_j have bank accounts and use mobile banking online transfers, using card payments, mobile banking implies that the payee's account is debited, and the payor's account is credited. Though cash in circulation is curtailed and the banking system does not lose deposits as would have been the case when payments require cash withdrawal, as noted the second scenario implies final payment and settlement between the banks.

2.2.3. Overview of Mobile Money Services in Botswana

Botswana introduced major policy reforms in the early 1990s to liberalise the financial sector. The main aim of the reforms was to create and increase healthy competition within the commercial banking sector (Harvey, 1996). These reforms, together with high and persistent profits recorded by incumbent banks, attracted new entrants into the banking industry. Thus, the number of commercial banks operating in Botswana grew from four in 1991 to nine in 2019 (Bank of Botswana, 2019). This led to competition amongst commercial banks accompanied by an increase in the number and diversity of innovative products and services offered. These include electronic payments systems, automated teller machines (ATMs), debit cards, credit cards and smart cards. The evolution of bank technological innovation in the late 2000s has reduced the need for brick-and-mortar infrastructure, and led to the widespread adoption of additional delivery channels, such as, internet banking, mobile banking and mobile money (Bank of Botswana, 2017). These financial innovations provide payments systems that are efficient and cost effective, hence increasing the level of financial inclusion in the country.

Mobile money was first launched in 2011 by Botswana's major mobile network operators (MNOs) such as, Orange Botswana with 57.4 percent market share in mobile money; and Mascom Wireless with 42.4 percent market share[2]. The latest mobile money providers in 2019 are Botswana Telecommunication Corporation (BTC) and Botswana Post Office. The MNOs offer products with many similarities, such as cash-in, cash-out, buying airtime, paying utilities, etc. Although mobile money registration is free, all transactions have predetermined charges or fees (Intermedia, 2012). The transaction fees vary between registered and unregistered users

[2] The management of mobile money is under the jurisdiction of the central Bank of Botswana. According to GSMA (2019), Botswana's regulatory framework on mobile money market has improved compared to other African countries.

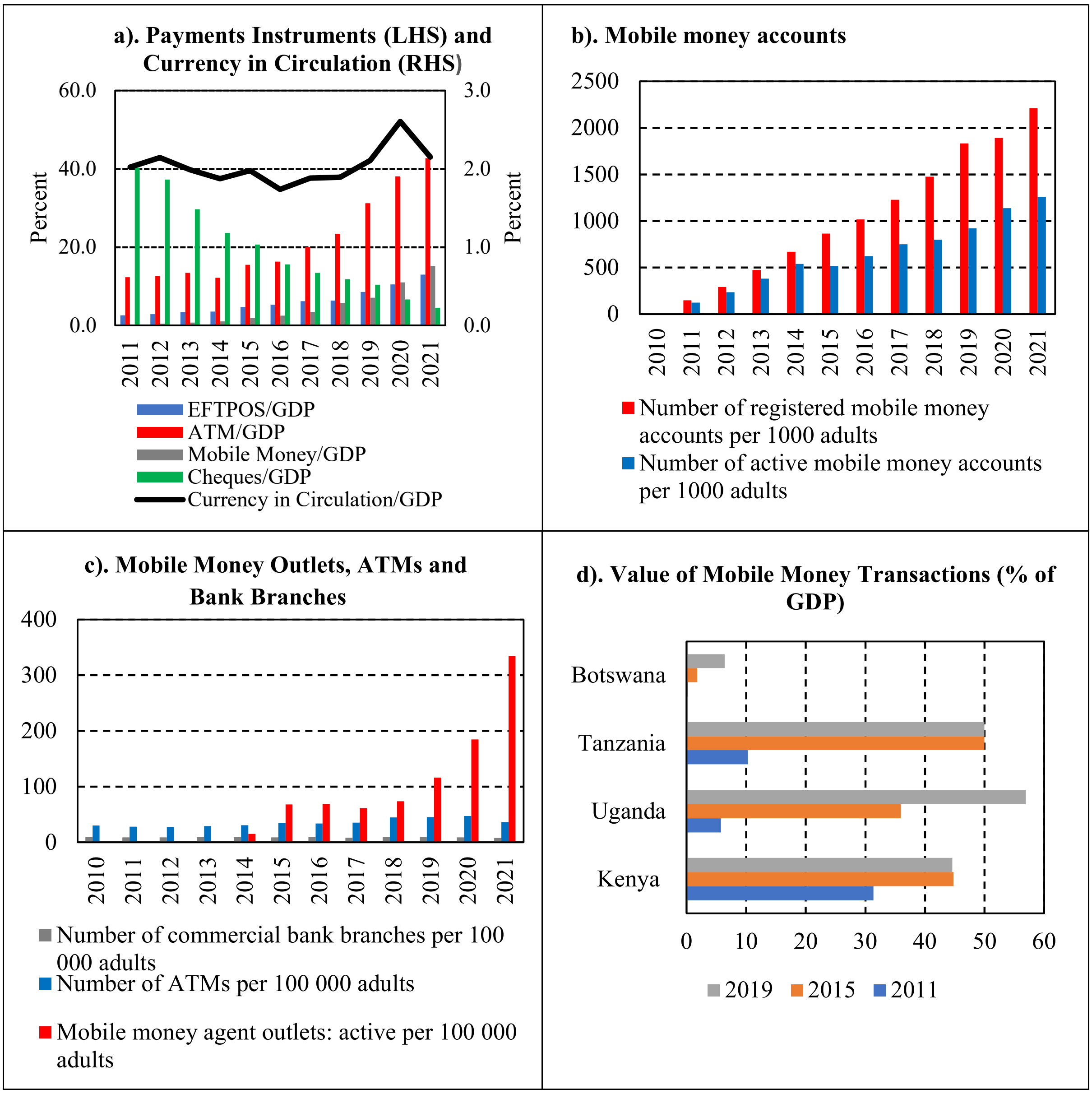
and depend on whether the transfer is from the same or to a different mobile network. Households are free to have other mobile money accounts from different MNOs to maximise flexibility and transaction costs. In addition, mobile money agents also offer various mobile money services by different MNOs, thus offering their customers flexibility in the choice of a service provider. Transaction fees also depend on the transfer channel, e.g., in a Person-to-person (P2P) or Person-to-Business (P2B) transaction, the sender is charged, while the recipient is not. On the other hand, the cash-in transaction is free whereas the transaction fees are charged upon withdrawal (cash-out).

Figure 2.4 (a) show that the use of cheque as a payment instrument has been declining over the past decade, while cash is a dominating payment media in Botswana's economy[3]. There are significant improvements in technological innovations, such as automated teller machines (ATMs), electronic fund transfers at the point of sale (EFTPOS), and mobile money services. We see a downward trend in the currency in circulation from 2011 except between 2019 and 2020 where the increasing trend was mainly due to significant increases in the net issuance of the banknote denominations. Therefore, a general decline in currency (notes and coins) in circulation indicates that EFTPOS and mobile money can potentially substitute cash as exchange media.

Statistics further show that the number of registered and active mobile money accounts has increased by fifteenfold and ninefold, respectively, between 2011 and 2021 (**Figure 2.4 (b)**). In real terms, the number of mobile money agent outlets have doubled over the past five years. **Figure 2.4 (c)** indicate that the density of the agent network recorded 334 active mobile money agents per 100 000 adults, more than tripling since 2014. On the other hand, the density of commercial bank branches in the same market remains unchanged between 2014 and 2021, averaging 9 per 100 000 adults. This shows that mobile money is gaining popularity in the payment system of Botswana.

[3] On February 21, 2022, Bank of Botswana announced that effective January 1, 2024, the use of cheques will be discontinued. The phaseout of a cheque is attributable to the rise of more cost-efficient, safe, secure, and convenient digital or electronic payment instruments in the country.

Figure 2.4: The rise of Mobile Money Services and Other Payments Instruments in Botswana



Source: Bank of Botswana and International Monetary Fund (IMF) Financial Access Survey

Over the past decade, the share of mobile money transactions to gross domestic product (GDP) has increased significantly from 0.2 percent in 2011 to 6.4 percent in 2019 (**Figure 2.4 (d)**). Nevertheless, the Botswana's uptake of mobile money is somewhat slow compared to the pioneers of mobile money services. This is mainly due to Botswana's efficient banking system and higher financial inclusion than Uganda and Tanzania, which adopted mobile money out of necessity due to poor banking networks.

According to Finmark (2020) the banked population in Botswana constitutes 56 percent of the adult population in 2020 compared to 45 percent in 2009. Most of the financially included population resides in cities/towns (72 percent) followed by urban villages (62 percent) and rural areas (32 percent). Botswana is ranked third in terms of financial inclusion in southern African region behind Mauritius and South Africa, respectively. Generally, consumers tend to use a mixture of financial products to meet their financial needs. Thus, households do not depend entirely on a formal sector to fulfil their financial needs. In total, the unbanked population declined from 24 percent in 2009 to 16 percent in 2020.

2.3. Literature Review

This section presents the literature review on the adoption of new payments media, which is closely related to network effects, strategic complementarities and switching costs. Firstly, the section discusses the theoretical literature on mobile money adoption in the context of financial inclusion, followed by network effects and switching costs. Secondly, the section analyses the empirical literature on the adoption of mobile money and network effects.

2.3.1. Theoretical Literature Review

2.3.2. Theories on adoption of payments technology

In all variants of models for adoption of new technology or product, there are different factors behind how people form beliefs about adopting new products or technology. These factors primarily relate to learning for which the relevance of social networks and cohort effects play a role. Thus, people may learn about the existence of a new product from their network of family, friends, or acquaintances (Mobius and Rosenblatt (2014)). The proportion of those informed of the new product tend to adopt it, and since adoption requires knowing about the new product, adoption spreads through social contact or interaction. Second, people learn about the qualities of a new product through its usage. The adoption may depend on what people know about the hidden attributes of the new product, such as how useful or reliable the product is. If there is limited information, the risk-averse individuals tend to abstain from adoption, whereas as people share information about the hidden qualities of the new product along social networks, adoption increases (Bala and Goyal (1998)). Diffusion along social networks may occur for other reasons beyond social learning. One specific example is network externalities or strategic complementarities (Saloner and Shepard (1995)). The usage of new technology by social neighbours may increase an individual's incentive to use it; hence an individual is more likely to adopt it following adoption by his neighbours. This may arise regardless of whether all agents have complete information about the existence and qualities of the product. Therefore, the utility of a product increases with its widespread usage.

Theoretical underpinnings of the adoption of mobile-based technologies for inclusive development through mobile money innovations are primarily traceable to new technology acceptance models (Asongu and Odhiambo (2020)). According to Rosenberg (1972) and Coleman (1988), human capital (i.e., knowledge, skill, and expertise) and human interactions are vital for people to adopt information technologies. There is a growing literature supporting the perspective that individuals continuously adopt mobile-based technologies mainly due to corresponding innovations that support societal needs such as financial inclusion (Abor *et al*., 2018). In line with the related literature, Yousafzai *et al*. (2010), and Asongu and Odhiambo (2020) discuss the main three theories on technology acceptance, namely: the technology acceptance model (TAM), the theory of planned behaviour (TPB) and the theory of reasoned action (TRA). These theories postulate that selecting, adopting, and using a specific technology depends on the type and anticipated innovative externalities attached to the underlying technology.

TAM was initially proposed by Davis (1989), and it emphasises that individuals' willingness to adopt and use a given technology depends on apparent usefulness and perceived ease of use. Perceived usefulness in adoption of mobile money services is characterised by the trust consumers have in utilising mobile money services. On the other hand, perceived ease of use incorporates how much a person operating mobile money services will be free of mental and physical exertion. The TRA implies that users of technological innovations are rational in their choices and are well informed of their actions regarding adopting such technologies, Ajzen and Fishbein (1980). According to Ajzen (1991) the TPB is an improved version of the TRA. The TPB is applicable when there are differences among individuals regarding conscious connections to their actions instead of those for which such conscious connections are not apparent. It is worth noting that two essential standard features are underlying the three theories: an individual's belief decisions, composite features (including psychological, social, personal) and utilitarian characteristics (Asongu and Odhiambo (2020)). Generally, many scholars adopt TAM mostly when examining factors affecting the adoption of mobile money services. The TAM framework was modified to incorporate other critical variables affecting the adoption of mobile money (Venkatesh and Davis (2000); Amberg *et al*. (2004)).

2.3.3. Strategic Complementarities, Network Effects and Switching Costs

The literature on technology adoption recognises the presence of strategic complementarities whereby a probabilistic model of adoption is postulated where the expected benefits to an agent who adopts a new technology is an increasing function of the proportion of agents already using it (see, Mansfield (1961); Milgrom and Roberts (1990); Obstfeld (1996); Ioannou and Makris (2018)). These studies use the game theoretic approach with strategic complementarities to capture setups, such as speculative attacks, start-up investments and new technology adoption under network externalities. Recently, Alvarez *et al* (2023) develop a dynamic model of technology adoption in the presence of strategic complementarities, which are an inherent property of payment instruments. The authors also apply a mean field game theoretic approach to obtain the solution to the social planner problem to determine the optimal subsidy needed to mitigate suboptimal equilibria that arise from network externalities. However, their approach does not capture the expectations formed about potential adopters and the probability of their success when quantifying the strategic complementarities as viewed from one such potential adopter as found in game theory models such as that of Myerson (1998).

The concept of network effects was originally analysed in the context of telephony industry in the early 1970's by Rohlfs (1974). The contribution to literature on network effects is typically associated with Katz and Shapiro (1985, 1986), Farrell and Saloner (1986), Arthur (1989), and Liebowitz and Margolis (1994, 1995). Liebowitz and Margolis (1994) have formally distinguished the network effects and network externalities, although the two terms are usually used interchangeably. A network externality arises when a network effect (direct or indirect) is not perfectly internalised through a competitive market mechanism. The first theoretical models of direct network effects are Katz and Shapiro (1985) and Farrell and Saloner (1986). The direct network effects means that an increase in usage of a particular good or service directly increase its value. A typical example is a telephone exchange, i.e., the value of the telephone increases with the network size of individuals who also use telephones. This concept is critical in the context of markets, particularly when examining the product, residential or technological choices.

Other authors such as Church *et al*. (2008) and Economides and Salop (1992) provide some earliest frameworks that captures the indirect network effects. Indirect network effects means that an increase in usage of a product or network leads to an increase in the value of a complementary good or network, and this results in an increase in the value of the original product. The earlier studies on network effects, particularly indirect network effects, typically focuses on consumers adoption decisions and ignore the pricing or other decisions by the platforms. Caillaud and Jullien (2001), Rochet and Tirole (2002) and Armstrong (2002) characterised the indirect network effects using a two-sided market or platform market. Generally, a two-sided market is a market in which at least two distinct set of agents or sides interact through an intermediary, the platform, such that the behaviour of each set of agents directly affect the utility of the other set of agents.

Liebowitz and Margolis (1994) posits that switching costs can generate an indirect network effect. For example, a merchant's customer does not directly gain higher utility with an increasing number of customers who switch to the same technology. Instead, customers care about the number of other customers subscribing to the chosen merchant, since this factor increases the probability that the merchant will survive in the market. Switching cost refers to the cost a consumer faces by switching from one product (or service) to a competing product. In general, these costs lead to consumer lock-in, whereby consumers repeatedly purchase the same brand regardless of competing brands becoming cheaper. The consequence of consumer lock-in is the ability of firms to charge prices above marginal costs. Theoretically, the consumer switching costs are more likely to give firms market power, allowing firms to charge higher prices, reduce product or service quality, create barriers to entry and obtain supernormal profits (von Weizsacker, 1984; Klemperer, 1987; Tarkka, 1995). Farrell and Klemperer (1987) define types of switching costs as learning, transactional and contractual costs. Learning switching costs occurs if a consumer who switches from firm (product) *A* to firm (product) *B* has no switching cost of later buying from either firm. Alternatively, transactional cost means that a consumer who switches from *A* to *B* will incur an additional switching cost if he switches back to *A*. Generally, both learning and transactional switching costs are assumed to be real social costs, but there can also be contractual costs that are not social costs.

Fundamentally, it has been argued that fiat money is a network good that derives its value from the total number of individuals in an economy who accept it as means of payment (Leibbrandt, 2002; Shy, 2001). Kiyotaki and Wright (1993) develop a simple model to capture trade between several commodities where one of these commodities assumes the role of fiat money. Other studies like Prescott (1987), and Santomero and Seater (1996) develop a theoretical framework to model agents' choice between cash and noncash instruments. While the mentioned studies focus only on money as media of exchange and store of value, other researchers applied network economics to model money as a unit of account. For example, Dowd and Greenway (1993) have developed a simple model on currency acceptance that captures both the network effects and switching costs of new or alternative currencies. The model demonstrates that agents may be reluctant to adopt another currency when network effects and switching costs are present, despite an inferior incumbent money. The model was further extended by Luther (2016) to analyse the acceptance of cryptocurrencies given the network effects and switching costs. He finds that cryptocurrencies like bitcoin have failed to gain widespread acceptance as means of payment.

Markose and Loke (2003) also developed a simple theoretical model to capture the network effects of EFTPOS (Electronic Fund Transfer at Point of Sale) card payment and ATM (Automated Teller Machine). The authors applied Baumol (1952) and Tobin (1956) model to elaborate that expansion in ATM networks by banks has enhanced the convenience yield of cash and reduced shoe leather costs by increasing accessibility to withdraw money closer to the point of sale. The authors concludes that the cost effectiveness of ATM cash dispensation has enabled cash to maintain its competitiveness versus EFTPOS instruments such as credit cards and debit cards. This, of course, assumes that cash or card payments are both feasible and does not consider the case of e-commerce where only electronic payment media is possible.

In summary, the theoretical literature discusses the acceptance of money and has diversely appreciated the importance of each type of network effects and switching costs theories, which are the focus of the present study. These theoretical concepts fulfil money's function as a medium of exchange, hence form a basis to any new or alternative money, e.g., mobile money in the payment systems.

2.3.4. Empirical Literature

There is an extensive empirical literature on the role of mobile phone technologies on fostering financial inclusion and growth, but it is mainly concentrated on the analysis of adoption and usage of mobile money services (Andrianaivo and Kpodar (2011); Gosavi (2018); Demirguc-Kunt *et al*. (2018); Abor *et al*. (2018); Asongu and Odhiambo (2019); Lashitew *et al*. (2019)). This is because mobile phones can be used to transmit market and other information, (Jensen, 2007), particularly in geographically dispersed societies, such as in Africa where bank branch penetration is low (Allen *et al*., 2014). Most of studies on mobile money and financial inclusion cut across worldwide cross-country studies using macro and micro data, small and large-scale interview studies, and randomised control trials (RCTs) in specific villages or regions. Ahmad *et al*. (2020) surveyed the literature on mobile money and its contribution to financial inclusion and development in sub-Saharan Africa. The authors found the results to be ambiguous, with many gaps in knowledge that new research is needed to fill. They highlighted issues that require further investigation, such as the take-up of mobile money, mobile money and financial inclusion, substitutability between mobile money and conventional finance, and regulatory structures for institutions providing mobile money services.

The literature on determinants of diffusion of mobile money innovation includes Mbiti and Weil (2011), Aker *et al*. (2013), Fanta *et al*. (2016), Aron (2018), Tangirala and Nlondiwa (2019), Lashitew *et al*. (2019), Asongu *et al*. (2021) and Coulibaly (2021). In general, this research finds that high rate of mobile phones network penetration and adoption, lack of affordable alternatives, and lower service fees relative to conventional bank account charges have resulted in rapid adoption and use of mobile money, particularly among rural communities in developing countries. Additionally, Economides and Jeziorski (2017) contend that mobile money is relatively cost-effective and efficient compared to incumbent money (cash). Thus, mobile money services, which requires no bank accounts and costly equipment, is convenient and crucial in promoting financial inclusion among the poor.

There is a growing body of literature on the role network effects on payments adoption. With the influence of studies such as Markose and Loke (2003), Gowrisankaran and Stavins (2004), and Jack and Suri (2014), understanding mobile money adoption and its relationship with the rapid network expansion has become research area of great interest. Several studies stipulate that an increase in network effects will contribute to acceleration in adoption of mobile money, such as MPESA in Kenya (e.g., Jack and Suri (2011); Jack *et al*. (2013); Chuang and Schechter (2015)). However, there has been surprisingly limited empirical work on investigating the impact of network effects on mobile money adoption (Suri, 2017). A few exemptions include Fafchamps *et al*. (2022), Murendo *et al*. (2018), Bongomin *et al*. (2018) and more recently

Agbo and Zabsonre (2022)[4]. In each of these papers, the network effects are “local”, viz., social network effects.

Fafchamps *et al*. (2022) study the pattern of adoption of airtime and transfers over time using a large dataset on phone calls and airtime transfers in Rwanda. Although not relying exclusively on mobile money, authors find that network effects turn to be negative after first adoption, and conclude that airtime transfers are substitutes among network neighbors. A similar study by Economides and Jeziorski (2017) analyse a mobile money network in Tanzania that is widely used to P2P transfers, to transport money without a transfer, and as a savings account. The study finds that the senders internalise to a significant extent the cash-out fees that the network imposes on receivers when money is cashed out. Because of high cash-out fees, most users cash out after only one transfer, and a significant percentage of transactions on the network do not involve transfers but are deposits and withdrawals by the same user. The network is also used for savings, despite a zero-interest rate, and used extensively for very short-term (less than two hours), short-distance transportation of cash because of extremely high crime.

Murendo *et al.* (2018) focused explicitly on information exchange within social networks by including variables describing the characteristics of networks. The study finds that social networks have a positive and significant effect on mobile money adoption in Uganda, and the effect is pronounced for non-poor households. Thus, although social networks represent an essential factor required to promote mobile money technology, the poorest households are likely to be excluded, hence policymakers need to develop more tailored policy programmes and assistance. Similarly, Bongomin *et al*. (2018) find a positive and significant impact of social networks in the relationship between mobile money usage and financial inclusion. On the other hand, a similar study by Kikulwe *et al*. (2014) proxied neighbourhood effects using the share of households owning a mobile phone at the village level and find a positive impact on mobile money use in Kenya. Agbo and Zabsonre (2022) empirically assessed the role of direct and indirect network effects on mobile money usage and adoption, using data from the FinScope survey conducted in 2016 in Burkina Faso. They find that there is no positive direct

[4] Authors argue that mobile phone users, especially the poor, rely on their closed networks of families, existing networks of friends, and peer groups to acquire and share useful information and knowledge about mobile phone use for saving, transferring, and sending money. Therefore, social networks may play a vital role in adoption and use of mobile money services especially among the poor who have no access to formal financial services.

network effect in mobile money adoption while the indirect network effects are significantly and positively present. Authors conclude that use of mobile money increases with the number of people with whom an individual (mobile money account holder) can communicate on phone.

In summary, previous studies have identified several important drivers and constraints to adoption and usage of mobile money but did not broadly assess the role of network effects and switching costs in adopting mobile money given the bank deposit-based money and incumbent money (cash). This chapter contributes to the existing growing literature on mobile payments (León (2021); Han and Wang (2021); Ahmad *et al*. (2020); Trütsch (2016); Economides and Jeziorski (2017), Jack and Suri (2011); Mbiti and Weil (2011)). Our contribution is to establish the impact of network effects and switching costs on adoption of mobile money, beyond traditional bank deposit-based payments system. In general, the idea that high network effects may be instrumental in generating a larger switch in technology adoption is not new in the policy discussion about payment systems.[5] There is a gap in the literature as to how to quantify the network effects and the methodology section of the paper will adopt game theoretical models of strategic complementarities. Our model as noted uses the Myerson (1998) model of a Binomial probability distribution to model the uncertainty of numbers of those who will adopt from the vantage of a potential adopter to derive the utility from expected network effects from new adopters. In forming expectations of others who will adopt, it is plausible to assume that potential adopters are conditioned by their own circumstances and expected differential rates of success of adoption. A few studies address the role of social network effects in the context of mobile money adoption (Kikulwe *et al*., 2014; Murendo *et al*., 2018; Bongomin *et al*., 2018). The paper argues that even though the banked population gains higher network effects due to high coverage, there is a critical mass at which mobile money becomes competitive, therefore financially excluded people in most African economies tend to leapfrog to mobile money than adopt bank accounts.[6]

[5] Gowrisankaran and Stavins (2004) analysed the extent and sources of network externalities for electronic payments markets using data on bank adoption and usage.

[6] Related study is conducted by Wang and Han (2021) explaining why developing economies like Kenya and China are lagging behind in adopting card payments but leapfrog into mobile payment systems. Authors find that lagging behind in mobile payment adoption does not necessarily mean that advanced economies have fallen behind in overall payment efficiency, even though they benefit less from the mobile payment innovation compared with developing countries.

2.4. Methodology

2.4.1. New Technology Adoption Model: Decision Framework with Network Effects and Switching Costs

The framework of a new payments adoption model with network effects involves pairwise switching from an incumbent option. We assume that cash, denoted by *c*, is universally held. For many individuals, i, who have yet to adopt bank based card payments and mobile money, the decision problem is a (0,1) binary choice a_{is} to adopt or not these payments media, given by $s \in S = \{m, b\}$. It is assumed that individuals know the total fixed population sample size, *N,* and which cohort, *q,* they belong to. At a population level the numbers of persons in each cohort, *q,* will be denoted as n_e *(financially excluded)*, n_b *(bank account holders only)*, n_m *(mobile money users only)* and n_a *(those who use both card and mobile money)* such that $N = n_e + n_b + n_m + n_a$. We denote the ratios of existing users of mobile money as $p_{m0} = \frac{n_m + n_a}{N}$ and bank account holders as $p_{b0} = \frac{n_b + n_a}{N}$. Here, the initial ratios at time *t*=0 will be assumed to evidence of successful adoption of the respective payments media. Thus, for example, p_{m0} gives the initial probability of success of mobile money adoption and $(1 - p_{m0})$ will be the probability of failing to do so. Note cohorts to which individuals belong to can also include income and demographic factors, which will not be specified here.

The payoff for an *ith* agent of type *q*∈*{e,b}* to adopt a new payment option *m* whose utility increases with the size of extant users $(n_m + n_a)$ and expected new adopters Ek_{qs} is:

$$V_q = a_{is}\left[U\left(\left[(n_m + n_a) + \sum_{q\in\{e,b\}} Ek_{qs}\right] - \tau_m\right)\right] \tag{2.1}$$

Here τ_m is the cost of mobile money adoption. Equation (2.1) implies that the payoff to an agent who does not adopt is zero, and to an agent who adopts is according to a value function $U\left(\left[(n_m + n_a) + \sum_q Ek_{qs}\right]\right)$[7]. We assume that U is a concave function of network effects, and has the following properties:

[7] This is a log utility function (utility = ln (n)), implying that the size of the network increases the value of the network. This function is adopted by Dowd and Greenway (1993), and Luther (2016) in the context of payment media adoption. The intuition here is that if more people adopt a payment media or technology, the network become more attractive and attract even more adopters. Note that the benefits of increasing the network size are always positive, ignoring switching and other costs, but they tend to get smaller as the network size gets larger.

1. $U\big((n_m + n_a), Ek_{qs}\big) > U(n_m + n_a)$ implies that mobile money display positive network effects
2. $U\big(\big[(n_m + n_a) + \sum_q Ek_{qs} - \tau_m\ \big]\big) > 0$ indicates an incentive to adopt mobile money across potential adopters.

At initial date, in their decision to adopt a new payments media, say *m*, it assumed that all *i* agents have to form expectations of how many will successfully adopt. This can be from the vantage of the population as a whole or the specific cohort the agent belongs to such as from the excluded or banked cohorts. For this, as is well known, the Binomial Probability will be used to determine the probability of success of exactly k_s numbers who will adopt from yet to adopt individuals denoted by z_s. Note at initial date *t=0,*

$z_{m0}^{Pop} = n_e + n_b$	:	denotes individuals who have yet to adopt mobile money at the population level
$z_{em0} = n_e$ and $z_{bm0} = n_b$	:	denote those who have yet to adopt mobile money from respectively excluded and banked cohorts.
$z_{eb0} = n_e$	:	denotes who have yet to adopt bank accounts from financially excluded cohort.

In the Binomial Decision problem stated below, yet to adopt individuals *i* symmetrically determine the expected numbers of mobile money adopters, including themselves as follows at initial date:

At the population level: $$Ek_{mt=1}^{Pop} = Bin\big(z_{m0}^{Pop}, k_{m0}^{Pop}, p_{m0}\big)k_{m0}^{Pop} \qquad (2.2)$$

From financially excluded: $$Ek_{emt=1}^{*} = Bin(z_{e0}, k_{em0}^{*}, p_{m0})k_{em0}^{*} \qquad (2.3)$$

From bank account holders only: $$Ek_{bmt=1}^{*} = Bin(z_{b0}, k_{bm0}^{*}, p_{m0})k_{bm0}^{*} \qquad (2.4)$$

We assume that yet to adopt individuals, at the population level, will take the mean of the Binomial probability distribution given by $k_{m0}^{Pop} = p_{m0}z_0^{Pop}$ to be their estimate of *ex ante* numbers of successful adopters. The probability of exactly k_{m0}^{Pop} succeeding will be given by the Binomial probability distribution:

$$Bin\big(z_0^{Pop}, k_{m0}^{Pop}, p_{m0}\big) = \binom{z_{m0}^{Pop}}{k_{m0}^{Pop}} {p_{m0}}^{k_{m0}^{Pop}} (1 - p_{m0})^{z_0^{Pop} - k_{m0}^{Pop}} \qquad (2.5)$$

Here the Binomial coefficient showing different ways of distributing k_{m0}^{Pop} successes in a sequence of z_{m0}^{Pop} trials is denoted by $\binom{z_{m0}^{Pop}}{k_{m0}^{Pop}} = \frac{z_{m0}^{Pop}!}{k_{m0}^{Pop}!\left(z_{m0}^{Pop} - k_{m0}^{Pop}\right)!}$.

2.4.2. Mixed Strategy Nash Equilibrium

All agents eligible to adopt a new payments technology already have an incumbent option. This makes the decision choice for all eligible agents to be a mixed strategy, where both payments media are held with some probability. Thus, a mixed strategy Nash equilibrium (MSNE) is the only outcome. In a MSNE all eligible users adopt *m* and the incumbent *(b,e)* with some probability such that the utility of the expected network effects and switching costs of each payment option is equal.

Proposition 1: Mixed Strategy Nash Equilibrium

At initial date the probability with which the new payments media is adopted is given by $(1 + Bin^{Pop})p_{m0} = p_{mt=1}$ *and the incumbent payments media are held with probability* $(1 - \ p_{mt=1})$ *and* $Bin^{Pop} = Bin\left(z_{m0}^{Pop}, k_{m0}^{Pop}, p_{m0}\right)$.

Specifying the utility of network effects at t=0 which includes the extant adopters of *m* and those expected to adopt given by $Bin^{Pop} k_{m0}^{Pop}$ in the first term implies, that these individuals will be reduced from the incumbent yet to adopt z_{m0}^{Pop} on the right hand side of equation (2.6). The MSNE requires that the switching costs adjustment utility for the two options will be equal.

$$U\left(n_{m0} + n_{a0} + Bin^{Pop} k_{m0}^{Pop}\right) - U(\tau_m) = U\left(z_{m0}^{Pop} - Bin^{Pop} k_{m0}^{Pop}\right) - U\left(\frac{\tau_c + \tau_b}{2}\right) \tag{2.6}$$

Here τ_c encapsulates the unit cost of using cash, such as handling, safekeeping, and fraud expenses; and τ_b is the adoption costs of a bank account, such as one-time fixed cost of opening account, annual account maintenance and transaction costs. Inserting $k_{m0}^{Pop} = p_{m0}\, z_{m0}^{Pop}$ into (2.6), we see that as per *Proposition 1*, the new technology is held with probability $p_{m0}\, Bin^{Pop}$ and the incumbent options are held with probability $(1 - \ p_{m0}\, Bin^{Pop})$. Thus,

$$U\left(n_{m0} + n_{a0} + p_{m0}\, Bin^{Pop} z_{m0}^{Pop}\right) = U\left((1 - \ p_{m0}\, Bin^{Pop}) z_{m0}^{Pop}\right) + U(\tau_m) - U\left(\frac{\tau_c + \tau_b}{2}\right) \tag{2.7}$$

Proposition 2: Critical Mass of New Payments Technology

The critical mass is defined as the minimum number of adopters, n_m^{Min}, and hence the minimum proportion of adopters, p_m^{Min}, of the new technology that is necessary to make adoption of new technology the best response strategy of any potential adopter (see Keser et.al., 2009).

Using equation (2.7), we solve for the minimum number of adopters, n_m^{Min}, as

$$U(n_m^{Min}) = U\left(\left(1 - p_{m0}\, Bin^{Pop}\right) z_{m0}^{Pop}\right) + U(\tau_m) - U\left(\frac{\tau_c + \tau_b}{2}\right) \tag{2.8}$$

Applying the log utility function to (2.8) yields

$$\begin{aligned} ln(n_m^{Min}) &= ln\left(1 - p_{m0}\, Bin^{Pop}\right) + ln(z_{m0}^{Pop}) + ln(\tau_m) - ln\left(\frac{\tau_c + \tau_b}{2}\right) \\ n_m^{Min} &= exp\left[ln\left(1 - p_{m0}\, Bin^{Pop}\right) + ln(z_{m0}^{Pop}) + ln(\tau_m) - ln\left(\frac{\tau_c + \tau_b}{2}\right)\right] \end{aligned} \tag{2.9}$$

Dividing through by N, $\frac{n_m^{Min}}{N} = p_m^{Min}$, gives the critical mass of mobile money adopters as:

$$p_m^{Min} = \frac{1}{N}\, exp\left[ln(1 - p_{m0}\, Bin^{Pop}) + ln(z_{m0}^{Pop}) + ln(\tau_m) - ln\left(\frac{\tau_c + \tau_b}{2}\right)\right] \tag{2.10}$$

The comparative statics give plausible results in that the critical mass of the new payment technology is higher with own costs and lower with the costs of competing payment options. We note that the larger the size of the incumbent cohort of z_{m0}^{Pop} of bank card and financially excluded, the larger the critical mass. Finally, the higher the Binomial probability and the initial proportion of new technology users with $p_{m0} > 0$, the lower the critical mass. In fact, all new technology adoption requires a non-zero 'seeding' probability of initial adopters of $p_{m0} > 0$.

2.4.3. Calibration of Binomial Adoption Model to Global Findex Data

From the Global Findex survey, total population N, initial probability of success of mobile money adoption p_m, successful adopters $p_m N$, and potential adopters z_m^{Pop}, are common knowledge. **Table 2.2** mirrors the Global Findex survey data for 2014-2022 where row 1 gives the numbers of extant mobile money adopters; row 2 gives the assumption regarding the probability of success, p_m, in any trial for mobile money; row 3 gives the number remaining to adopt; row 4 yields *ex ante* numbers of successful adopters; row 5 is the Binomial probability that exactly k_m^{Pop} adopt; row 6 yields the utility of expected network effects from mobile money; row 7 yields the utility of expected network effects from incumbent options; row 8 is the utility of cost of mobile money adoption; row 9is the utility of cost of incumbent option; row 10 yields the minimum number of adopters, n_m^{Min}; and row 11 yields the minimum proportion of adopters (critical mass), p_m^{Min}.

Table 2.2: Mobile Money Adoption using Binomial Distribution (N=1000) for General Population

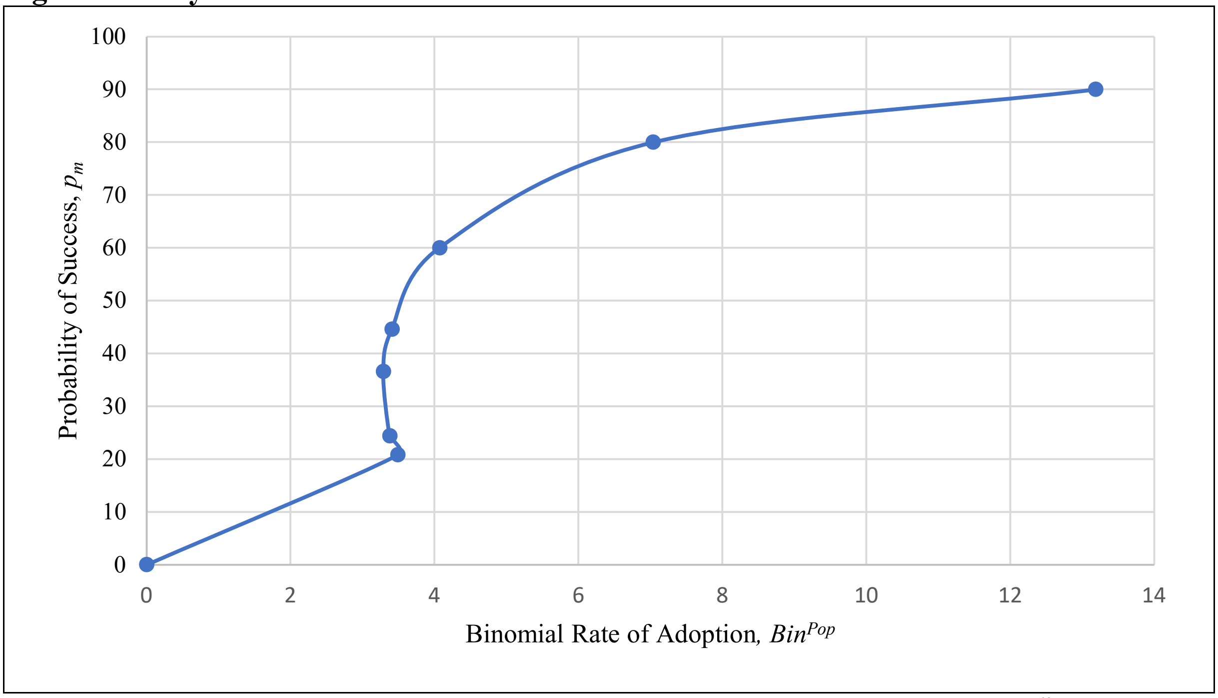
	2014	2017	2022	*2024**	*2026**
1. Numbers of mobile money adopters, $(n_m + n_a)$ from Global Findex Survey for Botswana, *N= 1000*	208	244	366	*445*	*600*
2. Initial probability of success, $p_m = \frac{n_m+n_a}{N}$	20.8%	24.4%	36.6%	*44.5%*	*60.0%*
3. Number of people yet to adopt mobile money (potential adopters), $z_m^{Pop} = (1 - p_m)N$	792	756	634	*555*	*400*
4. Estimate of *ex-ante* numbers of successful adopters (mean of Binomial distribution), $k_m^{Pop} = p_m z_m^{Pop}$	165	184	232	*247*	*240*
5. Binomial probability of getting exactly k_m^{Pop} successes out of z_m^{Pop}, Bin^{Pop}, (See equation (2.5))	3.49%	3.38%	3.29%	*3.41%*	*4.07%*
6. Utility of expected network effects from mobile money (see equation (2.6)), $ln(n_m + n_a + Bin^{Pop} k_m^{Pop})$	5.365	5.522	5.923	*6.118*	*6.413*
7. Utility of expected network effects from incumbent options (see equation (2.6)), $ln(z_m^{Pop} - Bin^{Pop} k_m^{Pop})$	6.667	6.620	6.440	*6.303*	*5.967*
8. Utility of cost of mobile money adoption, $ln(\tau_m)$	0.336	0.336	0.336	0.336	0.336
9. Utility of average cost of incumbent options *(c, b)*, $ln\left(\frac{\tau_c+\tau_b}{2}\right)$	0.922	0.922	0.922	0.922	0.922
10. Minimum number of adopters, n_m^{Min}, (See equation (2.9))		438	417	*349*	*304*
11. Critical mass of adopters, p_m^{Min}, (See equation (2.10))		43.8%	41.7%	*34.9%*	*30.4%*

Notes: Data for 2014-2022 covers actual figures from the Global Findex survey, and 2024-2026 are extrapolated figures. The cost of using cash, τ_c, is \$2.23; average cost of opening and using a bank account, τ_b, is \$2.80; and average cost of opening and using a mobile money account, τ_m, is \$1.40.
Source: Author's compilation from Global Findex Survey and World Bank (2018) [8]

[8] The costs are obtained from a World Bank report titled "Retail Payment Costs and Savings in Albania 2018". This report provides a practical guide for measuring retail payment costs. The data from the report is useful as a proxy for switching or adoption costs for different payment media in developing economies.

The results show that though z_m^{Pop} keeps falling (**Table 2.2**, Row 3) viz. the remaining people yet to adopt falls, the Binomial probability of adoption first falls and then increases (**Table 2.2**, Row 5). This follows from the concept that as more people adopt, p_m viz., the probability of success at each trial with time increases. However, in the early years, the latter is small at no more than 37% till 2022; and there is a backward bend to the Binomial probability of adoption as yet to adopt z_m^{Pop} falls even by a small number. Only when a substantial percentage of population adopts, around 45% and above do we find that initial probability p_m of success counteracting the fall in z_m^{Pop} and hence the Binomial probability rate of adoption rises. Thus, Binomial probability adoption rates proceed slowly at first, then take a backward bend and finally accelerate as the number of adopters crosses a threshold and as the population becomes saturated with adopters, hence generating a stylised S-curve for adoption (see **Figure 2.5**)[9].

Figure 2.5: Stylised S-curve



Notes: See **Table 2.2** rows 2 and 5, for data. We extended the curve by extrapolating p_m^p further with 80% and 90%.
Source: Author’s computation

9 Several innovation diffusion models display a tipping point as a critical mass of individuals that, once reached, can influence most (or all) of the population to adopt new technology. Critical mass is central to the Roger (1962) and Bass (1969) innovation diffusion theory, which characterises the uptake of innovations as an 'S-curve' and classifies human populations into successive proportions defined by their willingness to adopt innovations.

The mixed strategy Nash equilibrium (MSNE) shows that the required critical mass for mobile money adoption is around 44% in 2017 and 42% in 2022 (**Table 2.2**, Row 11). These respective critical mass values are greater than the actual initial p_m in the same periods, indicating that a tipping point of mobile money adoption is not yet achieved in Botswana. These results reinforce the findings for the S-curve. Further, we observe that the utility from expected network effects of mobile money monotonically increases with the network size while the utility from network effects of incumbent options decreases due to pairwise switching. Therefore, this model characterises the importance of strategic complementarity viz., utility of mobile money adoption increases with size of extant users and expected new adopters $Bin^{Pop} k_m^{Pop}$.

2.4.4. Cohort level Binomial Adoption Rates

Note, when evaluating at a cohort level, *ex ante* numbers of successful adopters from specific cohorts of financially excluded and banked only are estimated, respectively, as $k_{em0}^* = p_{m0} z_{em}$, and $k_{bm0}^* = p_{m0} z_{bm0}$. Here $Bin^e = Bin(z_{em0}, k_{em0}^*, p_{m0})$ and $Bin^b = Bin(z_{bm}, k_{bm}^*, p_{m0})$, respectively, denote the Binomial probabilities of adoption for excluded and banked cohorts.

Applying ***Proposition 1*** results,

i. Financially excluded individuals will adopt mobile money where the new technology is held with probability $p_{m0}\, Bin^e$ and the incumbent cash, *c*, is held with probability $(1 - p_{m0}\, Bin^e)$:

$$U(n_{m0} + n_{a0} + p_{m0}\, Bin^e z_{em0}) = U\big((1 - p_{m0}\, Bin^e) z_{em0}\big) + U(\tau_m) - U(\tau_c) \qquad (2.11)$$

ii. Banked only holders will adopt mobile money where the new technology is held with probability $p_{m0}\, Bin^b$ and the incumbent bank deposits money, *b*, is held with probability $(1 - p_{m0}\, Bin^b)$:

$$U\big(n_{m0} + n_{a0} + p_{m0}\, Bin^b z_{bm0}\big) = U\left((1 - p_{m0}\, Bin^b) z_{bm0}\right) + U(\tau_m) - U\left(\frac{\tau_c + \tau_b}{2}\right) \qquad (2.12)$$

The above scenarios yield a major testable hypothesis to see whether the utility of network effects for those who are financially excluded and those who have bank accounts but no mobile money condition their expectations according to the characteristics of their own segments of the population. As will be shown in the calibrated results in **Table 2.2** (General Population Level, row 6) and **Table 2.3** (Cohort Level, rows 8 and 9) the utility of expected network effects is larger in the case of the former as opposed to the latter.

We know the numbers of financially excluded z_{em} and banked z_{bm} individuals from the Global Findex survey. **Table 2.3** show that the Binomial probabilities for cohorts (Bin^{e} and Bin^{b}) are greater than the general population Bin^{pop}. Further, we observe that, despite Bin^{b} being more significant than Bin^{e}, the utility of expected network effects from mobile money is relatively higher for the financially excluded than banked individuals. These results underscore the importance of strategic complementarity within the population cohorts. In other words, it is plausible to assume that potential adopters are conditioned by their own circumstances and expected differential rates of success of adoption. Applying equation (2.10) from ***Proposition 2*** at cohort level, we find that more financially excluded individuals (29.9% in 2017 and 30.4% in 2022) are required to adopt mobile money than banked-only (17.2% in 2017 and 14.7% in 2022) in order to achieve critical mass.

Table 2.3: Cohort Level Utility of Expected Network Effects (N=1000)

	2014	**2017**	**2022**	***2024****	***2026****
1. Initial probability of success, p_m	20.8%	24.4%	36.6%	*44.5%*	*60.0%*
2. Financially excluded z_{em}	480	490	412	*344*	*220*
3. Banked only z_{bm}	312	267	222	*210*	*180*
4. Financially excluded expected to exclusively adopt mobile money, $k_{em}^* = p_m z_{em}$	100	120	151	*153*	*132*
5. Banked individuals expected to adopt, $k_{bm}^* = p_m z_{bm}$	65	65	81	*94*	*108*
6. $Bin(z_{em}, k_{em}^*, p_m) = Bin^e$	4.5%	4.2%	4.1%	*4.3%*	*5.5%*
7. $Bin(z_{bm}, k_{bm}^*, p_m) = Bin^b$	5.6%	5.7%	5.6%	*5.5%*	*6.1%*
8. Financially excluded individuals' utility from expected network effects for mobile money, $ln(n_m + n_a + Bin^e k_{em}^*)$, See equation (2.11)	5.359	5.518	5.919	*6.114*	*6.409*
9. Banked individuals' utility from expected network effects for mobile money, $ln(n_m + n_a + Bin^b k_{bm}^*)$, See equation (2.12)	5.355	5.512	5.915	*6.110*	*6.408*
10. Utility of expected network effects of financially excluded using cash, $ln(z_{em} - Bin^e k_{em}^*)$, See equation (2.11)	6.164	6.184	6.006	*5.821*	*5.360*
11. Utility of expected network effects of banked using bank deposits money, $ln(z_{bm} - Bin^b k_{bm}^*)$, See equation (2.12)	5.731	5.573	5.382	*5.322*	*5.156*
12. Utility of network effects of cash, $ln(N)$	6.908	6.908	6.908	*6.908*	*6.908*
13. Utility of network effects of financially excluded using cash, $ln\ (z_{em})$	6.174	6.194	6.021	*5.841*	*5.394*
14. Utility of network effects of exclusive bank account holders, $ln\ (z_{bm})$	5.743	5.587	5.403	*5.347*	*5.193*

Notes: Data for 2014-2022 covers actual figures from the Global Findex survey, and 2024-2026 (*italicised*) are extrapolated figures. Adoption rates for the general population are shown in **Table 2.2**. The population is categorised to capture heterogeneity across groups.
Source: Author's compilation from World Bank (2018) [10] and Global Findex Survey.

[10] The costs are obtained from a World Bank report titled "Retail Payment Costs and Savings in Albania 2018". This report provides a practical guide for measuring retail payment costs. The data from the report is useful as a proxy for switching or adoption costs for different payment media in developing economies.

2.4.5. Empirical Model Specification

Based on the Global Findex Survey, those who adopt mobile money account is coded 1 if a respondent has adopted mobile money and 0 otherwise. We employ nonlinear cross sectional probability models (Logit and Probit regression) to examine factors affecting the adoption of mobile money services. Most empirical models to date on new technology adoption, surveyed in **Section 2.3**, use only demographic variables such as age, income, education and gender. The main contribution of this Chapter is to examine the impact of network effects and switching costs on mobile money adoption, which is in addition to the demographic data. For this we use the micro-foundations of new payment technology adoption in **Section 2.4.1**. We will incorporate specially constructed variables for utility from network effects for the cross section of adults conditional on whether the individual is yet to adopt mobile money whether from the financially excluded cohort or the banked only cohort. The latter calculation is what we called population level utility from expected network effects (see **Table 2.5**). Similar calculations are done for the cross section of adults and their switching costs conditional on the cohort (see Appendix **Table 1.2A**). Finally, a variable for incumbent network effects is also included to represent the utility derived from network effect from the numbers who use extant payments media such as cash and banked deposits (see Appendix **Table 1.3A**).

The empirical specification for the cross sectional Logit/Probit models is given as follows:

$$y_i = \beta_1 + \beta_2 NE_i + \beta_3 S_i + \beta_4 INE_i + \ \beta_d X_{id} + \varepsilon_i \qquad (2.13)$$

Here, for the ith individual, y_i is a binary variable that equals 1 if an individual owns a mobile money account and 0 otherwise. NE_i is the network effect from mobile money[11], S_i is the switching costs and INE_i is the incumbency network effects. X_{id} where $d = 1,...,7$ is the set of respondent characteristics including age, education, income level, employment status, gender, cellphone ownership, and bank account status. The parameters of interest are β_2, β_3, β_4 and β_d. Note the specification in vector form of (2.13) is as follows: The dependent variable Y is a 1x1000 vector of 0's and 1's. The independent demographic variables such as gender ,

[11] The study of adoption of mobile money exhibit two different streams of network effects. One stream focuses on money with global network effects, Katz and Shapiro (1985), that is, the benefit for using a payment media depends on the total number of users in the network. The other stream considers social network effects, Murendo *et al*. (2018), in which an individual gains utility if his "neighbours" adopt the same payment media. Our empirical model falls into the first stream, because we assume that all members of a monetary network will have identical potential network benefits.

and cellphone are likewise 1x1000 vectors of 0's and 1's; education is 1x1000 vector of 1's "primary", 2's "secondary", and 3's "tertiary"; age categories is 1x1000 vector of 1's "15-24 years", 2's "25-34 years", 3's "35-44 years", 4's "45-54 years", 5's "55-54 years", and 6's "65 years and above"; income quintiles is 1x1000 vector of 1's "poorest", 2's "second", 3's "middle", 4's "fourth" and 5's "richest", corresponding to the agent in the *Y* vector obtained from the Global Findex Survey. Finally, the variables constructed from the micro foundations of Binomial Adoption model for new technology from 3 cohorts such as financially excluded, bank account only and both mobile and bank account with their respective indicator functions being 1 are then taken as product of the relevant utility of network effects calculations given in **Table 1.3A** in the Appendix. Applying the same procedure, relevant to switching costs given in Table 1.2A in the Appendix apply for these 3 cohorts.

Based on the discussions in empirical literature and theoretical model, the central question that this chapter seeks to explore is whether the coefficient on network effects is positive and statistically significant in the adoption of mobile money. The coefficients for the other non-demographic variables are expected to be positive for network effects, positive for switching costs as there is a premium in switching to mobile money, and negative for incumbency network effects. Regarding other covariates: being richer, more educated, younger, employed and owning a cellphone is expected to positively affect mobile money adoption.

2.5. Data Source and Variable Description

The study uses data from the Global Findex survey conducted in 2014, 2017 and 2022 by World Bank in collaboration with Gallup, Inc. Global Findex survey is a nationally representative household and individual survey of approximately 1000 people in at least 160 economies[12]. This paper will use Botswana's Global Findex survey data, and the target population are citizens aged 15 years and above. The survey provides numerous indicators on financial inclusion, which are critical to assessing the extent of account penetration, the use of financial services, the purpose and rationale behind the use, and the alternatives to formal finance. It also provides household characteristics such as gender, age, income, employment, education and ownership of mobile phone. **Table 2.4** provides a detailed description of the variables.

[12] It worth pointing out that the survey captures the population sample that is randomly selected across different points in time. For example, individuals chosen in period 2014 are not followed in the next in 2017 survey and so on. In this case the observations are independent and not identically distributed.

Table 2.4: Description of Key Variables from Global Findex Surveys

Variable	Definition
Mobile money account	"*Has a mobile money account*"-equal 1 (0 otherwise) if the respondent, personally, used mobile money service in the past year. Individuals use mobile money account to pay bills or to send or receive money; or received wages, government transfers, public sector pension, or payments for agricultural products.
Bank account	"*Has an account at a financial institution*"- equal to 1 (0 otherwise) if the respondent, personally or together with someone else, has an account at a bank or other financial institutions; has a debit card connected to an account at a financial institution with their name on it. Individuals use a bank account to received wages, government transfers, public sector pension, or payments for agricultural products; or pay utility bills or school fees.
Both Accounts	"*Has an account*"- equal 1 (0 otherwise) if the respondent, personally or with someone else, has both bank and mobile money accounts.
Financially excluded (cash users only)	"*Has no account with financial institution and mobile network operator*"- (1=Yes, 0=No)
Household income	Within-economy household income categorised into poor, second, middle, fourth and rich quintiles.
Age	Age of a respondent in years.
Age squared	Squared age of household (in years) captures the nonlinear relation between age and adoption of mobile money. Allen *et al*. (2016) posits that age squared capture the fact that adoption of account first increases and then declines with age.
Employment	Household in the workforce (1=Yes, 0=No)
Cellphone	Household with a cellphone (1=Yes, 0=No)
Gender	Gender of a household (1=Male)
Primary	Individuals who completed primary or less
Secondary	Individuals who completed secondary
Tertiary	Individuals who completed tertiary or more

Source: Author's compilation

2.5.1. Measuring Network Effects Variables

Empirically, the estimation of network effects variable is complex mainly due to lack of information about the size of technology adoption in terms of number of people adopting that technology. Since it is generally difficult to have such information, most studies use proxy variables (Agbo and Zabsonre (2022); Kikulwe *et al*. (2014)). Based on the Global Findex survey, this chapter deviates from other papers by constructing a new proxy for network effects of mobile money which incorporates the reality that there is a cross-section of beliefs regarding a total number of successful adopters. Specifically, we consider financially excluded and banked with no mobile money individuals to form expectations about how many people will adopt from the general population and their population cohort. Based on theoretical framework conditions (equations (2.6), (2.11) and (2.12) for mobile money adoption we calculate network effects as follows:

Table 2.5: The Relationship between Mobile Money and Network Effects

	General population network effects	**Segment/Cohort network effects**
1.Mobile money account	$ln(n_m + n_a)$	$ln(n_m + n_a)$
2.Both mobile and bank account	$ln(n_m + n_a)$	$ln(n_m + n_a)$
3.Bank account with no mobile money account	$ln(n_m + n_a + Bin^{Pop} k_{mo}^{Pop})$	$ln(n_m + n_a + Bin^{b} k_{bm0}^{*})$
4.Financially excluded	$ln(n_m + n_a + Bin^{Pop} k_{m0}^{Pop})$	$ln(n_m + n_a + Bin^{e} k_{em0}^{*})$

Notes: Column 1 in the respective rows show adopters (mobile money and both accounts holders) and potential adopters of mobile money (bank account with no mobile money account, and financially excluded). Individuals with mobile money account or both accounts will gain the generic utility from network effects in terms of the number of adopters $(n_m + n_a)$ in the sample. For those who are yet to adopt, Column 2 is the same for all cohorts if they do not consider their own cohort whereas column 3 is not the same for all cohorts because individuals consider their own cohort. the number of successful adopters $(n_m + n_a)$ given in sample; z_m^{Pop} is number of people yet to adopt (sum of z_{bm} is banked with no mobile money and z_{em} is financially excluded); k_m^{Pop} is the number of *ex ante* successful adopters determined by the mean of Binomial Distribution (k_{bm}^{*} is successful adopters from banked with no mobile money and k_{em}^{*} successful adopters from financially excluded); and p_m is initial probability of success calibrated to the number of adopters in the sample. For analytical purposes, having a cellphone is a condition for financially excluded and banked without mobile money to form expectations about the network effects of mobile money. The values of utility of expected network effects are in the Appendix **Table 1.3A**.

Source: Author's computations.

2.5.2. Measuring Switching Costs

Further, the paper uses the World Bank (2016) "Practical Guide for Measuring Retail Payment Costs" that provides an innovative methodology useful for countries to measure the costs associated with retail payment instruments, based on survey data, for the payment end users, payment service providers, and the total economy (see appendix, **Table 1.1A**).[13] The guide also enables countries to calculate projected savings in shifting from the more costly to the less costly payment instruments. The paper adopts cost values from the Albania's survey mainly because Botswana and Albania have approximately equal population size, gross domestic product (GDP), and GDP per capita, as well as being classified as upper middle-income economies. In this study, switching costs are defined as a bonus in terms of cost differentials for mobile money over and above both cash and bank account. **Table 1.2A** in the Appendix provides details on computation of switching costs across consumers.

[13] Albania and Guyana are the only countries that successfully implemented the guide.

2.6. Empirical Results

This section presents the descriptive statistics and empirical findings of the study. The first subsection discusses the descriptive statistics of variables used for analysis. This is followed by the Logit models estimation results.

2.6.1. Descriptive Statistics

Table 2.6 summarises the descriptive statistics of variables used in this study between 2014, 2017 and 2022. The latest survey shows that 91 percent of the population have cellphones, and only 48 percent of the population have a mobile money account[14]. **Table 2.6** of descriptive statistics also indicate that the proportion of the population with bank account is at least 50 percent between 2017 and 2022. At the same time, the proportion of individuals with both mobile and bank accounts increase to 38 percent. Further, a notable increase in the proportion of people with a bank account between 2017 and 2022 is observed. The overall results reflect an improved level of financial inclusion in Botswana mainly due to a significant increase in adoption of mobile money and bank accounts between 2017 and 2022. The proportion of financially excluded individuals has decreased by about 17 percentage points during 2017-2022.

It is observed that females represent 55 percent of the population, while males represent 45 percent in Botswana. In the sample, 24 percent, 65 percent, and 11 percent of the respondents have primary, secondary, and tertiary education levels, respectively. Individuals in workforce account for 63 percent and 37 percent is for out of workforce. The age variable shows that the average age of respondents is 37 years, and youth (age<45 years) account for about 72 percent of the population.

In terms of income distribution, the results for the same period suggest a rising proportion of individuals to 18 percent in poorest quintile, followed by a falling proportion in the lowest two income quintiles to 16 percent, and 17 percent in the second, and the middle, respectively.

[14] The small adoption of mobile money is not necessarily because it is poorly invented, rather it is because of characteristics of incumbent monies. The use of money as a medium of exchange is determined by the network size of agents who are mostly inclined to adopting incumbent monies. In other words, there is a systematic bias against monetary transition, Luther (2016). It is worth noting that the adoption of mobile money is expected to be successful mostly in developing countries with low levels of financial inclusion. Hence, widespread adoption of mobile money might be determined by the network effects associated with mobile money which is in competition with the bank-deposit based payments system.

Meanwhile, the highest two quintiles increase to 21 percent (fourth) and 29 percent (richest) during the same period. These statistics confirm that there is indeed a significant adoption variability across households from different income categories, and that these variables are likely to partly explain the differences in mobile money adoption behaviour.

Table 2.6: Descriptive statistics of variables used in this study [*Mean is the proportion of population (1000 sample size)*]

	2014		2017		2022	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Mobile money account	0.256	0.437	0.283	0.451	0.475	0.500
Bank account	0.575	0.495	0.500	0.500	0.572	0.495
Both accounts	0.228	0.425	0.221	0.415	0.378	0.485
Financially excluded	0.397	0.490	0.438	0.496	0.331	0.471
Employment			0.549	0.498	0.633	0.482
Cellphone			0.851	0.356	0.908	0.289
Female	0.552	0.498	0.690	0.463	0.547	0.498
Age	35.415	14.792	39.185	17.531	37.476	15.185
Age squared	1472.838	1332.851	1842.492	1678.035	1634.851	1373.758
Age categories						
<25	0.244	0.43	0.225	0.418	0.211	0.408
25-34	0.357	0.479	0.27	0.444	0.293	0.455
35-44	0.175	0.38	0.191	0.393	0.218	0.413
45-54	0.089	0.285	0.108	0.311	0.136	0.343
55-64	0.065	0.247	0.098	0.297	0.071	0.257
65+	0.07	0.255	0.108	0.311	0.071	0.257
Education						
Primary	0.265	0.442	0.373	0.484	0.239	0.427
Secondary	0.594	0.491	0.519	0.5	0.647	0.478
Tertiary	0.141	0.348	0.108	0.311	0.114	0.318
Income						
Poorest 20%	0.138	0.345	0.167	0.373	0.175	0.380
Second 20%	0.163	0.37	0.179	0.384	0.155	0.362
Middle 20%	0.19	0.392	0.203	0.402	0.174	0.379
Fourth 20%	0.214	0.41	0.197	0.398	0.209	0.407
Richest 20%	0.295	0.456	0.254	0.436	0.287	0.453

Notes: The results in this table are just simple unweighted descriptive statistics.
Source: Author's computation from Global Findex Survey (2014, 2017,2022)

Table 2.7 provides a detailed distribution of account adoption by household characteristics. The results show that, between 2017 and 2022, the proportion of men and women increases to around 42 percent and 32 percent, respectively, among individuals with mobile money account. In comparison, these proportions increase to 45 percent and 56 percent among individuals with bank account. These statistics show a greater gap between men and women in terms of usage of mobile money and traditional banking services. Men holding either mobile money account or bank account is more than women in Botswana. The proportions of mobile money account holders with at least secondary education levels compared to those with a primary or less education level have risen to almost 49 percent and 14 percent, respectively. On the other hand, these proportions increase to almost 55 percent and 39 percent, respectively, among respondents with bank account.

Table 2.7: Account Penetration Rates by Individual Characteristics in Botswana from Global Findex Surveys of 2014-2022

	2014		2017		2022	
	Mobile Money	**Bank Account**	**Mobile Money**	**Bank Account**	**Mobile Money**	**Bank Account**
Gender						
Female	19	46	21	41	32	45
Male	22	53	29	49	42	56
Age categories						
Young Adults (15-24 years)	23	44	28	35	35	45
Older adults (25+years)	20	51	23	49	37	52
Education						
Primary or less	5	31	9	36	14	39
Secondary or more	29	58	36	51	49	55
Income						
Richest	30	62	32	55	45	57
Poorest	7	30	12	30	24	39
Employment						
Labor force	25	55	34	55	44	59
Out of labor force	13	37	13	32	26	38

Source: Author's compilation from Global Findex Surveys

Mobile money account holders for young individuals (aged 15-24 years) compared to older adults (aged 25+ years) have increased to almost 35 percent and 37 percent, respectively. At the same time, the same proportions grow to 45 percent and to 52 percent for bank account holders, respectively. Thus, older individuals are interested in using mobile money services than younger individuals. In terms of income, the proportion of mobile money account holders for the highest income quintiles (middle, fourth and richest) is almost 45 percent compared to 24 percent recorded for the lowest income quintiles (poorest and second). Similarly, these proportions are above 50 percent and 30 percent for bank account holders. Therefore, there is a high tendency of owning mobile money and/or both accounts by the richest individuals in Botswana.

The ratios of individuals in the workforce holding a mobile money account compared to out of workforce individuals increase to 44 percent and 26 percent, respectively. In comparison, these ratios are around 59 percent and 38 percent, respectively, for bank account holders. Thus, in Botswana, individuals in the workforce are more likely to own bank account compared to mobile money accounts. In total, the analysis of individual characteristics of account penetration shows that men, richer individuals, older individuals, more educated and out of workforce individuals are more likely to own mobile money account.

2.6.2. Results of Cross Sectional Logit and Probit Regression

In this section we report the empirical cross sectional regression results based on Global Findex survey for 2022 while those of 2017 survey are in the Appendix for comparability. **Table 2.8** gives the Logit and Probit regression results for a number of model specifications for equation (2.13) ranging from 1- 6 where 'a' denotes Probit regression and 'b', the Logit regression.
Models (1a)-(1b) with demographic variables only is what most empirical studies do for mobile money adoption without explicit network effects and switching costs; Models (2a)-(2b) includes demographics and switching costs; Models (3a)-(3b) includes demographics, switching costs and general "global" population network effects; Models (4a)-(4b) include demographics, switching costs, general "global" population network effects and incumbent network effects; Models (5a)-(5b) include demographics, switching costs and cohort "local" network effects; and Models (6a)-(6b) include demographics, switching costs cohort "local" network effects and incumbent network effects.

Note that for models 3-6 we drop variables, such as bank account and cellphone, because the construction of network effects variables is conditioned on them. In practice, **Table 2.8** coefficients, which give direction of the impact of the predictors, it cannot be directly interpreted in terms of probability of adoption of mobile money. Hence, for ease of interpretation (Stock and Watson, 2020), we compute marginal effect coefficients from the Logit model (in **Table 2.9**) which measure the change in the probability of mobile money adoption for a unit change in the value of the predictors.

2.6.3. *Measures of Goodness of Fit and Model Selection Criterion*

The Probit and Logit models are estimated to compare their statistical performance in terms of goodness of fit measures. The results of these two models use the Maximum Likelihood Estimation (MLE) method, and as shown in **Table 2.8** they have comparable statistical performance in terms of the Wald Chi-square tests and also the pseudo R^2. The estimated likelihood ratios (LR) statistic (Wald chi-square) of both Probit and Logit models are statistically significant at 99% confidence level, implying that the coefficients of the estimated models are jointly significant (Stock and Watson, 2020). Likewise, we find similar goodness of fit for Probit and Logit models mobile money adoption in terms of high Pseudo R^2. We also apply the Hosmer-Lemeshow (HL) test for goodness of fit to establish how well the predicted probabilities match observed outcomes. The results of all models, except models (2a)-(2b), show that the HL χ^2 statistic is not significant at 99% confidence level. Therefore, we fail to reject the null hypothesis of no difference between the observed and predicted probabilities for all models except models (2a)-(2b). Therefore, we drop models (2a)-(2b) in our analysis.

In terms of model selection across Models 1-6, we also incorporate the results from Akaike information criterion (AIC) and Bayesian information criterion (BIC). Typically, the lower the values for AIC and BIC tests, we have a more superior model specification. That is , in addition to goodness of fit in terms of log likelihood values, AIC provides the trade-off between this, and the complexity of the models brought about by additional explanatory variables. In our case, these include the network effects variables and switching costs in addition to the demographic variables for mobile money adoption. We find that as models 3-6 show a lower AIC and BIC with models 4 and 6 having the lowest values, we are justified in adding the micro founded variables for new payment technology adoption as they improve the model fit with significantly enhancement of the likelihood function. Overall, we observe that Logit and Probit models perform the same in terms of model selection criterion and goodness of fit tests. However, we choose the Logit model for our analysis because of its advantage of easy computation of marginal effects and interpretation of coefficients (Gujarati, 2004).

Table 2.8: Maximum Likelihood Estimation of the Probit and Logit Models of Mobile Money Adoption

VARIABLES	(1a) Probit	(1b) Logit	(2a) Probit	(2b) Logit	(3a) Probit	(3b) Logit	(4a) Probit	(4b) Logit	(5a) Probit	(5b) Logit	(6a) Probit	(6b) Logit
Bank account	0.903***	1.509***	1.113***	2.042***								
	(0.0968)	(0.164)	(0.130)	(0.245)								
Cellphone	0.877***	1.518***										
	(0.211)	(0.376)										
Employed	0.173*	0.287*	0.301**	0.678***	0.544**	1.082**	0.429**	0.806	0.560**	1.099**	0.443**	0.833
	(0.0996)	(0.169)	(0.132)	(0.254)	(0.217)	(0.515)	(0.207)	(0.557)	(0.222)	(0.518)	(0.214)	(0.570)
Female	-0.0555	-0.0674	-0.0214	0.00802	-0.527*	-1.284	-0.674***	-1.440*	-0.542*	-1.323	-0.692***	-1.491*
	(0.0937)	(0.159)	(0.123)	(0.231)	(0.314)	(0.859)	(0.253)	(0.740)	(0.323)	(0.882)	(0.259)	(0.766)
Age Categories												
25-34	0.233*	0.396*	0.253	0.536*	0.225	0.336	-0.473	-1.256	0.234	0.348	-0.472	-1.259
	(0.125)	(0.211)	(0.158)	(0.297)	(0.454)	(1.096)	(0.518)	(1.988)	(0.467)	(1.130)	(0.533)	(2.018)
35-44	0.227*	0.364	0.270	0.563*	0.281	0.209	-0.0945	-0.405	0.302	0.252	-0.0847	-0.374
	(0.135)	(0.226)	(0.171)	(0.321)	(0.468)	(1.193)	(0.620)	(2.104)	(0.480)	(1.220)	(0.630)	(2.109)
45-54	0.0453	0.0664	0.521**	1.058***	0.0933	0.318	-0.477	-0.912	0.0902	0.309	-0.492	-0.939
	(0.164)	(0.280)	(0.207)	(0.410)	(0.444)	(1.061)	(0.563)	(1.664)	(0.461)	(1.111)	(0.586)	(1.732)
55-64	0.0203	0.0606	0.507	1.010*	0.220	0.486	-0.431	-0.907	0.202	0.452	-0.459	-0.958
	(0.227)	(0.392)	(0.308)	(0.575)	(0.561)	(1.248)	(0.689)	(1.863)	(0.575)	(1.300)	(0.711)	(1.936)
65+	-0.717**	-1.338**	-0.442	-0.987	-0.0945	0.00178	-0.743	-1.281	-0.0921	-0.0143	-0.753	-1.309
	(0.308)	(0.570)	(0.450)	(0.892)	(0.550)	(1.192)	(0.696)	(1.814)	(0.558)	(1.226)	(0.713)	(1.874)
Income Quintiles												
Second 20%	0.0962	0.156	0.327	0.658	0.959*	1.692	1.210*	2.010	0.981*	1.719	1.241*	2.081
	(0.167)	(0.286)	(0.229)	(0.425)	(0.531)	(1.520)	(0.719)	(2.171)	(0.541)	(1.538)	(0.737)	(2.244)
Middle 20%	0.207	0.324	0.772***	1.484***	0.862*	1.849*	0.596	1.156	0.882*	1.884*	0.600	1.165
	(0.160)	(0.276)	(0.204)	(0.389)	(0.442)	(1.022)	(0.368)	(0.823)	(0.457)	(1.049)	(0.378)	(0.833)
Fourth 20%	0.400***	0.650***	0.466**	0.899**	0.494	0.826	0.616*	1.175	0.513	0.857	0.642*	1.238*
	(0.147)	(0.248)	(0.207)	(0.401)	(0.379)	(1.041)	(0.334)	(0.719)	(0.391)	(1.067)	(0.346)	(0.748)
Richest 20%	0.528***	0.873***	0.827***	1.505***	1.404***	3.171***	1.254**	2.853*	1.437***	3.220***	1.288**	2.934*
	(0.141)	(0.240)	(0.187)	(0.352)	(0.478)	(1.012)	(0.542)	(1.579)	(0.488)	(1.022)	(0.558)	(1.597)
Education												
Secondary	0.814***	1.405***	1.673***	3.175***	1.464***	3.370***	0.965	2.335	1.456***	3.335**	0.954	2.337
	(0.149)	(0.260)	(0.254)	(0.495)	(0.549)	(1.288)	(0.650)	(1.967)	(0.558)	(1.332)	(0.660)	(2.010)
Tertiary	0.991***	1.730***	1.850***	3.479***	0.660	1.445	0.283	0.606	0.611	1.326	0.225	0.494
	(0.199)	(0.347)	(0.304)	(0.543)	(0.655)	(1.433)	(0.795)	(1.973)	(0.671)	(1.460)	(0.817)	(2.027)
Costs												
Switching Costs			2.356***	4.442***	11.67***	23.22***	11.09***	22.48***	11.32***	22.49***	10.87***	22.00***
			(0.166)	(0.325)	(1.054)	(3.103)	(1.160)	(3.920)	(1.047)	(3.074)	(1.185)	(4.034)
Network effects variables												
General Population network effects for mobile money					1.749***	3.466***	1.413***	2.888***				
					(0.147)	(0.450)	(0.156)	(0.467)				
Network effects for incumbent money							-0.470***	-0.957***			-0.457***	-0.924***
							(0.111)	(0.292)			(0.111)	(0.278)
Cohort network effects for mobile money									1.732***	3.429***	1.416***	2.890***
									(0.148)	(0.451)	(0.163)	(0.492)
Pseudo R^2	0.271	0.272	0.605	0.617	0.945	0.944	0.958	0.958	0.948	0.947	0.960	0.959
Wald χ^2 #	265.5	233.0	256.0	244.4	310.0	176.5	334.3	187.8	305.1	176.2	324.6	182.6
HL χ^2 ##	8.66	9.6	33.29	29.11	0.55	2.9	1.44	5.22	0.46	0.93	1.47	1.96
AIC	1040.1	1039.8	577.9	561.8	107.6	109.3	92.3	92.7	104.3	106.0	90.0	90.5
BIC	1118.6	1118.3	656.4	640.3	186.1	187.8	175.7	176.1	182.8	184.5	173.4	174.0
Observations	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000

Notes: Values in the parentheses are robust standard errors. ***, ** and * indicate that the corresponding coefficient is statistically significant at 1 percent, 5 percent, and 10 percent, respectively. # The Wald χ^2 were all found to be statistically significant at 99% confidence level. ## The Hosmer-Lemeshow statistic (HL χ^2) were all found to be statistically insignificant at 99% confidence level except for models (2a)-(2b).
Source: Author's computations using Global Findex survey (2022)

2.6.4. Logit Model Marginal Effects

This section will give a detailed interpretation of the marginal effects of the Logit Models 1 and 3-6 of **Table 2.8**. The main result here is that when the micro-founded variables for network effects and switching costs are incorporated, we find the statistical significance of the demographic variables, such as employment, education and income on mobile money adoption. We also find significant results for network effects variables and switching costs on mobile money adoption. To test for multicollinearity, we compute the variance inflation factor (VIF) for regressors in each model in **Table 2.9**. The results show no collinearity except for the incumbent network effects variable (see **Table 1.5A** in Appendix)[15]. This has reduced the statistical significance of predictors, especially the demographic variables in models 4 and 6. However, models 3 and 5 remedy this issue by excluding the incumbent network effects.

The impact of demographic and socioeconomic factors on mobile money adoption

Table 2.9 Model 1 results show that owning a bank account increases the probability of mobile money adoption. This is a plausible result because in some economies, like Botswana, mobile money is seen as complementary or add-on to existing banking services (Shirono *et al*., 2021; Demirgüç-Kunt *et al*., 2022). Therefore, mobile money adoption will increase with growth in bank account ownership. The results also show that compared to unemployed respondents, the estimate of the coefficient of those employed is positive and significant at 1%. This suggests that employed individuals are more likely to adopt mobile money technology. This result is mainly because of the broad definition of this variable, which includes self-employed individuals and those seeking employment. Further, the wages of individuals in the workforce are likely to be paid through a mobile money account. The coefficient of the cellphone is statistically significant at 1%, implying that individuals with a cellphone are more likely to adopt mobile money. The statistically insignificant coefficient value of the female variable suggests no gender-based effect on mobile money adoption in this context. We also find that young individuals (25-34) are more likely to adopt mobile money than older individuals (65 years and above). These results are consistent with the findings of other studies (Murendo *et al*. (2018); Munyegera and Matsumoto (2016)).

[15] Age squared severely correlates with all independent variables and therefore we dropped it for our regressions.

Concerning the income variable, the results highlight the increasing nonlinear marginal likelihood of consumers' mobile money adoption. Indeed, compared to individuals in the first income quintile, respondents in the fourth and richest quintiles have more likely to adopt mobile money. The higher likelihood of mobile money account adoption by richer individuals is attributable to the fact that an active mobile money account requires regularity regarding funds transfer. Therefore, these accounts are more active when held by individuals from the top income quintiles (fourth and rich quintiles) than individuals in the lower quintiles. This result supports empirical evidence from other studies (Mbiti and Mwega (2012); Coulibaly (2021)).

The estimated marginal effect of education highlights that compared to respondents with primary education or less, those with secondary education and at least tertiary education show an about 25% and 31% increase in the probability of mobile money adoption, respectively. This is because mobile money payments through mobile phones require reading about transfers and balances in mobile wallets. Meanwhile, less educated individuals might find it more challenging to conduct mobile money transactions than using cellphones to make calls. Therefore, they are less likely to adopt mobile money. These results confirm the results of other studies (Murendo *et al*. (2018); Munyegera and Matsumoto (2016)).

Table 2.9: Marginal effects estimated from the Logit model of Mobile Money Adoption with Network Effects and Switching Costs

SCENARIOS/MODELS VARIABLES	(1b) Mobile money	(3b) Mobile money	(4b) Mobile money	(5b) Mobile money	(6b) Mobile money
Bank account	0.252***				
	(0.0223)				
Cellphone	0.254***				
	(0.0619)				
Employed	0.0480*	0.0102*	0.00542	0.00995*	0.00545
	(0.0281)	(0.00526)	(0.00469)	(0.00510)	(0.00466)
Female	-0.0113	-0.0121	-0.00968	-0.0120	-0.00975
	(0.0267)	(0.00774)	(0.00657)	(0.00757)	(0.00652)
Age Categories					
25-34	0.0691*	0.00320	-0.00785	0.00318	-0.00762
	(0.0369)	(0.0105)	(0.0120)	(0.0104)	(0.0118)
35-44	0.0637	0.00197	-0.00261	0.00228	-0.00236
	(0.0395)	(0.0114)	(0.0133)	(0.0113)	(0.0131)
45-54	0.0117	0.00302	-0.00569	0.00281	-0.00570
	(0.0491)	(0.0101)	(0.0107)	(0.0101)	(0.0108)
55-64	0.0106	0.00467	-0.00567	0.00415	-0.00581
	(0.0688)	(0.0121)	(0.0119)	(0.0121)	(0.0121)
65+	-0.221***	1.67e-05	-0.00801	-0.000128	-0.00793
	(0.0838)	(0.0112)	(0.0121)	(0.0110)	(0.0122)
Income Quintiles					
Second 20%	0.0276	0.0150	0.0150	0.0145	0.0150
	(0.0506)	(0.0147)	(0.0168)	(0.0144)	(0.0168)
Middle 20%	0.0574	0.0164	0.00939	0.0159	0.00914
	(0.0489)	(0.0101)	(0.00746)	(0.00991)	(0.00713)
Fourth 20%	0.115***	0.00784	0.00952	0.00769	0.00962
	(0.0439)	(0.0103)	(0.00716)	(0.0100)	(0.00710)
Richest 20%	0.153***	0.0324***	0.0214	0.0317***	0.0214
	(0.0428)	(0.0107)	(0.0136)	(0.0104)	(0.0133)
Education					
Secondary	0.254***	0.0415*	0.0187	0.0383*	0.0177
	(0.0447)	(0.0212)	(0.0213)	(0.0204)	(0.0200)
Tertiary	0.314***	0.0223	0.00601	0.0189	0.00462
	(0.0624)	(0.0247)	(0.0215)	(0.0233)	(0.0203)
Costs					
Switching Costs		0.219***	0.151***	0.204***	0.144***
		(0.0290)	(0.0553)	(0.0272)	(0.0528)
Network effects variables					
General Population network effects for mobile money		0.0327*** (0.00402)	0.0194*** (0.00711)		
Network effects for incumbent money			-0.00643***		-0.00605***
			(0.00124)		(0.00118)
Cohort network effects for mobile money				0.0310***	0.0189***
				(0.00385)	(0.00696)
Observations	1,000	1,000	1,000	1,000	1,000

Notes: Values in the parentheses are robust standard errors. ***, ** and * indicate that the corresponding coefficient is statistically significant at 1 percent, 5 percent, and 10 percent, respectively.
Source: Author’s computations using Global Findex survey (2022)

The impact of general and cohort population network effects on mobile money adoption

Model **(3b)** extends the analysis to include the effects of switching cost and general population network effects for mobile money and other household characteristics on adoption of mobile money. Here we condition the expected network effects variables on individuals with mobile phones[16]. This assumption implies that potential adopters without mobile phones tend not to gain the benefits of mobile money, hence they will expect no network effects from mobile money and continue gaining network effects for incumbent money. As shown in **Table 2.9**, we find that the general population network effects of mobile money increase the likelihood of mobile money adoption by 3.3% in Botswana. The inclusion of incumbency effects in model (**4b**) results in general population network effects increasing the likelihood of mobile money adoption by about 1.9%. These findings implies that every new user of mobile money added to the network increases the value for existing users of mobile money (Murendo *et al*., 2018).

The results in model (**5b**) incorporates the effect of switching costs and cohort network effects. Here, we assume that potential adopters form expectations about how many people will adopt from their cohort, such as being financially excluded and banked with no mobile money. We find that the cohort network effects for mobile money increase the likelihood of adoption by 3.1%. Similarly, with incumbency effects in model (**6b**), we observe that cohort network effects for mobile money increase the likelihood of mobile money adoption by 1.9%. These results are consistent with our heterogeneous model for the adoption of new technology with network effects and switching to the incumbent option. They highlight the crucial role of local information in adoption decisions, showing that the adoption decisions of agents may be influenced not only by the direct effects of network effects from the general population but also by their estimation of this using information local to them

The impact of incumbent network effects on mobile money adoption

Consistent with theory, models **(4b)** and **(6b)** show that the network effects for incumbent money reduce the probability of mobile money adoption by about 0.64% and 0.61%, respectively. This is consistent with theory that in the early years, the adoption of new payment

[16] The Global Findex survey for the year 2014 does not have a specific question on mobile phone ownership, therefore the Global Findex surveys for the years 2017 and 2022 is suitable for our Logit model analysis of network effects.

media normally suffers from larger network effects favouring the incumbent payments due to the historical acceptance of incumbent money.

The impact of switching costs on mobile money adoption

The results in **Table 2.9** show that the switching costs have a positive and significant impact of between 14-22% on likelihood of mobile money adoption in Botswana. This means that there is a cost advantage of switching from incumbent media to mobile money, which in turn leads to an increase in the adoption of mobile money. However, the theory stipulates that regardless of the lower cost of switching from incumbent to mobile money, the network effects of incumbent money might impede mobile money from substituting incumbent money. All agents believe that adopting mobile money has greater benefits and would prefer to switch if they knew everyone would switch, but agents find it difficult to coordinate. This is because of shared knowledge on the historical acceptance of incumbent money, a dominant focal point. Everyone knows that everyone else has a history of transacting with incumbent money. In other words, there is a problem of excess inertia, which will persist because no agent will want to switch first (Luther, 2016). Hence, a justification to why consumers find switching from status quo to mobile money unattractive, hence the slow adoption of mobile money.

2.7. Conclusion

This chapter has contributed to the literature by operationalizing network effects in the adoption of new payments technology. Methodologically, we develop a theoretical approach based on strategic complementarities model used in game theory given in equations (2.6), (2.11) and (2.12) which is then tested by an empirical investigation. We incorporate expected network effects and switching costs in addition to demographic determinants of mobile money adoption in Botswana using a Logit model based on the cross-sectional data drawn from the 2022 World Bank's Global Findex survey. As per the Akaike this specification was found to be statistically more superior than the mainstream model which include only demographic variables. By fitting data to the theoretical framework in which the Binomial probability is used to determine rates of adoption among those yet to adopt, we find that in the early years mobile money adoption is slow and there is a backward bend to the adoption curve as number of yet to adopt individuals falls by a small number when the numbers of adopters increase from a small base of successful adopters registering low extant probability of adoption. However, only when a substantial proportion of population adopts increasing the latter probability can it counteract the fall in number of potential adopters and bring about an acceleration to Binomial probability adoption rates curve, which then peters out as population becomes saturated with adopters. This generates an S-curve effect of mobile money adoption. We further see that for a less developed economy such as Botswana a tipping point is not yet reached because financially excluded are still reluctant to adopting mobile money.

The empirical results show that the greater adoption of mobile money is mainly driven by factors such as being educated, employed and richer, as well as owning a bank money account and cellphone. The network effects have a positive and significant impact on the adoption of mobile money mainly because every new user of mobile money added to the network increases the value for existing users. Switching costs have a positive and significant impact on the adoption of mobile money. Therefore, regardless of low switching costs from incumbent to mobile money, the presence of network effects deters mobile money from substituting incumbent money mainly due to historical acceptance of incumbent money. As a result, consumers find switching from status quo to mobile money unattractive, hence the slow adoption of mobile money.

The heterogenous model with strategic complementarities provides insights into the potential barriers to adoption of new payment media and the impact of policy interventions aimed at promoting the adoption of new payment media. Overall, the results show that the adoption of mobile money account has been slow in Botswana, and a tipping point is not yet reached. However, it is worth noting that it is not necessarily because mobile money is poorly invented, rather it is because of attributes of incumbent monies. The use of money as a medium of exchange is determined by the network size of agents who are most inclined to accepting incumbent money with large network effects. Therefore, this study suggests that the government needs to address this problem of 'excess inertia' cautiously as it may reduce bank accounts. Note, we have made the distinction between governmentally sponsored mobile payment apps that operate on P2P transfers between bank accounts and mobile money for which bank accounts are not necessary. Due to lower costs of mobile money payments, active avenues of research investigate how Central Bank Digital Currency can replace cash and piggyback on deposits of mobile money customers in bank accounts of Mobile Network Operators which allow P2P payments for customers with no bank accounts. This can help improve the inclusion of the unbanked population in the financial system at lower costs than the attempts to increase bank accounts especially for those below poverty line (Markose *et al.,* 2020).

Similarly, the slow adoption of mobile money in Botswana could be associated with insufficient awareness policies regarding the attractiveness of mobile money services. This is reflected by the vulnerable population's lack of mobile money adoption, such as the poorer, unemployed, and less educated people. Therefore, this calls for concerted efforts by the government that aims at integrating the vulnerable segments of the population in the financial system via mobile money financial services. The young and working-age population need to be sensitised by mobile money services through financial literacy programs.

2.7.1. Limitations of the Study

It has always been challenging to get a suitable dataset to study the relationship between network effects and consumer adoption of payment media. It requires granular data with linked number of people adopting payment instrument and with whom they interact or transact with on a regular basis. It is even harder to study it in a dynamic setting. The availability of this granular dataset could allow us to construct a robust indicator of network effects, and easily address any forms of heterogeneity empirically. Further, the study does not capture the critical role that merchants can play in the network effects of mobile money services due to lack of data in Botswana.

Chapter 3

Cashlessness with the Adoption of Mobile Money and Bank Card Payments: Macro Trends with Extensive and Intensive Margins

Abstract

Chapter 3 deals with the derivation of the intensive margins of adoption of mobile money and bank cards. We will base this on the Chapter 2 Binomial distribution model for the expected new mobile money and card adopters. The latter yields the extensive margin when the numbers of people who are yet to adopt these payments media in the population begin to do so, they switch some part of their consumption expenditure from cash or card. This results in the change in the intensive margins or the portfolio weights in terms of the proportion of consumption expenditure transacted in the different payments media. The objective of Chapter 3 is to derive the macro-economy shares of consumption expenditure in the three payments media and thereby track the trend in cashlessness. Using a CAPM and Arrow (1964) inspired derivation, we show that optimal portfolio weights in equilibrium equal the aggregate consumption proportions transacted in each payments media. The Binomial probability based expected numbers of new mobile money adopters divided by the population who are yet to adopt is used to determine the equilibrium changes in portfolio weights for mobile money. We calibrate this model using the Global Findex data for Botswana and test this against the empirical macro-economic data for mobile money transactions, card payments and cash. We also use a second method to estimate how much consumption is switched by households based on their payment habits by collating the Global Findex survey with Household Expenditure Survey based on quintiles. While, both methods use the micro-founded Binomial model for mobile money adoption, the more direct application of this in the first method is found to be more successful in tracking the decline in aggregate expenditure share of cash. Further, the results show that households continue to allocate more of their retail payments to bank cards compared to mobile money mainly due to the high network effects of conventional banking system. Therefore, the microfoundations of adopting cashless payments in retail payment systems play a significant role in tracking the falling intensive margin of cash use at the macro level.

Keywords: Cash and cashless payments; extensive and intensive margins; optimal portfolio weights, consumer expenditure shares, Binomial probability

3.1. Introduction

Payment methods worldwide have undergone fundamental changes, the most recent being a shift from cash to electronic or digital payments, such as debit cards, digital wallets, or mobile money. The emergence of electronic payments, where payments are conducted electronically without physical cash (notes and coins), has attracted the interest of both academia and business in ideas about cashless economies. Theoretically, it is shown that cashless payments have advantages such as reducing transaction costs associated with the circulation of money, improving transaction quality (Fabris, 2019), combating the shadow economy (Schneider, 2017), and reducing illicit money transfers such as money laundering and counterfeiting (Rogoff, 2016).

With the emergence of new alternative means of payment, much has been said about the imminent disappearance of cash. However, this prediction is premature, and recent research argues that cash will be around for a while, mainly due to its unique features compared to noncash payment media (Shy, 2023). Markedly, there has been a decline in the use of cash worldwide over the past few years, with consumers increasingly relying on digital payment methods such as debit and credit cards, mobile payments, and online banking. Global trends show that transaction demand for cash decreased substantially in China, Norway, and Sweden relative to other countries (Shy (2023); Khiaonarong and Humphrey (2019)). Although cash use is trending down, the use of cash continues to be strong in other countries mainly because of the costs and risks associated with electronic infrastructure[17], and lack of digital skills among segments of the population (Srouji, 2020). Nevertheless, the transition to a cashless society is a continuing trend globally, and many countries are designing flexible policies to promote cashless payments. Therefore, achieving greater digital liquidity is the main objective of most of the central banks.

Generally, most of empirical studies on payments focus more on extensive margin – number of adopters of specific payment methods, and little research is done on intensive margin – usage of each payment media by the adopter (Koulayev *et al*. (2016); David *et al*. (2016); Comin and Hobijn (2014); Schuh *et al*. (2013)). This is mainly because of lack of micro-level datasets, which captures the intensity with which each adopter uses the technology. Furthermore, previous empirical research on payments ignores the microfoundations for the macroeconomic

[17] These include a lack of privacy, digital fraud, and technological glitches that could block access to funds.

trends in payments media. Therefore, the main contribution of this chapter is to examine how pairwise switching to a new payment technology affects the intensive margins or portfolio weights across the three payments media, namely cash, bank cards and mobile money. Here we consider an interesting property that individuals who switch for the first time to a new payments media have to do so by reducing the portfolio weights from one or the other payments media, viz. along the intensive margin of the extant portfolio weights of payments media. Therefore, changes in portfolio weights for household leads to macro changes which is equivalent to the probability of switching of the population. This is because when a household switches to a new payment media his portfolio weights will change automatically.

This chapter proposes a simple model based on different cohorts of the population who switch differently to adopt and use cashless payments such as bank cards and mobile money. Based on the model and results of Chapter 2, this chapter draws on the Binomial distribution model to quantify the network effects and adoption rates for the extensive margin using the Global Findex survey data. We compute the extensive margins of adoption of new innovative cashless media (mobile money) in the face of incumbent payment media such as cash and bank-based deposits. We also use the Binomial adoption rates model to quantify switching from cash to bank card payments by households within each cohort. Further, we contribute to the money demand literature by quantifying the intensive margin to track what proportion of consumption each household allocates to cashless payment instruments, and the extent to which it affects the respective portfolio weights of the three payments media. We use the market equilibrium conditions from Arrow (1964) to show that individual portfolio weights for s payment media ,w_{is}, equal the so called 'market value' weights w_s^A. The latter refers to the macro level ratio of amount of aggregate consumption expenditure transacted in a specific payments media to aggregate consumption expenditure. In equilibrium, the value of total goods transacted equals aggregate consumption expenditure.

This chapter uses two approaches to quantify the intensive margins for cash, bank deposit based money (card) and mobile money. First approach estimates the incremental changes in portfolio weights for households that is calculated as the product of respective Binomial probabilities of switching within different population cohorts and the proportion of those expected to switch relative to yet to adopt individuals in each of these cohorts. We use the Global Findex survey to estimate changes in portfolio weight for household, and add these changes to the initial aggregate or macro portfolio weight w_{st} for s payments media to find the calibrated portfolio weights in the next period w_{st+1}. Second approach estimates what proportion of consumption is switched by households in the different cohorts based on their payments habits. Here we combine the Global Findex Survey data which gives the ratio of households who use the three payments media with the equivalent quintiles of the Household Expenditure Survey.

We calibrate the model and test how it closely tracks the observed aggregate shares of cash and cashless payments in Botswana's economy. We consider the case of Botswana, a developing economy with a well-developed cashless deposit account based money, which we have found to mitigate the growth of mobile money. The results show that micro-foundations of adopting cashless payments, such as bank cards and mobile money, play a significant role in determining the intensity of cash usage in transactions. Consumers are increasingly substituting cash for card-based deposit money and mobile money. Further, the results show that households continue allocating more of their retail payments to bank card transactions than mobile money transactions, mainly due to the incumbency of the conventional banking system (high network effects).

The chapter is structured as follows: Section 3.2 analyses the trends of cash and cashless payments in the case of Botswana's economy. Section 3.3 reviews both theoretical and empirical literature related to this study. Section 3.4 discuss the methodology. Section 3.5 discusses data sources. Section 3.6 analyse the empirical results for the extensive and intensive margins for 3 payments media such as cash, bank cards, and mobile money. The last section provides conclusion and limitations of the study.

3.2. Stylised Facts: Trends of Cash and Cashless Payments in Botswana

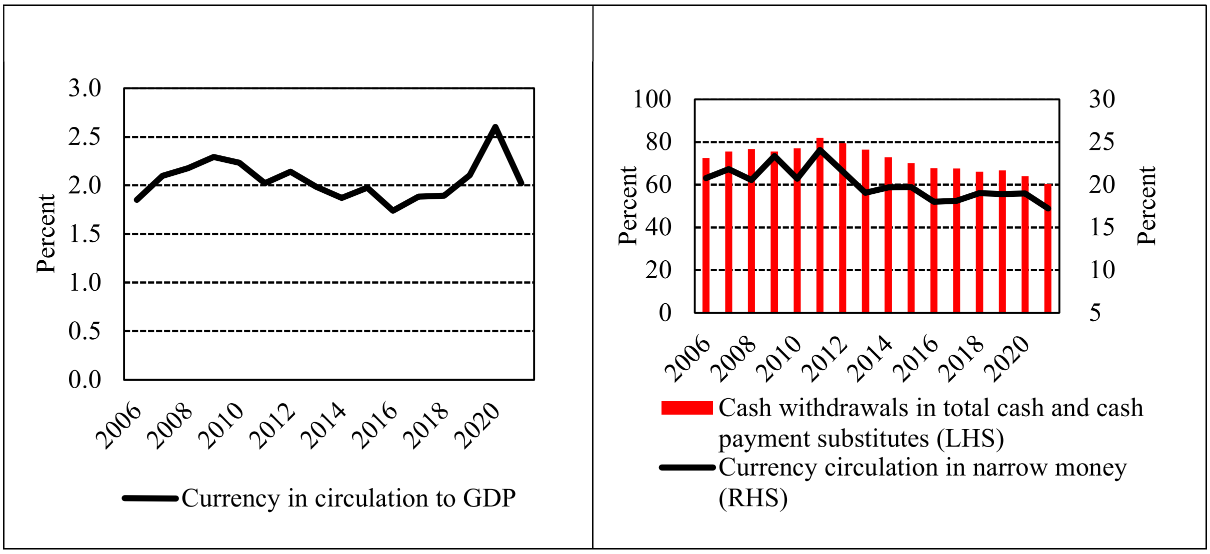
The anonymity of cash use makes it difficult to record cash payments, and hence, there is a paucity of direct evidence for the measure of cash use. This means that indirect methods can only estimate cash payment statistics (Krüger and Seitz (2014); Khiaonarong and Humphrey (2019)). The most popular method for estimating cash use across countries is a ratio of a country's currency in circulation to gross domestic product (GDP).[18] The second method calculates the total cash withdrawals at automated teller machines (ATMs) and bank counters as a ratio of total cash and cash payment substitutes (cards plus e-money). The third method uses the currency in circulation as a ratio of narrow money (M1). The final method calculates

[18] See, for example Krüger and Seitz (2014) and Rogoff (2016).

cash use as the residual value of total household expenditure minus the value of all non-cash payment instruments used in consumption.

Figure 3.1 charts different measures of cash use in Botswana between 2006 and 2021. The currency in circulation to GDP ratio shows a general downward trend of cash payments in the past decade, except for 2020, when the increasing trend was mainly due to significant increases in the net issuance of banknote denominations. All other cash use indicators show a significant decline after 2011 (the launch date of mobile money). The share of cash withdrawals in total cash and cash payment substitutes (cards plus e-money) has declined from 82% in 2011 to 60% in 2021. The share of currency in circulation in narrow money (M1) declined from 24% to 17% in the same period.

Figure 3.1: Cash Use Indicators in Botswana: 2006-2021



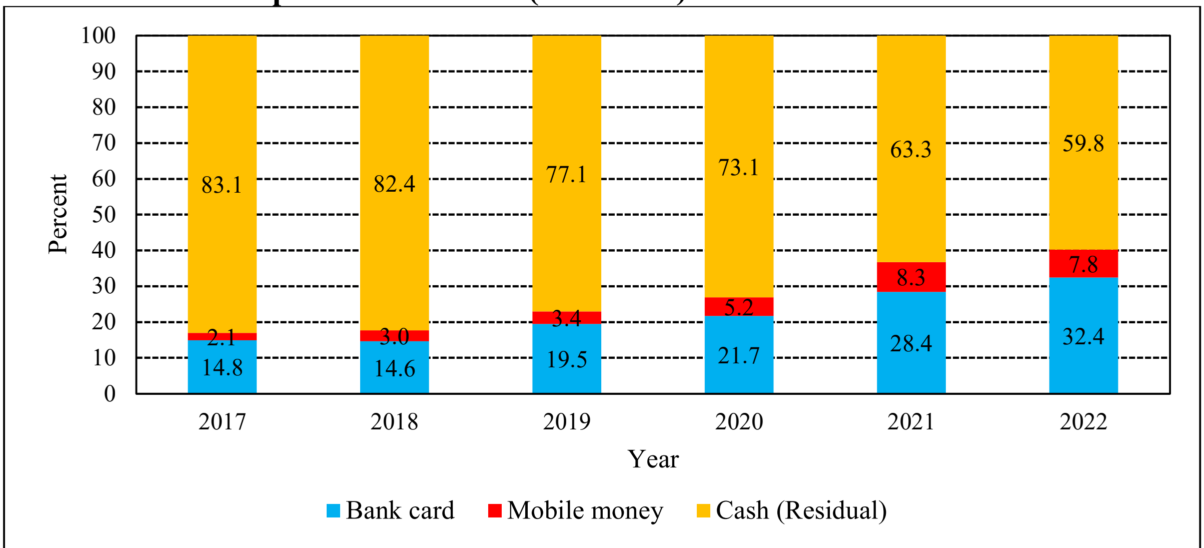
Notes: Currency in circulation (M0) comprises notes and coins outside the central bank and other depository corporations (e.g., commercial banks). Narrow money (M1) is the sum of M0 plus transferable deposits such as checks, direct debit/credit, electronic money (e.g., mobile money) etc.
Source: Bank of Botswana, *Botswana Financial Statistics,* and IMF Financial Access Survey.

Figure 3.2 shows the evolution of mobile money and bank-based money transactions on the use of cash in Botswana. The general downward trend in the proportion of cash transactions is mainly due to a significant increase in the adoption of cashless payments, such as mobile money and bank deposit-based money payments[19]. The impressive growth in the adoption and

[19] The empirical literature suggests that the adoption of innovative cashless media is expected to substitute for cash, viz., curb cash in circulation or cash use (Snellman *et al.* (2001); Markose and Loke (2003); Stix (2004); David *et al.* (2016)).

usage of cashless or digital payments was also accelerated by the COVID-19 pandemic (Auer *et al*., 2020). This has also led to an increase in new mobile money account registrations, hence a substantial growth in mobile money transactions in developing economies (GSMA, 2022). In Botswana, active registered mobile money accounts doubled from 1.4 million in 2019 to 3 million in 2022. Further, although cashlessness is mostly determined by bank card transactions in this economy, a new technology (mobile money) also plays a significant role in cashlessness (**Figure 3.2**). Therefore, we expect that as more and more people adopt mobile and bank deposit-based money, there will be a significant growth in cashless transactions. We study the aggregate or macro trends in **Figure 3.2** closely because they may have significant implications for aggregate demand, inflation, monetary aggregates, and welfare.

Figure 3.2: Proportions of Cash, Bank Cards, and Mobile Money Transactions at POS to Household Consumption in Botswana (2017-2022)



Notes: Total consumption is calculated as the total sum of transactions conducted using different payment media at the point of sale. Since the data on bank cards and mobile money transactions at POS is available, cash-based consumption is proxied by the residual between total household consumption and cashless methods (bank cards and mobile money), Khiaonarong and Humphrey (2019).
Source: Mobile Network Operators and Central Bank of Botswana.

The main aim is to provide the microfoundations for the macro trends in **Figure 3.2** on use of payments media in Botswana. Our model assumes that the extent to which consumers adopt a new payment media and reduce their proportion of cash-financed expenditures depends on the expected proportion of individuals who will switch from cash to cashless payments. Thus, it is not only the *extensive margin* resulting from changes in the fraction of people who choose to adopt cashless payments that matters, but also the *intensive margin* of using the cashless payments has to be accounted for as well.[20] In other words, we want to show that the microfoundations explaining the macro trends in **Figure 3.2** are mainly a result of both extensive and intensive margins activities.

3.3. Literature Review: Extensive and Intensive margins of payments methods

The workhorse model to study demand for money is Baumol-Tobin (BT) inventory model (Baumol, 1952; Tobin, 1956). Mulligan and Sala-i-Martin (2000) has extended the BT model to explicitly model the decision to adoption of a new payment technology, such as bank account (extensive margin), and switching between cash and bank deposits for people who use bank deposits regularly (intensive margin). They find that at low interest rate about one-half interest rate elasticity is attributable to the intensive margin and half to the new adopters or extensive margin. Further, they found that intensive margins are important for larger variations in interest rates whereas at low interest rates extensive margins is important since there is a lot of heterogeneity across households. In the spirit of Mulligan and Sala-i-Martin (2000), a study by Fung *et al*. (2012) investigates the impact of retail payments innovations on the intensive margin of cash use in Canada, and find that the use of contactless credit and store cards leads to reduction in expenditure share for cash.

Schuh and Stavins (2010, 2013) study the factors affecting adoption and use of multiple payments media in the United States (U.S.). They highlight that consumers first adopt each payment instrument, viz., extensive margin, and then choose how much to use each payment instrument for transactions conditional on whether the consumer have access to a bank account. They define intensive margin as a fraction of number of transactions consumer i made using j payment media to total number of payments made by consumer i in a month, i.e., n_{ij}/N_i where $\sum_j^J n_{ij} = N_i$. The authors find that payment characteristics such as cost, ease of use, and security significantly affect payment use, while setup and record keeping significantly affect payment media adoption.

[20] Empirically, most studies on adopting new technology highlight that adopters have some influence on non-adopter behaviour through networks (Young, 2009). These studies can be arguably considered to be focusing mainly on extensive margins of adoption (Mulligan and Sala-i-Martin (2000); David *et al*. (2016); Sekine *et al*. (2021); Alvarez and Argente (2020); Alvarez and Argente (2022); Alvarez *et al*. (2023)).

David *et al*. (2016) analyse the extensive margin of debit cards on the demand for cash. The authors use the survey data of French households to categorise daily cash payments into three population groups, namely: non-cardholders, ATM-only cardholders, and debit cardholders. They estimate the impact of debit card services, such as withdrawals and payments, on demand for cash by comparing cash holdings and cash usage of the three groups. The authors find that the negative effect of the card payment service on the demand for cash dominates the positive effect of the ATM service, resulting in an overall reduction in demand and use of cash.

Alvarez and Argente (2022) estimate the effect of the availability of cash as a payment option on the intensive and extensive margins of Uber trips in Mexico. The authors model extensive margin as a choice to adopt a credit card as payment method to have access to both cash and credit card, and the intensive margin as the number of trips to take with each of the available payment methods. They find that cash as payment option and changes in its availability has a substantial effect on number of Uber trips, fares, miles, and number of users, mainly among low-income households. No effect was found on prices implying that cash ban has little effect on riders who pay for their trips exclusively with cards. This evidence suggest that cash and card payments are imperfect substitutes at both the intensive and extensive margins, which magnifies the effect of policies that restrict the availability of payment methods.

A few research papers investigate the effects of other payment innovations, such as newly introduced mobile and contactless methods, on the use of cash. Brown *et al*. (2022) finds no significant effect of contactless card payments on cash use in Switzerland, although some slight effect is found for young urban consumers. Similarly, Chen *et al*. (2017) find no effect of contactless card payments on cash use in Canada, and only about a 2 percent drop in cash usage comes from single-purpose stored value cards. Felt (2020) estimates a significant negative effect of contactless credit cards on the intensive margins of cash use but not on the extensive margin of cash usage. Trutsch (2016) using a 2012 consumer survey for the U.S., finds no significant effect of mobile payments on consumer use of payment methods at the point of sale.

In developing and emerging economies, a new innovative payment instrument, mobile money, is launched to provide the unbanked population with cheap, secure, and convenient means to conduct transactions. Kipkemboi and Bahia (2019) study the effect of mobile money on cash use in selected sub-Saharan African economies such as Kenya, Uganda, Ghana, and Rwanda. They find a negative growth of the currency ratio outside the banking sector to broad money, suggesting that cash use fell while bank deposits increased. Some relatively recent literature on the adoption of new payment media, such as mobile money and other peer-to-peer (P2P) payments, include Murendo *et al*. (2016), Economides and Jeziorski (2017), Aron (2018), and Alvarez *et al*. (2023).

Previous studies on payments technology have focused on the extensive margin, with little research on the intensive margin. These studies use econometric models to estimate the factors affecting extensive and intensive margins of alternative payments methods, and the effect of these margins on demand for cash. However, they have overlooked the microfoundations for the macroeconomic trends in the payments media shares for household consumption transactions. In this context, this chapter seeks to close this gap by modelling the microfoundations and their implications on extensive margins and portfolio weights of cash and cashless payments media. The potential impact of this research on the field of economics and finance is significant, as it could provide a deeper understanding of payment technology and its implications for cash and cashless payments.

3.4. Model Framework

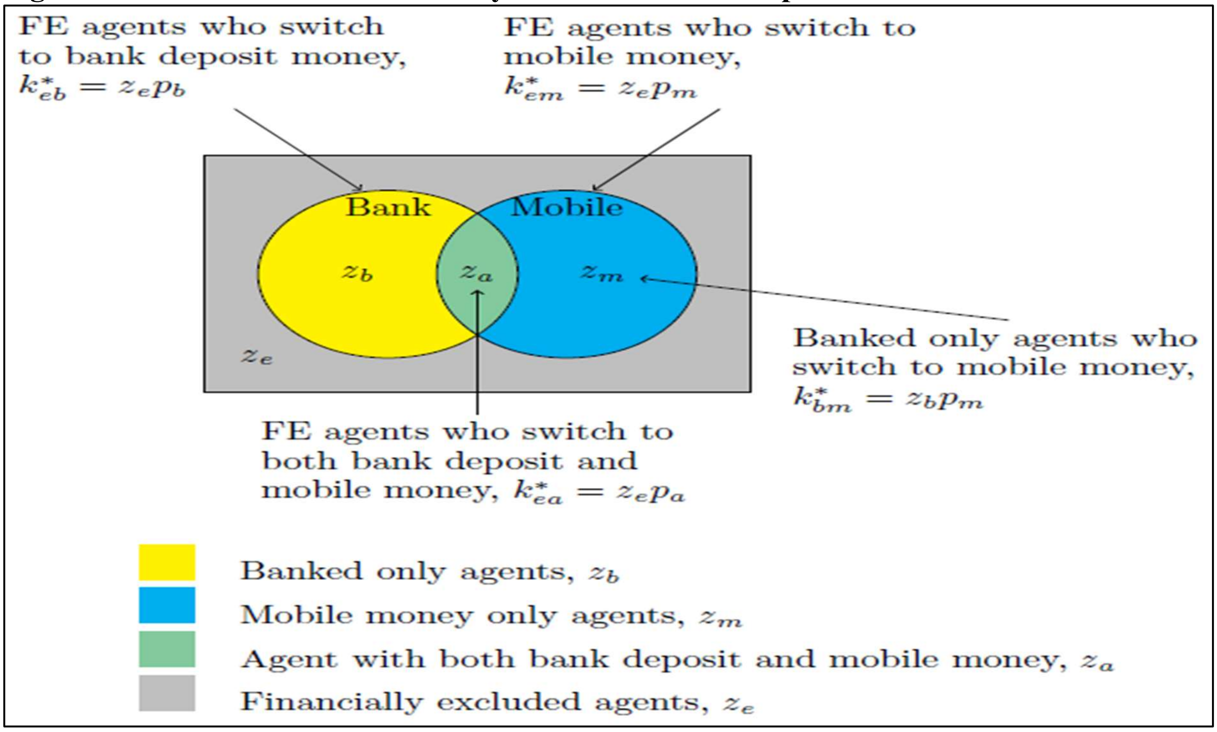
In this section, we develop a model to determine the effect of a new innovative cashless media (mobile money) in the face of incumbent payment media, such as cash and bank-based deposits, from a macro perspective. Our model assumes that there is a menu of payment media that can be used for transactions to facilitate household consumption (Markose and Loke (2003); Dutta and Weale (2001)). The main aim of this paper is to track what proportion of household consumption expenditure is transacted in the different payments media. We explicitly incorporate the micro-foundations of the adoption of new payment technology, which is characterised by strong strategic complementarities in a model within which macro trends can be examined. As mobile money payments are a form of cashlessness the consequences of this for deposit money, cash in circulation, inflation and monetary policy is critical to study (see **Chapter 4**). Further, we will calibrate the degree of strategic complementarity due to the adoption of mobile money across different population cohorts, such as the financially excluded (cash users only) and bank account holders without mobile money. We also calibrate the degree of strategic complementarity due to the adoption of bank-based deposits by financially excluded. We assume that potential adopters form expectations about how many will adopt a cashless payment media, therefore as the population becomes saturated by new adopters, cashless payment services become widely used to conduct transactions.

3.4.1. Extensive Margin for new payment media

When cash was the dominant payment media, the demand for money did not have to contend with other competing modes of transactions. In order to incorporate the switch in payment media in transactions, especially with payment innovations like mobile money, we use the heterogeneity found in households regarding their status and extent of financial inclusion as the starting point. In the case of financial exclusion, the household savings are in cash and the decision problem of yet to adopt households will follow the discussion in **Chapter 2**. The introduction of mobile money provides financially excluded (FE) and banked agents with an option to adopt mobile money, and some of them do switch, as denoted by the arrows in **Figure 3.3**. Also, some FE agents may switch to adopt bank deposits or both bank deposits and mobile money.

Households have a choice to transact their consumption expenditures using one of three payments media, such as cash c, bank deposit based money b, and mobile money m. Here the interesting property is that individuals who switch from one to the other payments media do so along the intensive margin, viz. the portfolio weights w_s for $s \in \{c, b, m\}$ payments media. Thus, financially excluded household had $w_{ict} = 1$ and hence the switching to cashless payments implies $w_{ict+1} < 1$ while $w_{imt+1} > 0$, and/or $w_{ibt+1} > 0$ such that $\sum_{s=1}^{3} w_{ist+} \;= 1$. These incremental changes in portfolio weight w_{is} for household that leads to macro changes are proportional to the probability of switching of the population. This is because when a household switches his portfolio weights will change automatically.

Figure 3.3: Number of individuals by cohort and those expected to switch



Notes: *N* is the sample size of the households defined as the sum of financially excluded (FE) z_e, banked only z_b, mobile money only z_m, and those with both bank deposit and mobile money z_a, i.e., $N = z_e + z_b + z_m + z_a$. The probability of adoption of mobile money is $p_m = \frac{z_m + z_a}{N}$, the probability of bank deposit adoption is $p_b = \frac{z_b + z_a}{N}$, and the probability of adoption of both bank deposits and mobile money is $p_a = \frac{z_a}{N}$. Arrows defines the number of households expected to switch to a new payment media successfully.
Source: Author's illustration

A Binomial probability distribution is utilised to calculate the extensive margin for adoption of new payment media as follows:

a) Denoting the number of financially excluded, z_{et+1}, after pairwise switching from financially excluded to mobile money and to bank deposits

$$z_{et+1} = z_{et} - (Bin(z_{et}, k^*_{emt}, p_{mt})k^*_{emt} + Bin(z_{et}, k^*_{ebt}, p_{bt})k^*_{ebt}) \tag{3.1}$$

Percentage change or growth for (3.1) becomes

$$\frac{z_{et+1}}{z_{et}} = 1 - \left(Bin(z_{et}, k^*_{emt}, p_{mt})\frac{k^*_{emt}}{z_{et}} + Bin(z_{et}, k^*_{ebt}, p_{bt})\frac{k^*_{ebt}}{z_{et}}\right)$$
$$\Rightarrow \lambda_c = \frac{z_{et+1}}{z_{et}} - 1 = -\left(Bin(z_{et}, k^*_{emt}, p_{mt})\frac{k^*_{emt}}{z_{et}} + Bin(z_{et}, k^*_{ebt}, p_{bt})\frac{k^*_{ebt}}{z_{et}}\right) \tag{3.2}$$

where $Bin(\cdot)$ denotes the Binomial probabilities of switching by financially excluded households to respective payments media. The switch probabilities from financially excluded to mobile money is $Bin(z_e, k_{em}^*, p_m)$, and financially excluded to bank deposit is $Bin(z_e, k_{eb}^*, p_b)$.

b) Denoting the number of banked only , z_{bt+} , after pairwise switching purely from banked only to mobile money

$$z_{bt+1} = z_{bt} - Bin(z_b, k_{bm}^*, p_m)k_{bm}^* \tag{3.3}$$

where $Bin(z_b, k_{bm}^*, p_m)$ is the Binomial probability rate of switching by Banked only households to mobile money.

Percentage change or growth for (3.3) becomes

$$\frac{z_{bt+1}}{z_{bt}} - 1 = -Bin(z_b, k_{bm}^*, p_m)\frac{k_{bm}^*}{z_{bt}} \tag{3.4}$$

However, there is an additional positive switching from financially excluded to bank deposits, $Bin(z_e, k_{eb}^*, p_b)\frac{k_{eb}^*}{z_{et}}$, gained from equation (3.2). Therefore, equation (3.4) by definition is extended to be:

$$\lambda_b \equiv -Bin(z_b, k_{bm}^*, p_m)\frac{k_{bm}^*}{z_{bt}} + Bin(z_e, k_{eb}^*, p_b)\frac{k_{eb}^*}{z_{et}} \tag{3.5}$$

Here λ_b is the total percentage change in number of banked individuals after switching.

c) The number of mobile money adopters is affected by positive pairwise switching from financially excluded to mobile money and banked only to mobile money. By definition

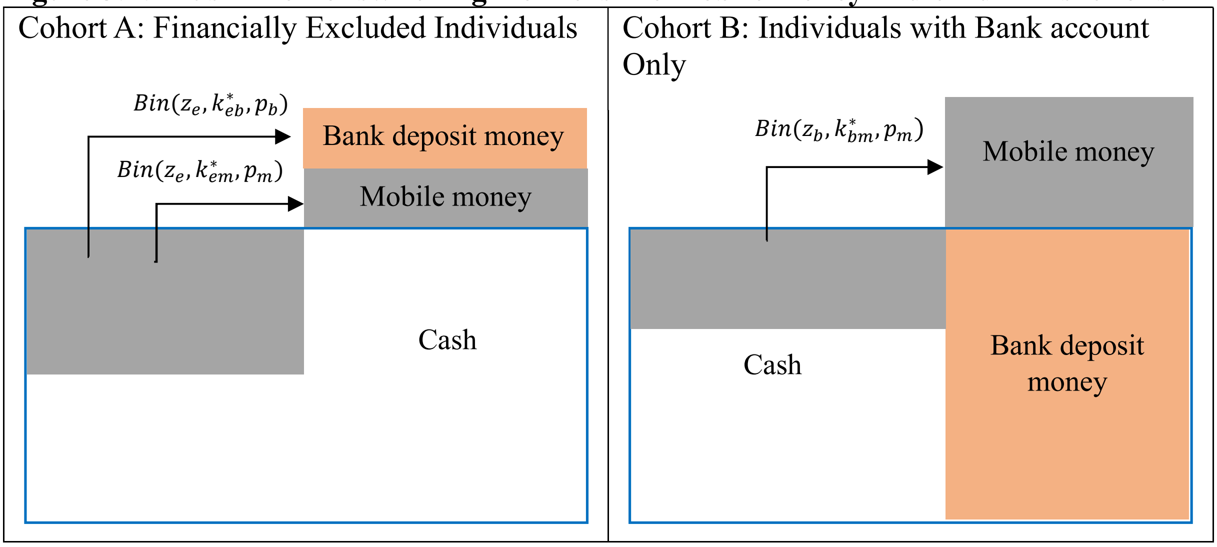
$$\sum_{s=1}^{3} \lambda_s = \lambda_c + \lambda_b + \lambda_m = 0 \qquad \Rightarrow \qquad \lambda_m = -(\lambda_c + \lambda_b)$$

Therefore, inserting λ_c from (3.2) and λ_b from (3.5) yields a percentage change or growth in the number of mobile money adopters , λ_m, as

$$\lambda_m = \frac{z_{mt+1}}{z_{mt}} - 1 \equiv Bin\left(z_e, k_{em}^*, p_m\right)\frac{k_{em}^*}{z_{et}} + Bin\left(z_b, k_{bm}^*, p_m\right)\frac{k_{bm}^*}{z_{bt}} \tag{3.6}$$

As an illustration, **Figure 3.4** shows that a certain fraction of individuals who own a bank account can choose to pay by cash or bank deposit money (bank card). However, given that mobile money is the cheapest payment alternative, some individuals with bank account may switch out of cash to adopt and pay with mobile money[21]. Similarly, financially excluded individuals use cash to purchase goods, while a certain proportion of these individuals may switch out of cash to adopt and use mobile money and/or bank deposits.

Figure 3.4: Illustration of switching from cash to mobile money and card transactions



Notes: The set of consumers in each of the cohorts is represented by a blue box, and the proportion of cash users who may switch to use mobile money payments is represented by a grey-shaded box. The orange box represents the proportion of bank deposit money (cashless card) by individuals.
Source: Author's illustration

Empirical example: Payments Adoption and Consumption Allocation

Table 3.1 shows a worked example on payments media adoption and consumption allocation across different population cohorts based on their financial inclusion status. The four main categories or cohorts are the financially excluded individuals; banked only with no mobile money account; mobile money account holders; and both accounts holders. We tabulate the proportion of households owning a given financial account; the Binomial probability of switching by potential adopters to adopt either a mobile money account and/or bank account; and the aggregate consumption share of cash, bank cards, and mobile money.

The results under the account ownership status heading of **Table 3.1** show the number or fraction of households owning different payments media. First, the number of financially

[21] Based on empirical evidence, it is justified to assume that mobile money is the cheapest payment alternative, Economides and Jeziorski (2017).

excluded households (cash-only users) is declining over the 2011-2022 period. This is mainly due to a substantial adoption of both bank and mobile money accounts over this period. The number of households owning both accounts increased by about 6.8 percentage points between 2014-2022. Second, the fraction of households owning bank account only shows a downward trend over the 2014-2022 period. This is attributable to the switching of individuals who are banked only to adopt mobile money accounts to attain a mix of payment options. Third, there is a sharp increase in mobile money adoption by about 15.8 percentage points between 2014 and 2022.

Table 3.1: Extensive Margin and Consumption Shares for Payment Methods in Botswana

<table>
<tr><th></th><th>Cohorts/Categories</th><th>Variable</th><th>2011</th><th>2014</th><th>2017</th><th>2022</th></tr>
<tr><td rowspan="4">Account ownership status or proportion of population (%)</td><td>Financially excluded</td><td>$\theta_e = z_e/N$</td><td>69.7</td><td>48.0</td><td>49.0</td><td>41.2</td></tr>
<tr><td>Banked only</td><td>$\theta_b = z_b/N$</td><td>30.3</td><td>31.2</td><td>26.7</td><td>22.2</td></tr>
<tr><td>Mobile Money</td><td>$p_m = (z_m + z_a)/N$</td><td>-</td><td>20.8</td><td>24.4</td><td>36.6</td></tr>
<tr><td>Both Accounts</td><td>$p_a = z_a/N$</td><td>-</td><td>18.0</td><td>18.2</td><td>27.7</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Probability of switching</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="5">Binomial probability of switching (%)</td><td>Prob. of mobile money adoption by financially excluded people, equation (2.3)</td><td>$Bin(z_e, k_{em}^*, p_m)$</td><td>-</td><td>4.5</td><td>4.2</td><td>4.1</td></tr>
<tr><td>Prob. of bank account adoption by financially excluded people</td><td>$Bin(z_e, k_{eb}^*, p_b)$</td><td>3.3</td><td>3.9</td><td>4.1</td><td>4.7</td></tr>
<tr><td>Prob. of both mobile money and bank account adoption by FE people</td><td>$Bin(z_e, k_{ea}^*, p_a)$</td><td>-</td><td>4.7</td><td>4.7</td><td>4.4</td></tr>
<tr><td>Prob. of mobile money account adoption by banked people from the cash part, equation (2.4)</td><td>$Bin(z_b, k_{bm}^*, p_m)$</td><td>-</td><td>5.5</td><td>5.7</td><td>5.6</td></tr>
<tr><td>Consumption Allocations</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Cash transactions</td><td>w_c</td><td>93.7</td><td>91.6</td><td>83.1</td><td>59.8</td></tr>
<tr><td rowspan="2">Aggregate Consumption shares (%) from Figure 3.2</td><td>Bank card transactions at POS</td><td>w_b</td><td>6.3</td><td>8.4</td><td>14.8</td><td>32.4</td></tr>
<tr><td>Mobile money transactions at POS</td><td>w_m</td><td>-</td><td>-</td><td>2.1</td><td>7.8</td></tr>
</table>

Notes: Dash denotes no information reported.
Source: Author's computation using Global Findex Surveys, mobile money transactions from Mobile Network Operators, and bank card transactions from Central Bank of Botswana.

The second heading of **Table 3.1** shows the Binomial probability of adoption for successful new adopters from potential adopters. On average between 2014-2022, about 4.3% of financially excluded individuals may switch to adopt a mobile money account and 4.2% of financially excluded individuals may switch to adopt a bank account. Data also show an increase in the probability of financially excluded households who may switch to adopt a bank account compared to a roughly constant rate of those who may switch to mobile money between 2014-2022. Further, on average about 5.6% of banked-only individuals switch to adopt mobile money account, and about 4.6% of financially excluded may switch to adopt both bank and mobile money accounts.

The third heading of **Table 3.1** shows the aggregate consumption proportions between the three payments media. The data show a substantial decline in the share of cash transactions between 2011 and 2022. Over this period, there is a sharp increase of about 26.1 percentage points in the share of bank card transactions. However, the share of mobile money transactions remains small at below 10%, with a significant 5.7 percentage points increase between 2017 and 2022. The trends also show that the share of mobile money consumption increases as the number of mobile money adopters increases. This suggests that as more and more people adopt mobile money, the share of mobile money consumption will significantly increase.

3.4.2. Aggregate Consumption and Different Payments Media

The model characterises an economy in which a household's allocation of payments media or transaction demand for money is determined by an exogenously given dollar value of consumption. The issue of which payment method to use in transactions is a portfolio allocation problem, viz., goods being purchased with either cash, bank card or mobile money. We assume a consumer has a fixed income Y at the beginning of each year to spend on all consumer goods. What must be noted is that only bank deposit earns interest. Hence, cash in circulation and mobile money do not earn interest. A consumer can choose to finance retail expenditures with proportion of cash w_{ca}, bank card w_b, and mobile money w_m. These proportions are subject to the constraint that they must add up to 1. The value of transactions made by cash is $w_c Con_i = Con_{ic}$, transactions by bank card is $w_b Con_i = Con_{ib}$, and transactions by mobile money is $w_m Con_i = Con_{im}$. The consumption expenditure of household i at time t is equal to the sum of expenditures using a specific payment media s:

$$Con_{it} = \sum_{s=1}^{3} Con_{ist} \tag{3.7}$$

where Con_{ist} denotes household *i*'s consumption expenditure using payment media *s*, at period *t*. Given (3.7) the aggregate consumption at period *t* is:

$$Con_t = \sum_{i=1}^{N} Con_{it} \tag{3.8}$$

where *N* is the number of households in a given year's sample. Based on the empirical data, aggregate portfolio shares for payment media *s*, w_s, is computed as

$$w_{st} = \frac{\sum_{i=1}^{N} Con_{ist}}{\sum_{i=1}^{N} Con_{it}} \tag{3.9}$$

3.4.3. Equilibrium conditions for consumer portfolio weights and market value weights

We have a model where consumers can choose from multiple payments media to implement their consumption expenditure. Let *s* denote the index for the different payments media that consumers can choose from, with $s = 1, \ldots, S$. Individual consumers, $i = 1, \ldots, N$ allocate different portfolio weights w_{is} for the proportion transacted using the *s* payment of their total consumption expenditure denoted by Con_{is}. Population is categorised into cohorts, $N = z_e + z_b + z_m + z_a$; where: z_e is financially excluded individuals who only use cash, z_b is banked only individuals without mobile money, z_m is mobile money only individuals, and z_a is both banked and mobile money individuals. Note that all cohorts can use cash.

We use results well known from Arrow (1964) and Capital Asset Pricing models (CAPM) in that individual portfolio weights for the *sth* payment media, w_{is}, equal the so called market value weights under conditions of market equilibrium. That is

$$w_{is} = w_s^A \qquad \text{with} \qquad \sum_{s=1}^{S} w_{is} = \sum_{s=1}^{S} w_s^A = 1 \tag{3.10}$$

Here superscript *A* in w_s^A denotes the aggregate or macro level of the economy's proportion of aggregate consumption expenditure transacted using payments media *s*.

In an exchange economy, the equilibrium condition requires the following:

$$\sum_{g=1}^{G} P_{gt}X_{gt} = Con_t = \sum_{s=1}^{S}\sum_{i=1}^{N} Con_{ist} \tag{3.11}$$

Here, the first term $\sum_{g=1}^{G} P_g\ X_g$ denotes the aggregate value of the goods being transacted, with g being the index of all goods in the economy with P_g and X_g, respectively, being the price and quantity of the good. In equilibrium, this equals the aggregate demand given by the value of the consumption expenditures made by all consumers using the different payments media $Con_t = \sum_{s=1}^{S}\sum_{i=1}^{N} Con_{ist}$ same as (3.8). Here, the share of the *ith* consumers consumption bundle that is transacted using payments media *s* given by the portfolio share w_{is} applied to his per capita consumption bundle

$$Con_{ist} = w_{ist}\frac{\sum_{g=1}^{G} P_{gt}X_{gt}}{N} \tag{3.12}$$

Taking *N* over to the left and aggregating over all *i* gives

$$\sum_{i=1}^{N} Con_{ist} = w_{ist}\sum_{g=1}^{G} P_{gt}X_{gt}$$

Bringing $\sum_{g=1}^{G} P_{gt}\ X_{gt}$ to the left hand side, we have from (3.12)

$$\frac{\sum_{i=1}^{N} Con_{ist}}{\sum_{g=1}^{G} P_{gt}X_{gt}} = w_{ist} \quad \rightarrow \quad \frac{\sum_{i=1}^{N} Con_{ist}}{\sum_{g=1}^{G} P_{gt}X_{gt}} = \frac{\sum_{i=1}^{N} Con_{ist}}{\sum_{s=1}^{S}\sum_{i=1}^{N} Con_{ist}} = w_{st}^{A} \tag{3.13}$$

This implies that the optimal portfolio weights, w_{is}, in equilibrium for the *ith* consumer are none other than the aggregate macro level proportions of aggregate consumption, w_s^A, that is transacted in a given payments media. Therefore, **Figure 3.2** macro ratios give the portfolio weights w_{st}. This has implications for the changes in extensive and intensive margins, respectively, as switches and new adopters occur in the different cohorts of the population. As the relative cost advantageous of the different payments media are assumed to remain unchanged, the macro trends in the use of the different payments media are determined by the adoption rates driven by network effects.

3.4.4. Proof linking the extensive margins to intensive margins

This section shows how the extensive margin pairwise switches relate to proportions of total consumption bundle that individual consumers transact in each of the payments media, w_{ist}.

The latter is the intensive margin. We use the results in subsection **(3.4.3)** to denote the following:

a) Initial aggregate share of bank deposit-based cards transactions where $Z_{bt} = z_{bt} + z_{at}$

$$w_{bt} = \frac{\sum_{i=1}^{Z_{bt}} Con_{ibt}}{\sum_{s=1}^{S} \sum_{i=1}^{N} Con_{ist}}$$

New share of bank deposit-based cards transactions

$$w_{bt+1} = \frac{\sum_{i=1}^{Z_{bt+1}} Con_{ibt}}{\sum_{s=1}^{S} \sum_{i=1}^{N} Con_{ist}}$$

By applying what a single individual spends using s payment media, w_{is}, to his per capita consumption bundle we get $Con_{ibt} = w_{ibt} \frac{\sum_{g=1}^{G} P_{gt} X_{gt}}{N} = w_{ibt} CapitaCon.$ As aggregate consumption and per capita consumption does not change, change or growth in share of bank cards transactions is given as follows:

$$w_{bt+1} - w_{bt} = \frac{\sum_{i=1}^{Z_{bt+1}} Con_{ibt} - \sum_{i=1}^{Z_b} Con_{ibt}}{\sum_{s=1}^{S} \sum_{i=1}^{N} Con_{ist}} = \frac{CapitaCon\left(\sum_{i=1}^{Z_{bt+1}} w_{ib} - \sum_{i=1}^{Z_b} w_{ib}\right)}{\sum_{s=1}^{S} \sum_{i=1}^{N} Con_{ist}}$$

$$w_{bt+1} - w_{bt} = \frac{CapitaCon\, w_{bt}(Z_{bt+1} - Z_{bt})}{\sum_{s=1}^{S} \sum_{i=1}^{N} Con_{ist}} \qquad (3.14)$$

Inserting $CapitaCon = \frac{\sum_{s=1}^{S} \sum_{i=1}^{N} Con_{ist}}{N}$ into (3.14) yields the following

$$\frac{w_{bt+1} - w_{bt}}{w_{bt}} = \frac{(Z_{bt+} \ - Z_{bt})}{N} \equiv \frac{(Z_{bt+} \ - Z_{bt})}{Z_{bt}}$$

Using equation (3.5) we express the above equation as follows:

$$\Delta w_{bt}\% = \lambda_b \equiv -Bin(z_b, k_{bm}^*, p_m) \frac{k_{bm}^*}{z_{bt}} + Bin(z_e, k_{eb}^*, p_b) \frac{k_{eb}^*}{z_{et}}$$

$$\equiv -Bin(z_b, k_{bm}^*, p_m) p_m + Bin(z_e, k_{eb}^*,) p_b \qquad (3.15)$$

b) Applying similar logic from above (see part **(a)**) to share of mobile money transactions gives

$$\frac{w_{mt+1} - w_{mt}}{w_{mt}} = \frac{(z_{mt+1} - z_{mt})}{N} \equiv \frac{(z_{mt+} \ - z_{mt})}{z_{mt}}$$

Using equation (3.6) we express the above equation as:

$$\Delta w_{mt}\% = \lambda_m \equiv Bin(z_b, k_{bm}^*, p_m)\frac{k_{bm}^*}{z_{bt}} + Bin(z_e, k_{em}^*, p_m)\frac{k_{em}^*}{z_{et}}$$
$$\equiv Bin(z_b, k_{bm}^*, p_m)p_{mt} + Bin(z_e, k_{em}^*, p_m)p_{mt} \quad (3.16)$$

c) Expressing the share of cash transactions as a residual of the bank deposit-based cards and mobile money transactions implies that $\sum_{s=1}^{3}\lambda_s = \sum_{s=1}^{3}\Delta w_s = 0$. Therefore,

$$\Delta w_{ct}\% = \lambda_c \equiv -\left(Bin(z_e, k_{em}^*, p_m)\frac{k_{em}^*}{z_{et}} + Bin(z_e, k_{eb}^*, p_b)\frac{k_{eb}^*}{z_{et}}\right)$$
$$\equiv -(Bin(z_e, k_{em}^*, p_m)p_{mt} + Bin(z_e, k_{eb}^*, p_b)p_{bt}) \quad (3.17)$$

Equations (3.15), (3.16) and (3.17) are proofs that changes in portfolio weights is equivalent to the product of the respective Binomial probabilities for switching given the different cohorts of the population and the proportion of those who are expected to switch relative to yet to adopt individuals in each of these cohorts. In other words, changes in portfolio weights of different payments media $\Delta w_{st}\%$ are determined by for changes in network effects.

3.4.5. Intensive margin of Payments media

Empirically, we already know information on household aggregate consumption allocation between the three payments media, probabilities of those who have already adopted specific payment media, and the rate of switching by potential adopters (**Table 3.1**). We do not know what proportion of consumption expenditure households will switch to cashless payments, such as mobile money and/or bank deposit money, depending on the cohort they belong to. We employ two approaches to calibrate the expected intensive margin (EIM) of switching: simple EIM and survey data EIM methods. These methods are utilised to estimate the aggregate portfolio weights of cash and cashless payments across time.

3.4.5.1. A Simple Expected Intensive Margin Approach

We take the product of the respective Binomial probabilities for switching given the different cohorts of the population and the proportion of those who are expected to switch relative to yet to adopt individuals in each of these cohorts to yield the change in the portfolio weights for the three payments media. This approach simply tracks what proportion of consumption each household allocates to cashless payment instruments and how much it affects the fraction of cash use. Given the initial aggregate portfolio weights of consumption for different payments media as well as the changes in extensive margins of switching set out in equations (3.15)-(3.17), a Simple EIM approach calculates aggregate portfolio weights of consumption as follows:

$$w_{mt+1} = w_{mt} + \left(Bin(z_{et}, k^*_{emt}, p_{mt})\frac{k^*_{emt}}{z_{et}} + Bin(z_{bt}, k^*_{bmt}, p_{mt})\frac{k^*_{bmt}}{z_{bt}}\right) \tag{3.18}$$

$$w_{bt+1} = w_{bt} + \left(Bin(z_{et}, k^*_{ebt}, p_{bt})\frac{k^*_{ebt}}{z_{et}} - Bin(z_{bt}, k^*_{bmt}, p_{mt})\frac{k^*_{bmt}}{z_{bt}}\right) \tag{3.19}$$

$$w_{ct+1} = w_{ct} - \left(Bin(z_{et}, k^*_{emt}, p_{mt})\frac{k^*_{emt}}{z_{et}} + Bin(z_{et}, k^*_{ebt}, p_{bt})\frac{k^*_{ebt}}{z_{et}}\right) \tag{3.20}$$

where w_c, w_m, and w_b are aggregate portfolio weights of cash, mobile money, and card transactions, the total sum of these weights is 1. The above equations imply that the change in portfolio weights is equivalent to the model expectation of change in number of adopters.

3.5. Data sources

Empirical results for macro trends in payments for Botswana (**Figure 3.2**) are obtained using a new database utilising data on mobile money transactions at point of sale (POS) from a leading mobile network operator (MNO) in Botswana for the year 2017 to 2022[22]. This dataset is combined with data from the Central Bank of Botswana (BoB)'s Economic and Financial Statistics, which report bank card transactions at POS and private final household consumption. The study uses Botswana's Global Findex surveys (GFS) for 2017 and 2022 conducted by the World Bank in collaboration with Gallup Inc[23]. We use the GFS to categorise households into cohorts, namely: those who are financially excluded, with bank account, with mobile money account, and both (mobile money and bank accounts). This information is useful to calculate the Binomial adoption rates of switching. These adoption rates are then applied to obtain the expected change in number of new adopters that is equivalent to changes in portfolio weights to yield the new portfolio weights from equations (3.15) – (3.17).

[22] Mobile money was first launched in Botswana in 2011. However, POS mobile money transactions data before 2017 are not available due to confidentiality in reporting and no Electronic Payments Services (EPS) regulations in place.

[23] GFS for Botswana was first published in 2011 and every three years after that, e.g., 2014, 2017, with the exception of the latest survey published in 2022 due to COVID-19 disrupting the data collection process in 2020.

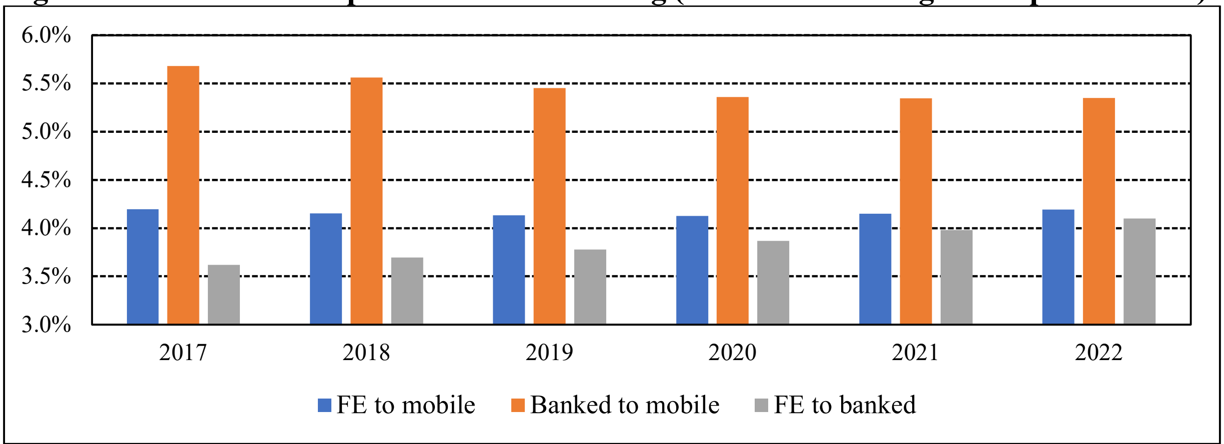
3.6. Empirical Results

This section aims at measuring how well the estimated portfolio weights of cash, card, and mobile money payments using a Simple intensive margin method replicates the observed shares for transaction of household consumption in **Figure 3.2**. We use year 2017 as the initial point since it covers the period of macro trends in **Figure 3.2** and the Global Findex survey (GFS) data. These results need to be interpreted with caution. This is because aggregate portfolio weights of different payments may be affected by fiscal and financial factors, which I have not controlled for in the model.

3.6.1. Extensive margins of switching analysis

Figure 3.5 displays the extensive margin of switching across different population cohorts. The results show that the banked population has the highest switching rate to mobile money. It is not surprising because card users do not necessarily stop using bank account, due to its high network (incumbency) effects, but instead they adopt mobile money to complement their card transactions. This result is consistent with Han and Wang (2021). What is interesting is that, to save on switching costs to adopt a bank account, most financially excluded households in the early years have switched to mobile money. However, despite the lower cost of switching to mobile money, more financially excluded households have switched to bank card payments over the years while their switch to mobile money has remained static. In 2022, financially excluded people switched to bank card payments at the same rate as they almost switched to mobile money. This finding justifies why, over the years, households in Botswana continue to adopt bank card payments rather than mobile money payments.

Figure 3.5: Binomial Adoption rates of Switching (Number switching in sample size 1000)



Source: Author’s calculations from Global Findex survey for 2017 as an initial point, and use equations (3.8) – (3.11) to extrapolate figures for 2018- 2022.

Further, we utilise the switching probabilities to estimate the number of new adopters across different cohorts. **Table 3.2** shows the equations for estimation of the expected proportions of population across different cohorts based on extensive margins.

Table 3.2: Extensive margin equations

Cohort	Proportions of Population across cohorts
Mobile money	$p_{mt+1} = \left(1 + Bin(z_{et}, k^*_{emt}, p_{mt}) + Bin(z_{bt}, k^*_{bmt}, p_{mt})\right)p_{mt}$
Banked	$p_{bt+1} = p_{bt} - Bin(z_{bt}, k^*_{bmt}, p_{mt})p_{mt} + Bin(z_{et}, k^*_{ebt}, p_{bt})p_{bt}$
Both accounts	$p_{at+1} = \left(1 + Bin(z_{et}, k^*_{eat}, p_{at})\right)p_{at}$
Financially excluded	$p_{et+1} = p_{et} - Bin(z_{et}, k^*_{emt}, p_{mt})p_{mt} - Bin(z_{et}, k^*_{ebt}, p_{bt})p_{bt} - Bin(z_{et}, k^*_{eat}, p_{at})p_{at}$

Table 3.3 compares the actual and estimated proportions of population with bank and/or mobile money accounts as well as those who are financially excluded. Our model slightly overestimates the proportion of those with mobile money and bank accounts for year 2022 by about 2% and 1%, respectively, compared to GFS data. On the other hand, the model underestimates the fraction of those with both accounts by about 4% and the proportion of financially excluded households by about 3%. These discrepancies are not alarming, and we generally conclude that our extensive margin model closely fits the data. The unique feature about this model is that we can predict the proportions of adopters (extensive margins) of different payments media for the periods not covered by GFS, which is very useful for the computation of the trends of aggregate portfolio weights (intensive margins) for the three payments media across time.

Table 3.3: Actual and Model Estimates of Proportions of Population across cohorts

	Mobile Money		Bank Only		Both		Financially excluded	
	Model	Data#	Model	Data#	Model	Data#	Model	Data#
2017	24.4%	24.4%	26.7%	26.7%	18.2%	18.2%	49.0%	49.0%
2018	26.8%		26.3%		19.1%		47.0%	
2019	29.4%		25.8%		20.0%		44.9%	
2020	32.2%		25.1%		20.9%		42.7%	
2021	35.3%		24.4%		21.9%		40.4%	
2022	38.6%	36.6%	23.5%	22.2%	23.0%	27.7%	38.0%	41.2%

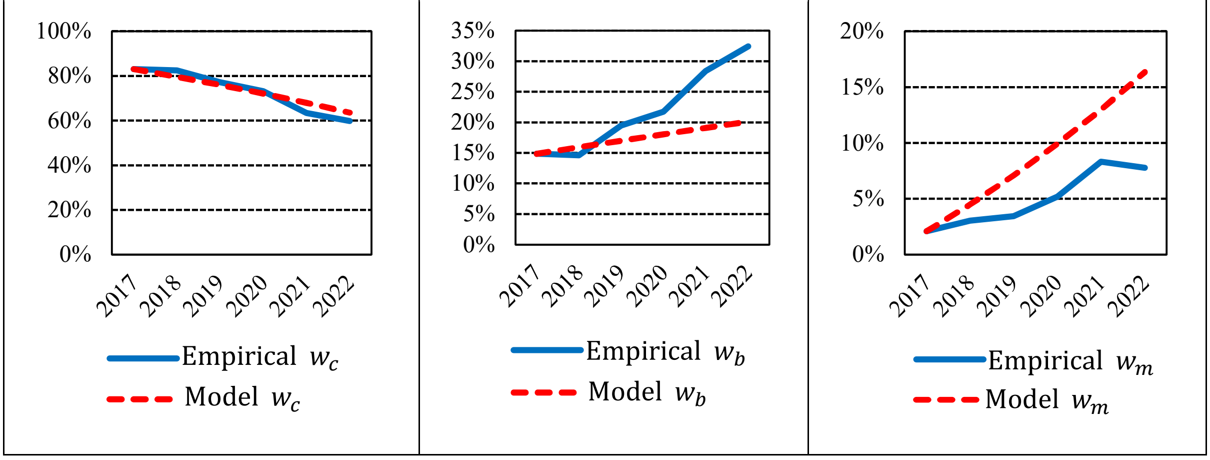
Notes: In the model, the values between 2018 and 2022 are estimated while the 2017 are initial values which are obtained from the GFS.
Source: Author's calculations using equations in **Table 3.2**, and Data# is from Global Findex Surveys.

3.6.2. Simple EIM Approach: Analysis of Aggregate Portfolio Weights

Figure 3.6 shows the estimated share of cash, bank card, and mobile money transactions in retail expenditure for different scenarios. The estimated portfolio share of cash in Scenario 1 closely fits the actual data for macro portfolio weight of cash consumption and is consistent with downward trend for cash use in **Figure 3.2**. In terms of cashless payments (Scenario 2 and 3), despite model not closely fitting data, the results show that households continue to allocate more of their retail payments to bank cards transactions compared to mobile money mainly due to the incumbency (high network effects) effects of conventional banking system.

Figure 3.6: Shares of Cash and Cashless on Retail Payments by Simple EIM Compared with Macro Portfolio Weights (Figure 3.2)

Scenario 1: *Portfolio weight of cash w_c due to FE switch to bank deposits (card), FE switch to mobile money and FE switch to both mobile money and bank deposits*	**Scenario 2:** *Portfolio weight of bank deposits (card) w_b due to FE switch to bank deposits(card) and Banked-only switch to mobile money.*	**Scenario 3:** *Portfolio weight of mobile money w_m as a result of FE switch to mobile money and Banked-only switch to mobile money*

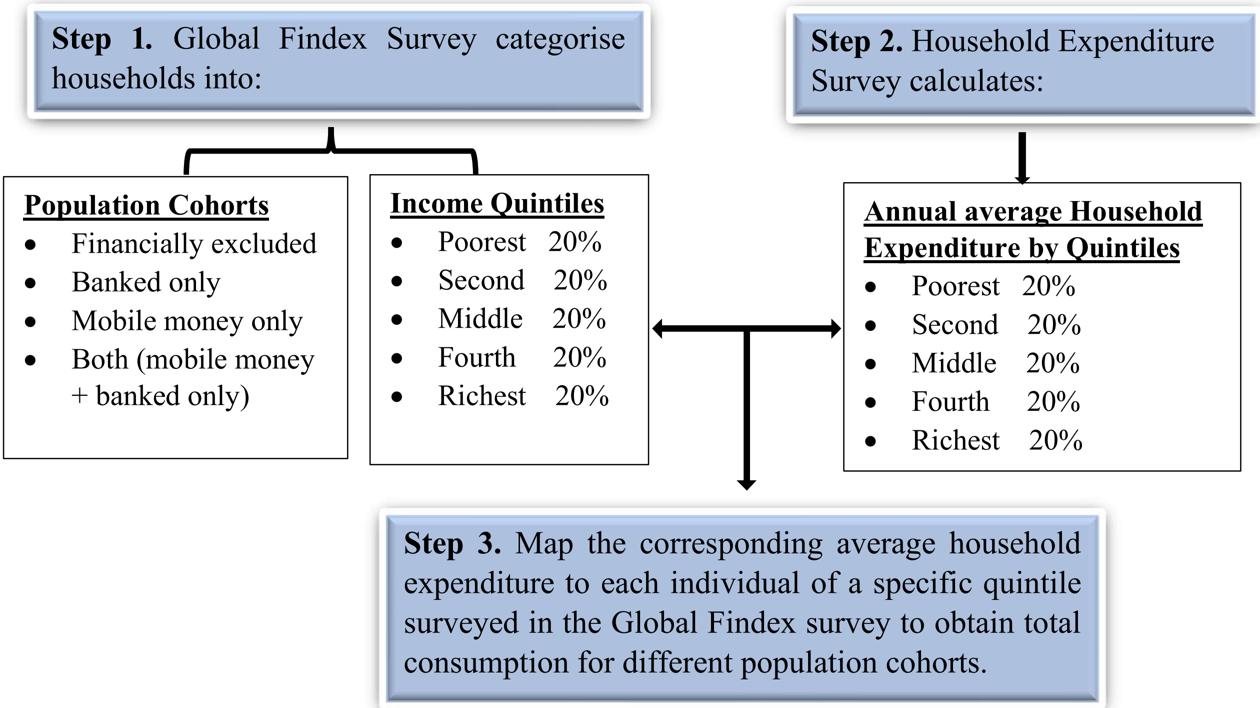


Notes: Empirical w_c, w_b, and w_m denote the proportion of three payments media on retail expenditures obtained from the data in **Figure 3.2**, and model w_c, w_b, and w_m are the proportions of three payments media on retail expenditures obtained from the model calibration.
Source: Author's computations from equation (3.18) – (3.20)

The charts for Scenarios 2 and 3 show that a percentage change in the portfolio weight of mobile money, λ_m, grows faster than a percentage change in the portfolio weight of bank deposit money, λ_b. This is because λ_m is due to a positive switch from banked-only and FE agents to mobile money, while λ_b is due to a positive switch from FE to card use and a negative switch when banked-only switch to adopt mobile money for the first time. Overall, the results verify our hypothesis that as more and more households adopt cashless payment media such as bank cards and mobile money, the usage of cash for consumption tends to decline. In other words, the portfolio weight of cash is determined by the extensive margin and intensive margin activities of cashless payments media. Therefore, the microfoundations of adopting cashless payments in retail payment systems play a significant role in determining the intensity of cash usage.

3.6.3. Expected Intensive Margin Using Household Expenditure Survey Data

We collate the Global Findex Survey data based on income quintiles which gives the ratio of households who use the three payments media with the equivalent quintiles of the Household Expenditure Survey (see diagram below for steps).[24] This yields a different method to show what proportion of consumption expenditure is switched by households in the different cohorts based on their payments habits.



We use the Botswana Multi-Topic Household Survey (BMTHS) for the year 2015/16 to calculate the average annual household expenditure quintiles. Further, we use the Botswana's Global Findex surveys (GFS) for 2017 and 2022 proportions to divide the household expenditure for each quintile into four cohorts of the population, such financially excluded, banked only, mobile money only, and both (see **B.1** in Appendix for details). The GFS data is then scaled up to the total population to determine macroeconomic variables. The GFS sample

[24] I acknowledge the fact that expenditure quintiles are not necessarily equivalent to income quintiles, however due to unavailable data on expenditure quintiles for GFS dataset, we cautiously assume both quintiles to be equivalent in order to combine the two surveys.

size is 1000, therefore using the quintile approach I scale up variables by the following *scale factor*:

$$scale\ factor\ = \frac{x_q}{200} \times \frac{Pop}{5} \tag{3.15}$$

where x_q is the members of the relevant cohort of households in each quintile, which is made up of 200 (i.e., 1000/5) people, *pop* is the total adult population of the economy, and 5 is the number of quintiles. For example, aggregate retail expenditure for FE households in the Poorest 20% quintile is obtained as $C_{t,poor}^{FE} = \left(\frac{x_{poor}^{FE}}{200} \times \frac{Pop}{5}\right) \times AvgRE_{poor}$ where $\text{AvgRE}_{\text{poor}}$ is the annual average retail expenditure of the Poorest 20% quintile obtained from the household expenditure survey. Therefore, the scaled up annual average household consumption for FE is $C_t^{FE} = \sum_q C_{qt}^{FE}$.

Applying switching probabilities yields a new scaled-up annual average household consumption for each cohort after switching as follows:

$$C_{t+1}^{FE} = \left(1 - Bin(z_{et}, k_{emt}^*, p_{mt})\frac{k_{et}^*}{z_{et}} - Bin(z_{et}, k_{ebt}^*, p_{bt})\frac{k_{ebt}^*}{z_{et}} - Bin(z_{et}, k_{eat}^*, p_{at})\frac{k_{eat}^*}{z_{et}}\right) C_t^{FE} \tag{3.21}$$

$$C_{t+1}^{FI_b} = \left(1 - Bin(z_b, k_{bm}^*, p_{mt})\frac{k_{bm}^*}{z_b} + Bin(z_{et}, k_{ebt}^*, p_{bt})\frac{k_{ebt}^*}{z_{et}}\right) C_t^{FI_b} \tag{3.22}$$

$$C_{t+1}^{FI_m} = \left(1 + Bin(z_{et}, k_{emt}^*, p_{mt})\frac{k_{emt}^*}{z_{et}} + Bin(z_b, k_{bm}^*, p_{mt})\frac{k_{bm}^*}{z_b}\right) C_t^{FI_m} \tag{3.23}$$

$$C_{t+1}^{FI_a} = \left(1 + Bin(z_{et}, k_{eat}^*, p_{at})\frac{k_{eat}^*}{z_{et}}\right) C_t^{FI_a} \tag{3.24}$$

Here C_{t+1}^{FE} is total cash consumption by FE after some switch to mobile money and/or bank deposit, $C_{t+1}^{FI_b}$ is total consumption of banked only households after some switch to mobile money, and FE switch to bank deposits, $C_{t+1}^{FI_m}$ is total consumption of mobile money after FE and banked agents switch to mobile money, and $C_{t+1}^{FI_a}$ is total consumption for individuals with both bank deposits and mobile money after FE switch to both mobile money and bank deposits payments.

Table 3.4 provides estimated data of the scaled up household consumption based on switching probabilities of different cohorts of the population.

Table 3.4: Scaled up household consumption for cohorts using switching probabilities for Botswana (P Million)

	Change in Portfolio Weights based on switching probabilities across cohorts				Scaled up aggregate household consumption from survey data across cohorts (P Million)				
Year	**FE to mobile**	**Banked to mobile**	**FE to banked**	**FE to both**	C_t^{FE}	$C_t^{FI_b}$	$C_t^{FI_m}$	$C_t^{FI_a}$	**Total, C_t**
2017	1.02%	1.39%	1.62%	0.85%	22353	22651	5236	28974	79214
2018	*1.11%*	*1.49%*	*1.68%*	*0.89%*	*21572*	*22704*	*5363*	*29221*	*78859*
2019	*1.21%*	*1.60%*	*1.73%*	*0.94%*	*20778*	*22746*	*5502*	*29481*	*78507*
2020	*1.33%*	*1.73%*	*1.78%*	*0.99%*	*19971*	*22774*	*5657*	*29758*	*78161*
2021	*1.46%*	*1.89%*	*1.84%*	*1.05%*	*19152*	*22787*	*5830*	*30054*	*77822*
2022	*1.62%*	*2.07%*	*1.90%*	*1.12%*	*18318*	*22776*	*6025*	*30369*	*77489*

Notes: Values for year 2017 (initial period) are obtained from the Global Findex survey and Household expenditure survey. The italicised values in grey shaded cells are extrapolated using equations (3.21) – (3.24).
Source: Author's calculations.

In the next step, we use aggregate portfolio weights of consumption for different payment media obtained by a simple EIM approach to generate the annual average aggregate household consumption of cash, mobile money, bank deposits, and both mobile money and card transactions across cohorts. Formally, scaled-up aggregate household consumption for the three payments media for period $t=1,2\ldots,T$ is

$$\begin{bmatrix} 1 & w_{ct} & w_{ct} & w_{ct} \\ 0 & (1-w_{ct}) & 0 & w_{bt} \\ 0 & 0 & (1-w_{ct}) & w_{mt} \end{bmatrix} \begin{bmatrix} C_t^{FE} \\ C_t^{FI_b} \\ C_t^{FI_m} \\ C_t^{FI_a} \end{bmatrix} = \begin{bmatrix} C_{ct} \\ C_{bt} \\ C_{mt} \end{bmatrix} \tag{3.20}$$

The above matrix is simplified as $Ax = y$ where coefficient matrix A measures the estimated aggregate portfolio weights of consumption for different payment media by a simple EIM approach, column matrix x is scaled up aggregate consumption for each cohort, and column matrix y represents the aggregate household consumption for specific payment media. Since FE use cash only, it implies that their proportion of cash to consumption is 100% before switching, i.e., $w_c = 1$. Therefore, the survey data aggregate portfolio weights for cash, bank deposits, and mobile money, respectively, are calculated as follows:

$$w_{ct} = \frac{C_{ct}}{C_{ct}+C_{bt}+C_{mt}},\ w_{bt} = \frac{C_{bt}}{C_{ct}+C_{bt}+C_{mt}},\ \text{and}\ w_{mt} = \frac{C_{mt}}{C_{ct}+C_{bt}+C_{mt}} \tag{3.21}$$

3.6.4. Empirical Results for EIM Using Survey Data Approach: Analysis of Aggregate Portfolio Weights

Equations (3.20) and (3.21) yields the results in **Table 3.5**. The results for this approach are different from those of a simple EIM for two main reasons: i) though using the same changes in portfolio weights from **Table 3.2**, this approach will apply them explicitly on scaled up household expenditure from the survey data, and ii) using portfolio weights by a simple EIM we calculate the household consumption of cash, mobile money, bank deposits, and both mobile money and card transactions from scaled up consumption depending on a cohort a household belongs to.

Table 3.5: Estimated Intensive Margins from the scaled up survey data (P Million)

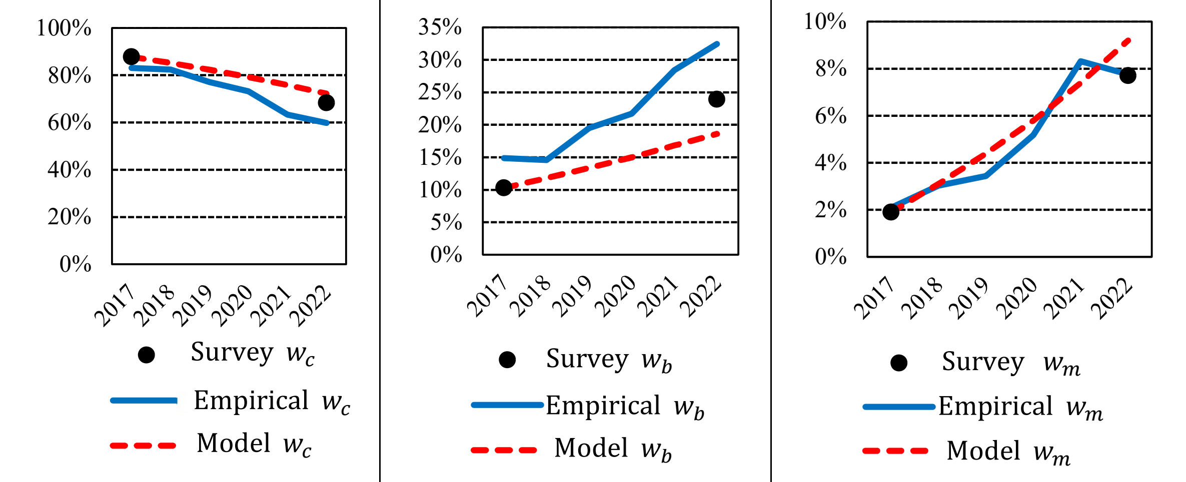
	Cash Transactions, C_{ct}					**Card transactions, C_{bt}**			**Mobile money transactions, C_{mt}**		
Year	FE	Banked	Mobile	Both	**Weight, w_{ct}**	Banked	Both	**Weight, w_{bt}**	Mobile	Both	**Weight, w_{mt}**
2017	22353	18815	4350	24067	**87.8%**	3836	4299	**10.3%**	887	608	**1.9%**
2018	*21572*	*18065*	*4267*	*23250*	***85.2%***	*4639*	*4653*	***11.8%***	*1096*	*1317*	***3.1%***
2019	*20778*	*17262*	*4175*	*22373*	***82.3%***	*5485*	*5012*	***13.4%***	*1327*	*2097*	***4.4%***
2020	*19971*	*16399*	*4074*	*21428*	***79.2%***	*6375*	*5376*	***15.0%***	*1584*	*2955*	***5.8%***
2021	*19152*	*15473*	*3959*	*20408*	***75.8%***	*7313*	*5743*	***16.8%***	*1871*	*3903*	***7.4%***
2022	*18318*	*14475*	*3829*	*19300*	***72.2%***	*8302*	*6109*	***18.6%***	*2196*	*4961*	***9.2%***

Notes: Values for year 2017 (initial period) are obtained from the scaled up aggregate consumption of Household expenditure survey, and equations (3.20) and (3.21). The italicised values in grey shaded cells are extrapolated using equations (3.20) and (3.21).
Source: Author's calculations.

Figure 3.7 analyse the shares of cash and cashless retail payments by EIM using survey data (**Table 3.5**) compared with macro portfolio weights (**Figure 3.2**) and survey data portfolio weights. Results show that the model portfolio weight of cash transactions is overestimated, and that of card transactions is underestimated, with the exception of the share of mobile money (excluding COVID-19 spike), which closely fits the model. We also compared the model weights of different payment media with those obtained directly from the collated Global Findex Survey and Household Expenditure survey. The results show that our model closely fits the scaled up survey data in 2022, except for Scenario 2. Generally, the falling portfolio weight of cash is well tracked by a simple method (**Figure 3.6**) than the longwinded survey method (**Figure 3.7**).

Figure 3.7: Shares of Cash and Cashless Retail Payments by EIM using survey data Compared with Macro Portfolio Weights (Figure 3.2) and Survey Portfolio Weights

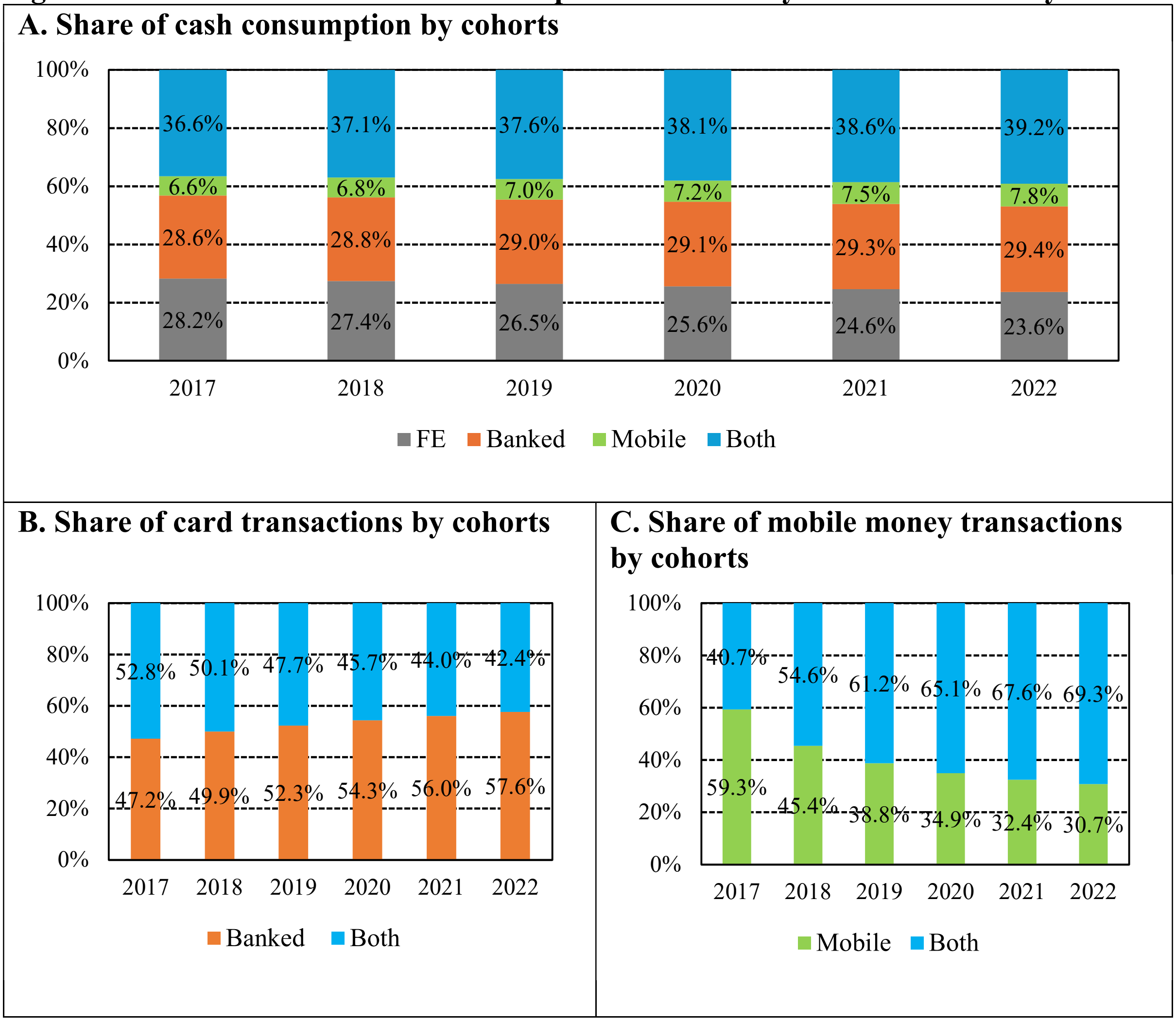
Scenario 1: *Portfolio weight of cash w_c due to FE switch to bank deposits (card), FE switch to mobile money and FE switch to both mobile money and bank deposits.*	**Scenario 2:** *Portfolio weight of bank deposits (card) w_b due to FE switch to bank deposits(card) and Banked-only switch to mobile money.*	**Scenario 3:** *Portfolio weight of mobile money w_m as a result of FE switch to mobile money and Banked-only switch to mobile money.*



Notes: Actual or empirical w_c, w_b, and w_m denote the proportion of three payments media on retail expenditures obtained from the data in **Figure 3.2**, and model w_c, w_b, and w_m are the proportions on retail expenditures obtained from the model calibration. Survey data weights are actual portfolio weights from the scaled up household expenditure from the collated Global Findex survey, and household expenditure survey for the 2017 and 2022.
Source: Author's calculations.

The results in **Figure 3.8** show that, on average, in terms of cash transactions, households with both bank and mobile money accounts consume 38%, banked-only consume 29%, financially excluded consume 26%, and mobile money holders consume 7%. Regarding card transactions, banked-only households consume 53%, and those with both bank and mobile money accounts consume about 47%. Those with mobile money and both accounts, respectively, consume, on average, about 40% and 60% of mobile money transactions in the review period. These findings suggest that the adoption of both bank and mobile money accounts significantly increases household consumption, especially cashless transactions, which will, in turn, enhance liquidity in the banking sector. Therefore, it is crucial for central banks and regulators to promote interoperability between banking and mobile money platforms in order to increase consumption, improve financial inclusion and stimulate economic activity.

Figure 3.8: Model Based Share of Consumption for Each Payment Instrument by Cohorts



Source: Author's calculations.

3.7. Conclusion

This paper contributes to literature by analysing the critical role of micro-foundations of adoption of payments media on macro portfolio weights for consumption that is transacted with different payments media. Following Arrow (1964) we prove that the optimal portfolio weights in equilibrium for each consumer are equivalent to the aggregate macro level share of aggregate consumption that is transacted in a specific payments media. These equilibrium conditions have implications for the changes in extensive and intensive margins across different cohorts of the population. Assuming a constant cost advantage in different payments media, the macro trends in the use of different payments media are determined by the adoption rates driven by network effects. This implies that changes in portfolio weights for household that leads to macro changes are proportional to the switching probability of households.

By extending the Binomial Probability model discussed in Chapter 2, this paper calibrates the extensive and intensive margins of cash, bank cards and mobile money payments in Botswana. We find that micro-foundations of the adoption of cashless payments, such as bank cards and mobile money, play a significant role in determining the intensity of cash usage in transactions. It is observed that consumers are increasingly substituting cash for card-based deposit money and mobile money. Further, the results show that households continue to allocate more of their retail payments to bank card transactions than mobile money, mainly due to the incumbency (high network effects) of the conventional banking system.

The unique thing about this paper is that the applied model can also predict the adoption rates for the periods not covered by the Global Findex survey, which is very useful for computing the trends of aggregate shares of consumption for the three payment media across time. This innovative model will serve as a guide or tool for central banks to track the extent to which consumers switch from cash to cashless payments, which is key for policy making decisions.

3.7.1. Limitations of the Study

I acknowledge that measuring cash use is based on surveying consumers' or economic agents' payment behaviour, e.g., payment diary surveys conducted by central banks of developed economies, such as Deutsche Bundesbank, Federal Reserve Bank, Bank of Canada, etc. However, developing economies, such as Botswana, have not yet conducted a payment diary survey; instead, they use financial access consumer surveys to measure consumer payment behaviour. These surveys include the Global Findex survey by World Bank and Finscope by Finmark Trust. As a limiting factor, comprehensive surveys are conducted only infrequently and face sample selection bias and the problem of obtaining truthful responses to questions about cash use (Krüger and Seitz, 2014). Therefore, survey data provides a snapshot of a specific point in time, which is likely to be negligibly inconsistent with the data on volumes and values of payment transactions reported by the banking sector.

Chapter 4

Cashless Payment Effects on Monetary Policy: Implications for Monetary Base, Interest rates and Inflation

Abstract

One of the near universal monetary phenomena the world over is the decline of cash use and the shrinking of state supplied monetary base, also known as, high powered money or M0. The main objective of this chapter is to show how changes in payment habits, viz., switching away from cash to cashless payments by consumers, which leads to smaller transaction demand for cash, influence monetary policy variables such as interest rates, monetary base and inflation. For this, we extend Marimon *et al*. (1997) and Markose and Loke (2002) macroeconomic models by incorporating a micro-founded framework based on the Myerson (1998) model of adoption of new payments media based on network effects. This framework provides a comprehensive measure of cashlessness, whereby we consider pairwise switches from cash to cashless payments, which is measured as extensive and intensive margins of adoption of bank card and mobile money payments given in Chapter 3. The consequence of cashlessness in payments is that less money leaves the banking system and increases its liquidity. A general equilibrium model developed here analyses the link between central bank interest rate policy, the role of the banking sector in setting optimal nominal deposit interest rates, inflation rate and the dynamics of cash-to-cashless payments substitution governed by network effects. The determinants of a fall in optimal deposit interest rates and inflation rates in recent years are the primary concerns for this study. This macroeconomic model is calibrated and tested against the macroeconomic data for Botswana. This paper identifies the two main factors of optimal deposit interest rates to be: i) the falling ratio of optimal cash transaction balances to monetary base, and ii) the rising share of non-interest bearing deposits to total deposits. These factors proxy for enhanced liquidity in depository institutions due to the switch from cash payments to bank deposit based card payments and mobile money. In the last part of this chapter, we derive inflation rate considering the micro-founded changes in payment habits by households. Interestingly, we find that an increase in cashless retail expenditures, on average, contributes to a lower rate of inflation compared to the empirical growth in consumer price index (CPI). This result justifies our hypothesis that cashlessness which leads to a fall in transaction demand for cash due to substitutions to electronic or mobile money innovations negatively impacts inflation. Therefore, it is crucial for central banks to consider the microstructure of changes in payments habits in their pursuit of determination of price changes or inflation rate.

4.1. Introduction

In this chapter, we seek an answer to the question: has the rise in cashless payments media such as bank cards and mobile money transactions impacted the monetary policy variables in Botswana? In particular, we seek to find out whether cashless payments have contributed to a slowdown in growth of monetary base, interest rates and also a fall in inflation. Studies have debated the future of cash in circulation in the face of new payments innovations (Dowd, 1998; Friedman, 1999; King, 1999; Drehmann *et al*., 2002; Goodhart, 2000; Shy, 2023). It has been argued that digital money substitutes affect the transactions demand for cash, and in turn affects the demand for reserves, monetary control, and monetary policy transmission (Berentsen, 1998). The central banks focused on inflation targeting appear to overlook the extent to which technology driven changes in payments habits associated with substituting away from cash to cashless digital payments have curbed inflation.

Marimon *et al*. (1997) stated that "High inflation episodes seem to be problems of the past, as if society had become immune to the disease. This success in curbing inflation is usually attributed to better monetary policy management to achieve price stability. Payments systems, particularly electronic payments, have gone through a major transformation. But maybe the right incentives have been created by the widespread development and use of cash substitutes. Who deserves credit? An implication of the paper will be that the role of electronic money in curbing inflation probably has been undervalued". For developing economies, the former Governor of Central Bank of Ghana noted that the country's overreliance on cash as a means of payment allows for an increase in cash outside banking system, which increases inflation and interest rates. To reduce inflation, he called on commercial banks to adopt more electronic payment systems to promote efficiency in the banking industry and ensure effective implementation of monetary policy[25].

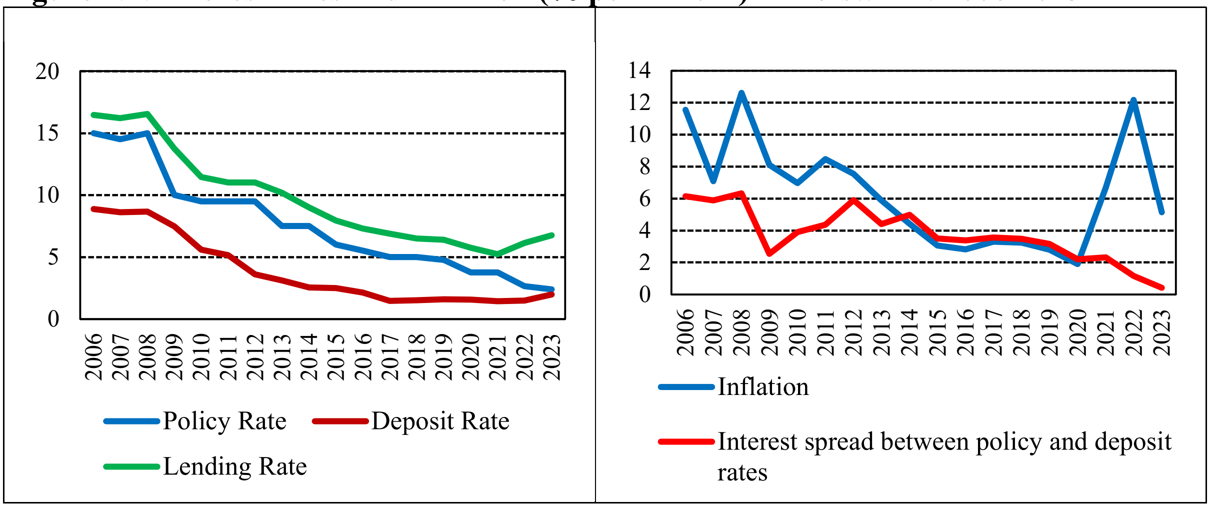
In the past two decades, global trends show that inflation has been falling or very low, with the post-COVID-19 period being the exception, and the Phillips curve has become flatter (Blanchard (2016); Agarwal and Kimball (2022)). The mainstream explanation for the flattening of the Phillips curve is that central banks have succeeded in controlling inflation and

[25] Governor, Dr. Duffour speaking on the theme "Banking in the next millennium, expectations, opportunities and challenges" at the 28th anniversary of Ghana's Chartered Institute of Bankers in Accra in November 1998. https://www.ghanaweb.com/GhanaHomePage/NewsArchive/Governor-calls-for-cashless-society-4351

structural changes due to cheap goods from China resulting from globalization[26]. In the post COVID-19 period, the helicopter drops of Furlough money to support businesses from laying off workers led to high global inflation from enhanced consumer demand not backed by GDP growth (Galí, 2020).

Figure 4.1 shows trends on interest rates and inflation rates in Botswana. During the Great Recession, like other economies, Botswana quickly cut the policy rate and maintained its downward trend for years (**Figure 4.1**, left pane). However, the COVID-19 pandemic presented a unique challenge, leading to a further cut of the policy rate to around 2 percent. The other types of nominal interest rates such as deposit rate and lending rate follow a similar downward trend since they are determined by the effect of policy rate (**Figure 4.1**, left pane). It is obvious from **Figure 4.1** that lending rate is a slight markup on the policy rate while the spread between policy rates and deposits rates was diminishing from 2014 to 2023.

Figure 4.1: Interest rates and Inflation (% per annum) in Botswana: 2006-2023



Notes: Inflation rate is calculated based on the consumer price index with 2018 as the base year.
Source: International Monetary Fund, *International Financial Statistics*, and Bank of Botswana

In Botswana, inflation fell from double digits and mostly remained within the country's medium-term objective range of 3-6 percent from 2013 to 2020 (**Figure 4.1**, right pane). The inflation spike between 2021-2022 partly emanated from prolonged supply chain disruptions from the COVID-19 pandemic and the Russia-Ukraine war. This high inflation is also attributable to the growth of money supply due to government support of industry and

[26] According to Bean (2006), cheap goods from China is another explanation for the drastic fall in core inflation in developing countries. Also, the lack of upward pressure on factor prices, such as wages, is another reason inflation remains low once it falls.

parastatal sectors to overcome post-COVID-19 recession (Bank of Botswana, 2023). In 2023, inflation fell within the objective range mainly due to the diminishing impact of the increase in administered prices in 2022 (base effects), the impact of the declining fuel prices during the year, subdued domestic demand and reduction in trading partner countries' inflation (Bank of Botswana, 2023).

However, technological developments and transformations in electronic payment systems coincide with Botswana's low inflation period. Chapters 2 and 3 establish that technology-driven digital transformations of payment systems, such as debit cards and mobile money, have allowed consumers to switch from cash to cashless payments. Therefore, it is inevitable that the prevalence of cashless payments media directly reduces the demand for cash. Hence, the focus of this paper is to establish how cashless payments affect inflation as well as bank liquidity which impact the setting of deposit interest rates, for given levels of policy rate and lending rate. Theoretical papers that encompass the feature of declining or zero transaction demand for cash cannot shed light on what happens to inflation due to price level indeterminacy. This is the main assumption of their models rather than a fact of the real world. In contrast, Woodford (1998, p.217) reinstated the price level determinacy but concluded that modelling the fine details of the payments system and the sources of money demand is not essential. This approach effectively became a baseline model for studies on cashless economy. However, it ignores one of the crucial developments in monetary history, viz., the erosion of governments' role in the supply of monetary base and its implications for inflation.

The major contribution of this chapter is to develop a new macroeconomic model, which is micro-founded by changes in payment habits in cashlessness, to explain the fall in growth of monetary base and the subsequent trends in interest rates and inflation rates. We extend Marimon *et al*. (1997) and Markose and Loke (2002) models by incorporating a micro-founded framework based on the Myerson (1998) model of adoption of new payments media based on network effects. Our framework provides a comprehensive measure of cashlessness, whereby we consider pairwise switches from cash to cashless payments, measured as extensive and intensive margins of adoption of bank cards and mobile money payments given in Chapter 3.

The general equilibrium results identify the main determinants of optimal deposit interest rates to be: i) falling ratio of optimal cash transaction balances to monetary base (B^*/H), and ii) the rising share of non-interest bearing deposits to total deposits (Σ=TNIB/D). These factors proxy for increase in liquidity in depository institutions due to the switch from cash payments to bank deposit-based card and mobile money payments. Further, the calibrated inflation with dynamics in cash-to-cashless payments substitution shows that cashlessness contributes to a lower inflation rate. Therefore, central banks need to consider the microstructure of technology driven changes in payments habits in pursuit of monetary policy.

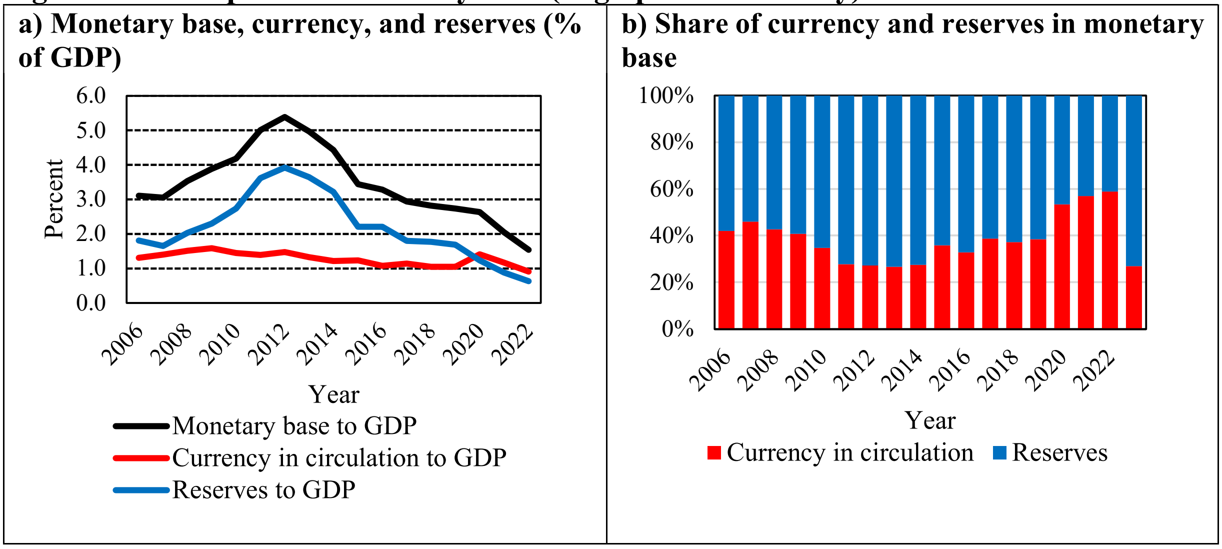
This chapter is structured as follows. Section 4.2 analyses the trends of monetary aggregates in Botswana's economy. Section 4.3 summarise literature on cashlessness and monetary policy. Section 4.4 develops a macroeconomic model incorporating the microfoundations of changes in payment habits in cashlessness. Section 4.5 derives the monetary policy analysis such as, interest rate transmission mechanism, implications for liquidity and inflation determination. Section 4.6 discusses the data and calibrated model results, and Section 4.7 concludes.

4.2. The Monetary Trends of Botswana

4.2.1. Trends in monetary base

Monetary base (also known as high-powered money) consists of two components, namely: currency in circulation which include, bank notes and coins held by agents outside the banking system, and bank reserves held by commercial banks. On average in Botswana, the shares of monetary base to GDP and currency in circulation to GDP is 3.5% and 1.3%, respectively, for 2006 to 2022 period. From 2012 onwards, we see a decline in share of monetary base to GDP mainly attributable to a fall in share currency in circulation to GDP (with the exception of COVID-19 period) and ratio of reserves to GDP (see **Figure 4.2** (a)). The downward trend in monetary base corroborates the inflation downward trend observed in **Figure 4.1**. Therefore, this implies that monetary base may play a significant role in determining Botswana's level of inflation. We observe that currency in circulation constitutes less than 50% (with exception of COVID-19 period) of monetary base compared to reserves (**Figure 4.2** (b)). The notes and coins are predominantly used to purchase goods and services, therefore, the adoption and usage of cashless payments, such mobile money and bank cards payments may directly affect the use of cash in retail transactions.

Figure 4.2: Components monetary base (High powered money) in Botswana: 2006-2023

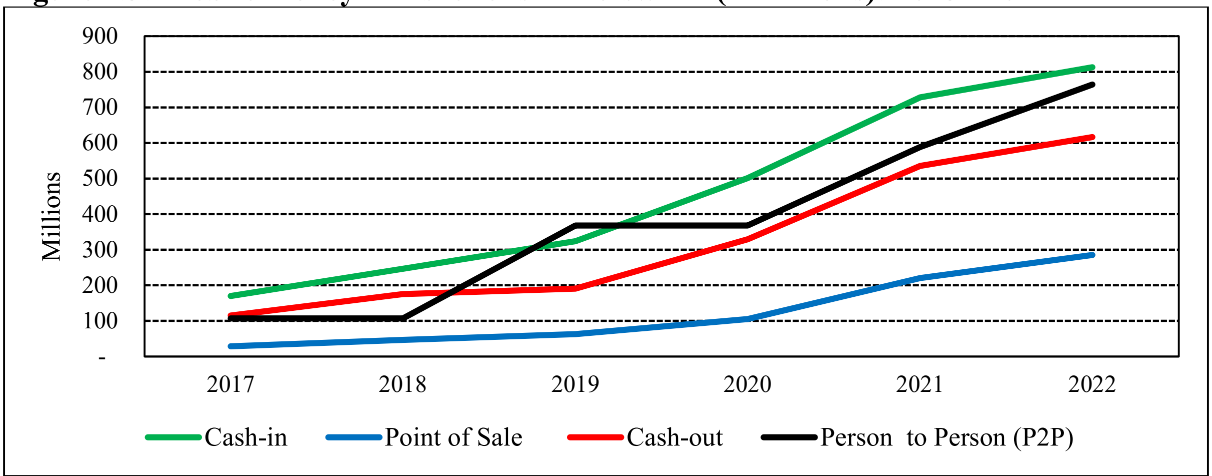


Notes: Monetary base excludes the vault cash of commercial banks.
Source: Bank of Botswana

4.2.2. Mobile money transactions

Generally, we observe an upward trend in transactions of mobile money services for the period 2017 to 2023 in Botswana (**Figure 4.3**). Therefore, we envisage a change in the composition of the money supply due to an increase in mobile money transactions, which may have some implications for the country's monetary policy transmission (Nizam, 2022).

Figure 4.3: Mobile money transactions in Botswana (P Millions): 2017 - 2022



Notes: BWP denotes Botswana's currency, and BWP10 ≈ US$1.
Source: Mobile network operators (MNOs) and Bank of Botswana

In Botswana, mobile money accounts are primarily used for transfer money across users (P2P), as a savings account to store money for safekeeping (cash-in) and cash withdrawals (cash-out).

We observe a modest growth in mobile money use in purchasing goods and services at point of sale (POS) in Botswana. Cash-out transactions increase cash in circulation, while cash-in, POS, and P2P transactions indirectly increase liquidity in the banking system via a bank account of a mobile money agent. In **Figure 4.3**, empirical cash-in transactions exceed cash-out transactions, implying that mobile money plays a role in increasing liquidity in the banking sector.

Mobile money services *versus* Bank services

	Cash in circulation	**Cashless**
a). Mobile Money transactions		
Person to Person (P2P)	Reduce	Increase
Cash-in (Person to Agent)	Reduce	Increase
Cash-out (Agent to Person)	Increase	Reduce
Point of sales (POS)	Reduce	Increase
b). Bank account transactions		
Debit cards point of sales (POS)	Reduce	Increase
ATM withdrawals	Increase	Reduce
Online banking	Reduce	Increase

Source: Author's illustration.

Mobile money is accounted for in monetary statistics as part of current or transferable deposits. Studies on whether mobile money has led to a decline in cash use find that the use of cash has declined while bank deposits have increased (Kipkemboi and Bahia (2019); Shirono *et al.* (2021)). In terms of bank services, increase in ATM withdrawals lead to an increase in cash in circulation while increase in debit card transactions and online banking transactions increase cashlessness.

4.3. Literature Review

The existing theoretical literature on payments innovations and monetary policy focuses primarily on whether central banks will lose power in a cashless economy (Friedman, 1999; Woodford, 2003). Marimon *et al*. (1998, 2003) analysed the impact of electronic money competition on policy outcomes. They found that electronic money competition can result in lower equilibrium inflation rates and may result in the Friedman rule being non-credible. Most recent papers use the Lagos and Wright (2005) and Rocheteau and Wright (2005) model, a framework that extensively incorporates the microfoundations of payments into a macroeconomic model. These studies use search and matching theory to model multiple payments media but do not focus on the major trends we observe from data and cannot give answers to our study. Further, papers using this model (Rocheteau and Nosal (2017); Ait Lahcen and Gomis-Porqueras (2021)) assume that money supply is exogenous. This implies that these models do not give a link between money supply and inflation due to changes in payments habits of households. In contrast, we explicitly determine the demand for cash, card and mobile money transactions which then determine the equilibrium of money supply. In Botswana, we observe a general decline in currency in circulation and high-powered money since 2012, and this downward trend corresponds to a fall in the interest rate and inflation rate, a relationship that these models do not address. Markose and Loke (2002) deviate from mainstream literature by developing a general equilibrium which incorporates the microstructure of retail payments to analyze the dynamics of cash-card substitution in transmission of monetary policy.

4.3.1. Empirical Literature

The empirical literature on the impact of mobile money on monetary policy has focused mainly on money demand, velocity of money, money multiplier and the transmission of monetary policy. Ndaringu and Nyamongo (2015) analysed the impact of financial innovations on the conduct of monetary policy by testing the stability of income velocity of money, money multiplier and money demand in Kenya. They found evidence of instability in velocity, money multiplier and money demand after 2007 (the mobile money inception period in Kenya), which could be attributed to financial innovations, the most prominent of which was the introduction of mobile money in Kenya. The authors further found improved effectiveness of monetary policy on GDP, which they consider to be an indication that there has been an improvement in the effectiveness of monetary policy post-mobile money introduction.

Mawejje and Lakuma (2019) postulate that mobile money negatively affects monetary policy effectiveness through the interest rate channels. These authors also ascertain that mobile money has a moderate effect on monetary aggregates, indicating the possibility of its impact on monetary policy. Nizam (2022) found that mobile money significantly contributes to monetary aggregates, suggesting that mobile money could indeed impact money supply and interest rates. Simpasa *et al*. (2011) raised concerns about the potential inflationary effect of mobile money in developing economies. They argue that the issuance of mobile money increases the velocity of money which could undermine monetary policy effectiveness and lead to price instability.

On the contrary, Aron *et al*. (2015) developed inflation forecasting model for Uganda and found no sufficient evidence of inflationary effects of mobile money. Similarly, Adam and Walker (2015) found no evidence supporting the claim of mobile money being inflationary. They argue that the results by Simpasa *et al*. (2011) were based on a short period, and therefore, they might be subject to uncertainty. They also emphasise the importance of understanding the velocity of money and money multiplier in the context of prevailing monetary policy frameworks in the East African region that target quantity of money.

Recently, Wiafe *et al*. (2022) analysed the effectiveness of monetary policy in the advent of mobile money in Ghana, employing structural Vector Autoregressive (VAR) methodology and using the value of mobile money transactions to represent mobile money. They found that monetary policy becomes less effective under mobile money growth. The authors observed that policy rates respond to mobile money growth in Ghana and recommended that central banks accommodate mobile money in framing monetary policy. Huang *et al*. (2024) established that mobile money development has accompanied stronger monetary policy transmission (measured by the responsiveness of interest rates to the policy rate), growth in bank deposits and credit, and efficiency gains in financial intermediation (measured by the lending-to-deposit rate spread). This evidence is more pronounced in countries where e-money development takes off in a context of limited financial inclusion. The authors also highlight the potential benefits of mobile money in strengthening monetary policy transmission, especially in countries with limited financial inclusion.

The electronic mobile money balances (e-money) are fully backed by bank deposits of MNOs with a bank, implying that no new money is created in the process of issuing mobile money. Since agents convert their cash into electronic mobile money, a substantial amount of mobile money increases bank deposits. Adam and Walker (2015) argue that banks may utilise these additional bank deposits via mobile money to boost lending and hence increase in broad money or money supply. Other scholars found that besides making money transfers, some households use their mobile money accounts for savings and that the increase in mobile money balances comes from informal savings (Mbiti and Weil, 2016). The authors also ascertain that mobile money subscribers use their accounts to deposit money for safety, especially when travelling.

The empirical literature on impact of payments innovations such as mobile money on the effectiveness and conduct of monetary policy shows inconclusive results. These studies use econometric models, and do not explicitly incorporate the microfoundations of changes in payments habits and cashlessness when modelling the impact of mobile money on the conduct of monetary policy. Our contribution is to establish the effect of cashless payments such as bank deposits and mobile money on the growth of monetary base, interest rates and inflation in Botswana. To the best of our knowledge, no research is conducted to analyse slowdown in growth of monetary base and price level determination with multiple payments media such as cash, bank cards and mobile money in Botswana.

4.4. Model

In this section we develop a macroeconomic model with multiple payment technology infrastructure that governs the decisions of individuals at extensive and intensive margins in the choice of the payment media for transactions in the goods market. We allow heterogeneity regarding payment habits for households and relax the assumption that the banking sector is available to all individuals in the population[27]. Further, we extend the model by incorporating mobile money, an alternative low-cost innovative cashless media offered by non-banks or mobile network operators, which does not require households to have a bank account[28]. Banks provide access to bank deposits, which can be used to purchase goods and services via bank cards, while non-banks or mobile network operators (MNOs) offer electronic mobile money, which can be used to buy goods and services via mobile phones.

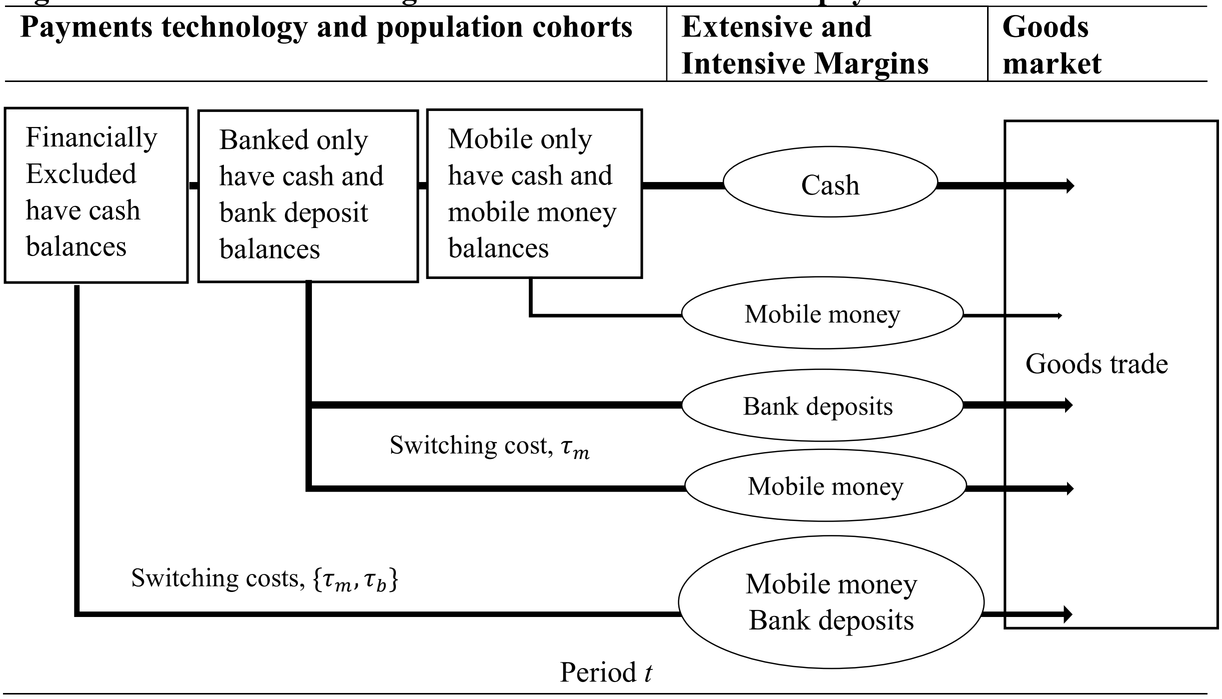
Figure 4.4 shows that a household is faced with multiple payment media and can switch to adopt and use cashless payments. Households differ in how they allocate consumption in terms of three payments media: cash, bank deposits, and mobile money. Everyone in all cohorts have an option of using cash. Those who are financially excluded may switch to adopt mobile money and/or bank deposits while banked-only households may adopt mobile money. In the payment technology market, households face a fixed switching cost to bank deposits τ_b and/or switching cost to mobile money τ_m, depending on their cohorts. In Chapters 2 and 3, we applied a

[27] Ait Lahcen and Gomis-Porqueras (2021) extended the Lagos and Wright (2005) model to incorporate heterogeneity of households in terms of payments habits. However, their model assumes that all households can access the banking sector. These scholars measure of financial inclusion is condition to individuals having access to the credit market whereas in our chapter financially excluded individuals are those without bank account and mobile money account.

[28] MNOs are mostly telecommunication companies. Like conventional banks, MNOs that issue mobile money are regulated by the central bank and subject to regulatory requirements that mandate capital levels, reserve ratios, and other financial obligations.

Binomial probability model to determine the extensive and intensive margins of cash and cashless payments. Cash is assumed to be universally accepted unless it is e-commerce or online payment.

Figure 4.4: Pairwise switching of different cohorts to a new payment media



Source: Author's illustration

The macroeconomic model consists of three agents: households, central bank or monetary authority, and financial intermediaries of two types, namely banks and mobile money operators (MNOs). The major step here is to incorporate the microstructure of changes in payments habits from the household sector into the macroeconomic model. The central bank sets the official short-term interest rate, which is known as the repo rate r_E. Banks optimally set the deposit rate r_D to maximize profits given that the lending rate r_L is set close to the money market rate r_E. Our model focuses on studying the cash transactions demand and dynamics of cashless payments on inflation and interest rate spread based on the deposit interest rate (which is determined in the model by banks) and the policy interest rate (which is set by the central bank).

4.4.1. Household sector

The role of the households in this model is to choose from multiple payments media to implement their consumption expenditure. Thus, individuals who adopt a new payments media from one payment media to the other payments media do so along both extensive and the intensive margins. The intensive margins are the portfolio weights viz., the proportion of consumption expenditure transacted in the relevant payments media. The portfolio weights are the key variable that bridges the relationship between household's payments habits as developed in Chapter 3 and the bank's retail operations. Recalling that equation (3.13) from Chapter 3 is defined as follows:

$$w_{ist} = w_{st}^{A} = \frac{\sum_{i=1}^{N} Con_{ist}}{\sum_{s=1}^{S} \sum_{i=1}^{N} Con_{ist}} \tag{4.1}$$

where w_{is} denotes household's optimal portfolio weights for *sth* payment media. Using CAPM style result and Arrow (1964) model, in equilibrium optimal portfolio weights is given by the aggregate macro level proportions of aggregate consumption, w_s^A, that is transacted in a given payments media. Further, Chapter 3 gives the conditions on how the changes in extensive margins relate to changes in intensive margins. This model assumes that the value of household consumption expenditure Con_t and switching costs are held unchanged. Therefore, the extent of switching from cash to cashless payments such as bank cards and mobile money is determined by changes in aggregate portfolio weights w_s^A which is a function of adoption rates driven by network effects.

Aggregate proportions of expenditure transacted in a payments media relative to total expenditure, w_s, where *s* belongs to cash *c*, mobile money *m*, and bank deposit based money *b*, will change when the new adopters of cashless payments media switch from the incumbent monies (*c*, *b*) implying that we now have non-zero portfolio weights for these new adopters for mobile money and bank deposits based card. The switching at the extensive margin is given below as Binomial probability of success weighted ratio of new adopters to yet to adopt individuals for the relevant payments media. Following Chapter 3 (equations (3.15), (3.17), and (3.18)) we derive the measure of such switches as:

$$\Delta w_m\% \equiv \lambda_m = Bin(z_{et}, k_{emt}^{*}, p_{mt})\frac{k_{emt}^{*}}{z_{et}} + Bin(z_{bt}, k_{bmt}^{*}, p_{mt})\frac{k_{bmt}^{*}}{z_{bt}} \tag{4.2}$$

$$\Delta w_b\% \equiv \lambda_b = Bin(z_{et}, k_{ebt}^{*}, p_{bt})\frac{k_{ebt}^{*}}{z_{et}} - Bin(z_{bt}, k_{bmt}^{*}, p_{mt})\frac{k_{bmt}^{*}}{z_{bt}} \tag{4.3}$$

$$\Delta w_c\% \equiv \lambda_c = -\left(Bin(z_{et}, k_{emt}^{*}, p_{mt})\frac{k_{emt}^{*}}{z_{et}} + Bin(z_{et}, k_{ebt}^{*}, p_{bt})\frac{k_{ebt}^{*}}{z_{et}}\right) \tag{4.4}$$

Here $Bin(\cdot)$ denotes the Binomial probabilities of switching by individuals in the different cohorts to respective payments media; λ_m denotes the change in portfolio weight for mobile money transactions, w_m, due to switching by financially excluded (z_e), and banked-only (z_b) individuals to mobile money. In the case of λ_b which brings about change in portfolio weight for card transactions, w_b, note in (4.3) there is a positive switch from financially excluded individuals to card use and there is negative switch when card use users adopt mobile money for the first time. Finally, in equation (4.4), λ_c incorporates the reduction in w_c brought about by those who are financially excluded who have switched either to mobile money or card payments. Thus, changes in portfolio weights of different payments media due to changing payments habits which are governed by network effects will directly affect the bank's retail operations. For instance, the decrease given by λ_c will reduce cash in circulation outside the banking system N^*; an increase in λ_m will increase mobile money funds *MM*, and an increase in λ_b will increase direct non-interest bearing bank deposits *NIB*.

4.4.2. Monetary authorities or Central bank

The central bank's main objective (Bank of Botswana) is to preserve the purchasing power of the domestic currency by keeping the inflation rate low, stable and predictable. In Botswana, monetary policy formulation and implementation involves setting the policy rate and conducting open market operations (OMO) through weekly and monthly auctions of Bank of Botswana Certificates (BoBCs). By assuming the standard Taylor (1993) rule, the monetary policy rate function is expressed as follows:

$$r_{E_t} = D_1 + D_2(rpix_t - rpix^*) + D_3 y_t \tag{4.5}$$

where r_E is the repo rate or money market interest rate set by the central bank. The repo rate r_E is determined by the deviation of realised retail price index $rpix_t$ from the retail price index target $rpix^*$, and output gap y_t which is the percentage deviation of real output from the trend. The policy rate is set to balance the short-run trade-off between stabilizing inflation around the 3-6 percent medium-term objective range and supporting development in the real economy. The repo rate can be adjusted when the retail price index is above or below the target, and with $D_2 > 0$, the central bank can raise or lower the repo rate to meet the target. In such a policy, a central bank can influence the cost of making reserves available to the banking system.

However, the effectiveness of controlling bank liquidity by repo rate only can be limited in an environment where banks practice active liability management. Further, Bank of Botswana through open market operations (*OMO*), buys and sells government securities in the open market to influence the level of bank reserves and, hence, the monetary base. The Bank injects reserves into the banking system by buying government securities, which increases the monetary base and allows banks to create more deposit money.

Formally, the monetary base is defined as

$$H_t = N_t^* + R_t \tag{4.6}$$

Here monetary base *H* (also known as high-powered money, M0) consists of two components, namely: cash in circulation outside banking system *N**, and bank reserves R held by commercial banks. Cash in circulation refers to bank notes and coins held by non-bank public agents. Bank reserves refer to the required reserves or funds that commercial banks must hold with the country's central bank in which they operate. The monetary base plays a critical role in determining an economy's inflation level.

The major assumption is that a large part of cash in circulation outside banking system is cash withdrawn for transactions. Hence, cash in circulation outside the banking system is a function of cash transactions and other factors defined as follows:

$$N_t^* = f(B_t^*, v_t) \equiv B_t^* + v_t \tag{4.7}$$

Here B^* represents the aggregate transaction balances, and v is other factors affecting cash demand, such as black economy, precautionary demand, and anonymity. In recent years, developed economies such as UK and Euro area have observed a decreasing share of cash transactions, and increasing cash demand due to the above-cited factors, a phenomenon referred to as the "*cash paradox*" (Jiang and Shao, 2020).

The standard Baumol (1952) and Tobin (1956) model (B-T) define the individual's total cost of cash use as $\tau_c = T_c\mu_c + r_D \frac{w_c Con}{2T_c}$; where μ_c is the 'shoe leather' cost of cash withdrawals, T_c is the number of cash withdrawals, r_D is the opportunity cost of holding cash, w_c is aggregate portfolio weight of cash transactions, and Con is household consumption expenditure. Minimising τ_c with respect to T_c yields the optimal number of cash withdrawals as standard B-T square root rule $T_c^* = \sqrt{\frac{r_D w_c Con}{2\mu_c}}$, and the 'shoe leather' cost becomes $\mu_c = \frac{r_D w_c Con}{2T_c^{*2}}$. Note that at the level of given individual, the average cash holdings is different from the average size of cash withdrawals. The latter is $B^* = \frac{w_c Con}{T_c}$, while the average size of individual cash holdings is $B^{\#} = \frac{w_c Con}{2T_c}$ given the assumption that an individual spends the cash withdrawn at a uniform rate. However, as all of the cash that is withdrawn is spent in a cash economy, the cash payments from one individual increases the cash balances of another. Hence, at the aggregate level, we use $B^* = \frac{w_c Con}{T_c}$ as the aggregate cash balances.

The optimal individual's cash balances become,

$$B^{\#} = \frac{w_c Con}{2T_c^{\#}} = \sqrt{\frac{w_c Con \mu_c}{2r_D}} \tag{4.8a}$$

The optimal aggregate cash transaction balances equal the average optimal size of cash withdrawals,

$$B^* = \frac{w_c Con}{T_c^*} = \sqrt{\frac{w_c Con \mu_c}{r_D}} \tag{4.8b}$$

The second equality of equation (4.8a) and (4.8b), respectively, is obtained by substituting $T_c^{\#} = \sqrt{\frac{r_D w_c Con}{2\mu_c}}$ into first equality of $B^{\#}$ and $T_c^* = \sqrt{\frac{r_D w_c Con}{\mu_c}}$ into first equality of B^*. As number of cash withdrawals are typically mediated via ATMs, we will proxy this by data on ATM cash withdrawals.

The major hypothesis here is that the observed fall in w_c the world over has reduced the largest part of high powered money. In other words, changes in w_c yields the microfoundations for technology driven changes in payment habits underlying substitution away from cash in transactions. Therefore, a part of cash in circulation outside banking system N^* will directly reduce by the fall in w_c.

4.4.3. Financial intermediaries

There are two types of financial services providers: banks that issue bank deposit money and mobile network operators (MNOs) agents that issue mobile money. The central bank regulates these financial services providers via regulatory requirements such as minimum capital levels, reserve ratios, and other financial obligations.

4.4.3.1. Banks

A representative risk neutral bank maximises its profit by optimally setting the deposit rate r_D based on the repo rate r_E and the lending interest rate r_L. Bank assets include loans L_t, and reserves R_t, while liabilities include deposits D_t, external financing E_t, and equity or bank capital, K_t. In our model, we explicitly capture electronic mobile money funds which form part of the deposit liabilities of the commercial bank. The bank's balance sheet becomes:

$$L_t + R_t = D_t + E_t + K_t \tag{4.9}$$

For simplicity, we assume that banks do not hold excess reserves; therefore, the required reserves equal total reserves R_t. Here reserves are held as a proportion of deposits,

$$R_t = \gamma_t D_t \tag{4.10}$$

where γ_t is the empirically determined reserve ratio.

Non-interest bearing bank deposits (NIB) are expressed as

$$NIB_t = \sigma_{D_t} D_t \tag{4.11}$$

Mobile money deposits (MM) are expressed as

$$MM_t = \sigma_{M_t} D_t \tag{4.12}$$

where σ_D and σ_M denote the shares of non-interest bearing bank deposits and mobile money funds to total deposits, respectively.

Demand for deposits is assumed to equal the supply of deposits. The supply of bank deposits is governed by the deposit multiplier rule given as γ_t. Therefore, using definition of high powered money, *H*, in (4.6) and deriving reserves *R* in terms of *H* and *N**, we get a relationship between deposits D_t in terms of high powered and cash in circulation outside banking system as follows:

$$D_t = \frac{H_t - (B_t^* + v_t)}{\gamma_t} \tag{4.13}$$

The intuition of (4.13) is that as more households switch away from cash transactions, i.e., a fall in w_c, the cash in circulation *N** falls leading to an increase in bank deposits *D*. In other words, to focus on the role of the transaction demand for cash and substitution from cash to cashless payments, we explicitly incorporate the changes in portfolio weight for deposit demand for consumption.

Demand for loans is assumed to be exogenous and expressed as

$$L_t = \phi_t D_t \tag{4.14}$$

where ϕ_t denotes a procyclical time-varying coefficient that measures the loan demand's behavioural aspects. When demand for credit is high, $\phi_t > 1$, and during severe recession time, $\phi_t < 1$ is assumed.

Inserting reserves and loan demand equations into (4.9) the banking sector's stock of external financing, E_t, is given by:

$$E_t = (\gamma_t + \phi_t - 1)D_t - K_t \tag{4.15}$$

Here E_t is the liquidity that can be financed through the government bond market, the private repo market or by private issuance of liabilities in the form of certificates of deposits (CDs). Hence, the money market includes both the market for government debt as well as the CD market. Thus, if loans are less than deposits, it implies that $\phi_t < (1 - \gamma_t)$ and $E_t < 0$, hence the bank becomes a net lender in the money market. This will lead to commercial banks gaining liquidity profit of r_E per unit dollar in the money market. In contrast, if loans are greater than deposits, it implies that $\phi_t > (1 - \gamma_t)$ and $E_t > 0$, hence the bank becomes a net borrower in the money market[29]. In this scenario, the bank will seek external financing to meet the loan demand and incur a cost of r_E per unit dollar to finance the funds in money market.

The objective of a representative bank is to maximise the following profit function:

$$V_t = r_L L_t - r_D(D_t - NIB_t - MM_t) - r_E E_t \tag{4.16}$$

Inserting *NIB*, *MM*, *L* and *E* into *V* yields

$$V_t = \left(r_L \phi_t - r_D\left(1 - \left[\sigma_{D_t} + \sigma_{M_t}\right]\right) - r_E(\gamma_t + \phi_t - 1)\right) D_t + r_E K_t$$

Further, inserting equation (4.13) into bank's profit function *V,* yields

$$\max_{r_D} V_t = [r_L \phi_t - r_D(1 - \mathbf{\Sigma}_t) - r_E(\gamma_t + \phi_t - 1)] \frac{H_t - (B_t^* + v_t)}{\gamma_t} + r_E K_t \tag{4.17}$$

Here, the term in square parentheses represents the net interest rate earned per unit dollar of deposits D_t, and $\mathbf{\Sigma}_t = [\sigma_{D_t} + \sigma_{M_t}]$ is the sum of proportions of non-interest bearing bank deposits and mobile money funds.

Result 1: *Taking first order conditions for (4.17), and applying the standard B-T interest rate sensitivity of optimal cash transaction balances yields*[30]

$$\frac{\partial V_t}{\partial r_D} = -(1 - \mathbf{\Sigma}_t) \frac{H_t - (B_t^* + v_t)}{\gamma_t} + [r_L \phi_t - r_D(1 - \mathbf{\Sigma}_t) - r_E(\gamma_t + \phi_t - 1)] \frac{1}{\gamma_t} \frac{B_t^*}{2 r_D} = 0 \tag{4.18}$$

and solving for the optimal deposit interest rate from (4.18), we get

$$r_D^* = \frac{[r_L \phi_t - r_E(\gamma_t + \phi_t - 1)] B_t^*}{(1 - \mathbf{\Sigma}_t)(2(H_t - v_t) - B_t^*)} \tag{4.18a}$$

[29] Generally, data shows that banks in Botswana are net lenders since their loans *L* are less than deposits *D* (see **Table 4.1**, Row 8 and Row 9).

[30] Using equation (4.8b), we obtain the standard B-T interest rate sensitivity of optimal cash transaction balances as $\frac{\partial B^*}{\partial r_D} = -\frac{B^*}{2 r_D}$.

Equation (4.18a) shows that optimal deposit rate r_D^* is a function of high-powered money H_t, optimal cash transaction balances B_t^*, v_t other factors affecting cash demand, lending rate r_L, repo rate r_E, proportion of cashless payments to total deposits $\boldsymbol{\Sigma}_t$, proportion of loans ϕ, and reserve ratio γ.

Result 2: *The ratio of non-interest rate bearing deposits and mobile money funds to total deposits* $\boldsymbol{\Sigma}_t$ *affects the optimal deposit interest rate positively. Formally,*

$$\frac{\partial r_D^*}{\partial \boldsymbol{\Sigma}_t} = \frac{[r_L\phi_t - r_E(\gamma_t + \phi_t - 1)]B_t^*}{(2(H_t - v_t) - B_t^*)(1 - \boldsymbol{\Sigma}_t)^2} > 0 \tag{4.19a}$$

The optimal deposit rate is positively determined by $\boldsymbol{\Sigma}_\mathrm{t}$ as shown in (4.19a). In other words, a fall in $\boldsymbol{\Sigma}_\mathrm{t}$ implies that the optimal deposit rate falls for any given positive r_L and r_E; as a result, this will increase the spread between the repo rate and deposit rate. Further, lower σ_D and/or σ_M implies a higher proportion of deposits earns interest rate, and hence the bank incurs higher total deposit interest rate costs, thereby reducing the bank's profitability. The bank's response will be to lower deposit rate for a given positive r_L and r_E.

Result 3: *The ratio of optimal cash transaction balances to monetary base (B^*/H) positively affect the optimal deposit interest rate*[31]*. Formally,*

$$\frac{\partial r_D^*}{\partial \left(\frac{B^*}{H}\right)} = \frac{2[r_L\phi_t - r_E(\gamma_t + \phi_t - 1)]}{\left(2(1 - \frac{v_t}{H_t}) - \frac{B_t^*}{H_t}\right)^2 (1 - \boldsymbol{\Sigma}_t)} > 0 \tag{4.19b}$$

In other words, as B^*/H falls, the optimal deposit rate falls for any given positive r_L and r_E. Therefore, a lower B^*/H implies that more liquidity is retained in the depository institutions. Hence, any level of loan demand can be satisfied at lower deposit interest rates with a smaller B^*/H, which arises from the reduced demand for cash transactions.

[31] We first multiply the denominator and numerator of equation (4.18a) by $1/H$, and then solve for $\partial r_D^*/\partial(B^*/H)$.

4.4.3.2. Mobile Money Agents

Mobile money is deposited by MNO with a commercial bank, implying that electronic mobile money (e-MM) is fully backed by bank deposits[32]. It is worth noting that e-MM does not earn nominal interest. The assets side of the mobile money agent includes mobile money deposits MM_t, and the liabilities side consists of the consumer's outstanding mobile money balances. This means that MNO shall ensure that at any time, funds held on their dedicated cash (deposit demand) account are equal to the outstanding issued electronic money. Therefore, the mobile money agent's balance sheet identity is simplified as:

$$MM_t \geq \varphi_t^m MM_t \tag{4.20}$$

where φ^m is a fraction of the outstanding mobile money balances. The profit function of a representative mobile agent Π^m takes the following formula:

$$\Pi_t^m = MM_t - \varphi^m MM_t \tag{4.21}$$

This sector is competitive, and free entry implies that $\Pi_t^m = 0$, and equilibrium occurs at $\varphi^m = 1$.

4.5. Monetary Policy Analysis

4.5.1. Interest rate transmission mechanism

The main mechanism is that changes in the central bank interest rates affects the bank liquidity through the bank's adjustment of its optimal deposit rates derived in equation (4.22). Therefore, at equilibrium the bank can attain demand for credit and inflow of deposits in line with its objective to maximize profits following a change in the official/repo rate by optimal adjustment of deposit rate and lending rate.

Result 4: *Using equation (4.18a), optimal adjustment of deposit rates is derived as*

[32] The regulations require that MNOs hold their entire outstanding mobile money liabilities as deposits at a regulated financial institution such as a bank (Botswana's Electronic Payment Services (EPS) Regulations 2019; Shirono *et al*., 2021).

$$\frac{dr_D^*}{dr_E} = -\frac{\left[\left(\gamma_t + \phi_t - 1\right)\right]B_t^*}{(1 - \boldsymbol{\Sigma}_t)(2(H_t - v_t) - B_t^*)} + \frac{\phi_t B_t^*}{(1 - \boldsymbol{\Sigma}_t)(2(H_t - v_t) - B_t^*)}\frac{dr_L}{dr_E}$$
$$= \frac{B_t^*}{(1 - \boldsymbol{\Sigma}_t)(2(H_t - v_t) - B_t^*)}\left(\phi_t\left(\frac{dr_L}{dr_E} - 1\right) + (1 - \gamma_t)\right) > 0 \qquad (4.22)$$

The result above implies that deposit rate moves in the same direction as the repo rate.

4.5.2. Implications for liquidity in depository institutions

The main result here is to show that as cashlessness in transactions increases and less cash is withdrawn from deposits for retail expenditures, depository institutions have greater liquidity which can lead to lower equilibrium deposit interest rates. The effect of an increase in money market rate r_E on banking liquidity is transmitted by the following: a) responsiveness of deposit interest rate to money market rate r_E, and b) the substantial increase in deposits that is associated with the switching away from cash that follows from a fall in w_c, hence reduced transactions balances B*.

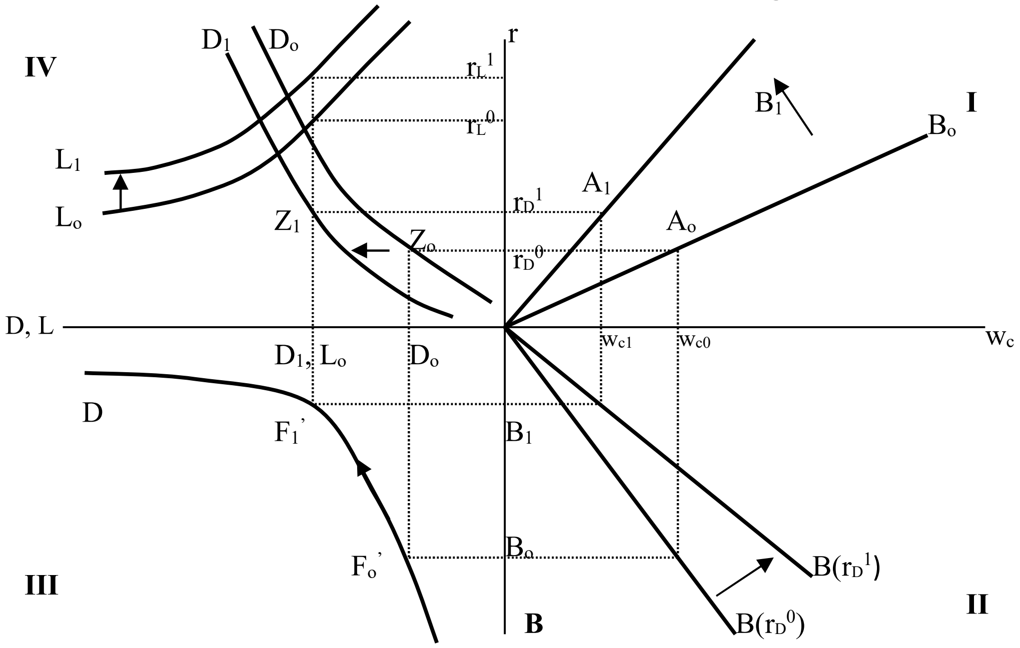
Result 5: *The transmission mechanism that affects bank's liquidity is derived as follows:*

$$\frac{dD_t}{dr_E} = \frac{dD_t}{dB_t^*}\frac{dB_t^*}{dr_D}\frac{dr_D}{dr_E}$$
$$= \frac{B_t^*}{2r_D\gamma_t}\left[\frac{B_t^*}{(1 - \boldsymbol{\Sigma}_t)(2(H_t - v_t) - B_t^*)}\left(\phi_t\left(\frac{dr_L}{dr_E} - 1\right) + (1 - \gamma_t)\right)\right] > 0 \qquad (4.23)$$

Here $\frac{dB_t^*}{dr_D} = -\frac{B^*}{2r_D}$ *denotes interest elasticity of substitution between cash-cashless payments,* $\frac{dr_D^*}{dr_E}$ *measures optimal adjustment of deposit rate in equation (4.22), and* $\frac{dD_t}{dB_t^*}$ *is obtained from equation (4.13).*

Figure 4.5 demonstrates the interest rate transmission mechanism with banking and households sectors.

Figure 4.5: Interest Rate Transmission Mechanism with Banking and Household Sectors



Source: Author's illustration Adapted from Markose and Loke (2002)

The quadrants (I and II) on the right-hand side represent dynamics for households, and quadrants (III and IV) on the left-hand side are for banking sector. In quadrant I, A_0 is the initial optimal demand for cash balances, B_0, at (r_D^0, r_E^0). An increase in repo rate from r_E^0 to r_E^1, the $\frac{dr_D^*}{dr_E}$ gives the new r_D^1 in quadrant I where A_1 is the new optimal demand for cash transaction balances, B_1. The optimal demand for cash transaction balances has declined from A_0 to A_1 due to an increase in repo rate. Corresponding to this in quadrants III and IV, deposits have increased by the amount $\frac{dD_t}{dr_E}$ from Z_0 to Z_1.

However, an unchanging credit or loan market condition, despite higher r_L^1, implies that the banking sector is able to service consumer credit by utilizing the inflow of deposits into loans without resorting to external financing. In other words, high cashless economies that yield good opportunities for cash economization as deposits rates rise, pose a problem to curbing a credit boom in household loanable funds market (Markose and Loke, 2003). Likewise, attempts to maintain low inflation of the economy by cutting interest rates may perversely contract bank liquidity which may results in cash resurgence as in equation (4.18a). In next section we will empirically quantify the above properties and their implications for the effectiveness of interest rate policy.

4.5.3. Market clearing conditions and equilibrium inflation rate with cash-cashless payments

Generally, traditional monetary models determine price level using a function of supply of monetary base, and assume that inflation rate is proportional to the growth rate of monetary base (Sidrauski (1967) and Brock (1974)). The neutrality results of Sidrauski-Brock (S-B) model do not consider multiple payments media and mediation of monetary base by the banking system. The results of these kind of models have been deemed unsatisfactory (Markose and Loke, 2002). Markose and Loke (2002) have argued that technological innovations in e-money that have transformed payments behaviour by substituting away from a government-supplied monetary base have brought about a permanent fall in the retail price index inflation. Therefore, in our model, we allow the supply of monetary base, payments media and liquidity to be mediated by the banking system, while the household's payment habit determines transaction demand. The main objective here is to compare the actual inflation rate as measured by the percentage change in the consumer price index (CPI) for the entire economy with the inflation rate calibrated exclusively from the retail expenditures financed by cash, bank cards, and mobile money. We hypothesize that cashlessness and a fall in transaction demand for cash due to substitutions to electronic or mobile money innovations somehow negatively impact inflation.

Result 6: *The market clearing condition is given as*

$$H_t = N_t^* + R_t$$

Substituting for $N_t^* \equiv B_t^* + v_t$ *from equation (4.7)*

$$H_t = B_t^* + v_t + R_t$$

Replacing B^* *from (4.8b) yields*

$$H_t = \frac{w_{ct} Con_t}{T_{ct}^*} + v_t + R_t$$

Household consumption expenditure, Con_t*, can be defined as* $Con_t = \xi_t P_t Q_t$ *where* ξ_t *denotes consumption income ratio,* P_t *is price level,* Q_t *is total output, and* $P_t Q_t$ *is nominal gross domestic product (GDP). Thus, the above equation becomes*

$$H_t = \frac{w_{ct} \xi_t P_t Q_t}{T_{ct}^*} + v_t + R_t$$

Solving for price level P_t gives

$$P_t = \frac{T_{ct}^*(H_t - v_t - R_t)}{w_{ct}\xi_t Q_t}$$

Taking log difference of the above equation solves for change in price level P_t or inflation rate π_t, (i.e., $\Delta lnP_t = \pi_t$):

$$\begin{aligned} \Delta lnP_t = \pi_t &= \Delta ln(H_t - v_t - R_t) - \Delta lnw_{ct} - \Delta ln\xi_t Q_t + \Delta lnT_{ct}^* \\ &= \Delta ln(H_t - v_t - R_t) - \hat{\lambda}_{ct} - g_t + \Delta lnT_{ct}^* \end{aligned} \tag{4.24}$$

Here $g_t = \Delta ln\xi_t Q_t$ denotes output growth of household consumption, and ΔlnT_{ct}^* measures a change (%) in number of cash withdrawals. Equation (4.24) underscores the importance central banks need to put on the microstructure of changes (%) in payments habits $\hat{\lambda}_c = \Delta lnw_c$ in their pursuit of determination of price changes or inflation rate. Here we expect that an increase in substitution from cash to cashless transactions, i.e., a fall in $\hat{\lambda}_c$, has a deflationary effect.

4.6. Empirical Results

4.6.1. Data and Sources

The study uses Botswana's data from International Financial Statistics (IFS) compiled by International Monetary Fund (IMF), and Botswana Economic and Financial Statistics (BEFS) compiled by Central Bank of Botswana (BoB), covering the period from 2017-2022[33]. This period range is suitable for computation of aggregate portfolio weights for cash w_c, card w_b, and mobile money w_m transactions as shown in Chapter 3. Based on equation (4.8b), we use aggregate cash portfolio w_c to estimate the aggregate cash transactions balances and optimal cash portfolio w_c^* to estimate optimal cash transactions balances $B*$. The optimal number of cash withdrawals T_c^* is set to equal the historical size of ATM cash withdrawals. **Table 4.1** provides the historical data that is used for all the calibration exercise.

[33] Though mobile money was first launched in Botswana in 2011, the detailed data of mobile money transactions was reported from year 2017.

Table 4.1: Monetary and Financial Data for Botswana: 2017 - 2022

A. Historical (Actual) Data	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
1.Total Household Expenditure, *Con (P million) BoB GDP Tables*	69541.2	74961.8	79029.0	82616.7	89201.9	104810.2
2. Empirical share of cash w_c, *Residual ratio based on BoB data on Card and Mobile Money*	0.831	0.824	0.771	0.731	0.633	0.598
3. Empirical Cash transactions, $w_c Con$ *(P million)* viz. Row2*Row1	57763.0	61756.7	60931.6	60417.8	56467.2	62693.5
4. Empirical Number of ATM withdrawals, T_c (*'000 units*), *BoB data*	39756	41671	52778	62293	76354	98846
5. Empirical Cash Transactions per withdrawals, $B = w_c Con/T_c$, viz. Row 3/ Row 4	1452.9	1482.0	1154.5	969.9	739.5	634.3
6. Empirical Total notes and coins (Cash) in circulation, *N** *(P million)*, *BoB data*	1892.2	1819.9	1882.7	2409.4	2418.3	2279.0
7. Empirical Monetary Base, *H (P million), BoB data*	4827.5	4866.0	5357.3	4378.0	4766.6	4396.3
8. Empirical Deposits, *D (P million)*, *BoB data*	54417.0	58208.2	64811.7	67418.6	69204.4	72008.2
9. Empirical Loans, *L (P million)*, *BoB data*	52147.0	56185.4	60199.5	62784.6	66107.4	70577.3
10. Empirical Reserves, *R (P million)*, *BoB data*	2935.3	3046.1	3474.7	1968.7	2348.3	2117.3
11. Empirical loan ratio, $\phi = L/D$, Row 9/Row 8	0.96	0.97	0.93	0.93	0.96	0.98
12. Empirical reserve ratio $\gamma = R/D$, Row 10/Row 8	0.05	0.05	0.05	0.03	0.03	0.03
13. $\Sigma = TNIB/D$, *BoB data*	0.29	0.27	0.28	0.32	0.33	0.33
14. Empirical Deposit rate, r_D, *BoB and IMF data*	0.0144	0.0152	0.0159	0.0156	0.0143	0.0149
15. Empirical Lending rate, r_L, *BoB and IMF data*	0.0688	0.0650	0.0640	0.0575	0.0525	0.0613
16. Empirical	0.0450	0.0450	0.0425	0.0375	0.0375	0.0265

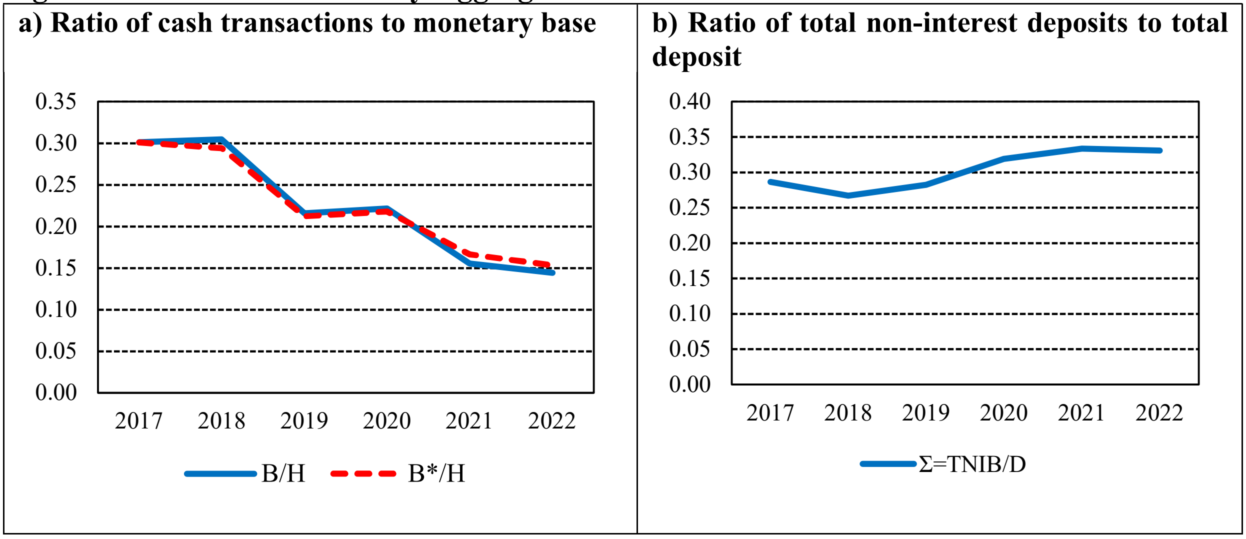
Money market rate, r_E, *BoB data*						
18. Empirical Inflation, π, *BoB data*	0.033	0.032	0.028	0.019	0.067	0.122
19. Household Consumption spending growth, $g = \Delta lnCon_t$	0.014	0.052	0.031	0.023	0.025	0.030
20. Other factors of cash demand $v_t = N_t^* - B_t$	439.3	337.9	728.2	1439.5	1678.8	1644.7
B. Calculated values						
21. Calibrated w_c^* based on Binomial probabilities of switching	0.831	0.796	0.759	0.720	0.679	0.636
22. Calibrated optimal transaction balances $B^* = w_c^* Con/T_c$. Row 21*Row1/Row 4	1452.9	1431.3	1136.3	955.0	793.3	673.9
23. Model based $\lambda_c = \Delta w_c^*$ from equation (4.4)		-0.035	-0.037	-0.039	-0.041	-0.044
24. Calibrated $\hat{\lambda}_c = \Delta lnw_c^*$		-0.043	-0.047	-0.052	-0.059	-0.066

Source: Historical data in part A is from Bank of Botswana (BoB) and International Monetary Fund (IMF), while Calibrated values in part B are author's calculations from the model.

4.6.2. Monetary Aggregates Ratios

Figure 4.6 shows trends of the ratio of optimal cash transaction balances to monetary base (B^*/H) and the ratio of total non-interest bearing bank deposits to total bank deposits (TNIB/D). In **Figure 4.6 (a)** we observe that the calibrated ratio of optimal cash transactions balances to monetary base B^*/H closely track the historical data B/H. The ratio of aggregate cash transaction balances to monetary base (B/H) slightly increased between 2017-2018, and sharply fell from 30.5% to 14.4% between 2018-2022, mainly due to a general fall in the portfolio weight of cash transactions over this period. On the other hand, **Figure 4.6 (b)** show that ratio of total non-interest bearing deposits to total deposits, Σ, slightly declined (from 28.6% to 26.7%) between 2017-2018 and increased between 2018-2022 (from 26.7% to 33%). This is plausible given that the portfolio weight of mobile money and card-financed transactions increased over the same period.

Figure 4.6: Ratios of Monetary Aggregates in Botswana: 2017 - 2022



Notes: The calculation of optimal transaction balances is in equation (4.4), where B is obtained using actual cash weight w_c, a residual ratio based on historical data on card and mobile money, and B^* is obtained using w_c^*, a calibrated cash weight based on Binomial probabilities of switching. *TNIB* is total non-interest bearing bank deposits (current accounts or transferable deposits), which include both non-interests bearing bank deposits and mobile money funds, and *D* denotes total bank deposits, thus $\Sigma = TNIB/D$.
Source: Author's computations

Table 4.2 compares the percentage change in the ratio of aggregate cash balances to monetary base (B/H) with the percentage change in the ratio of total non-interest bearing deposits to bank deposits in Botswana. These results complement those in **Figure 4.6**. We observe a significant 2.8% increase in B/H in 2020 mainly attributable to the effects of the COVID-19 pandemic, which increased household's cash holdings due to precautionary motives. These results are consistent with the findings by Guttmann *et al.* (2021).

Table 4.2: Percentage Changes in B/H and Σ in Botswana: 2018 - 2022

Year	% Changes in B/H	% Changes in Σ=TNIB/D
2018	0.012	-0.068
2019	-0.292	0.058
2020	0.028	0.129
2021	-0.300	0.047
2022	-0.070	-0.010

Source: Author's computations

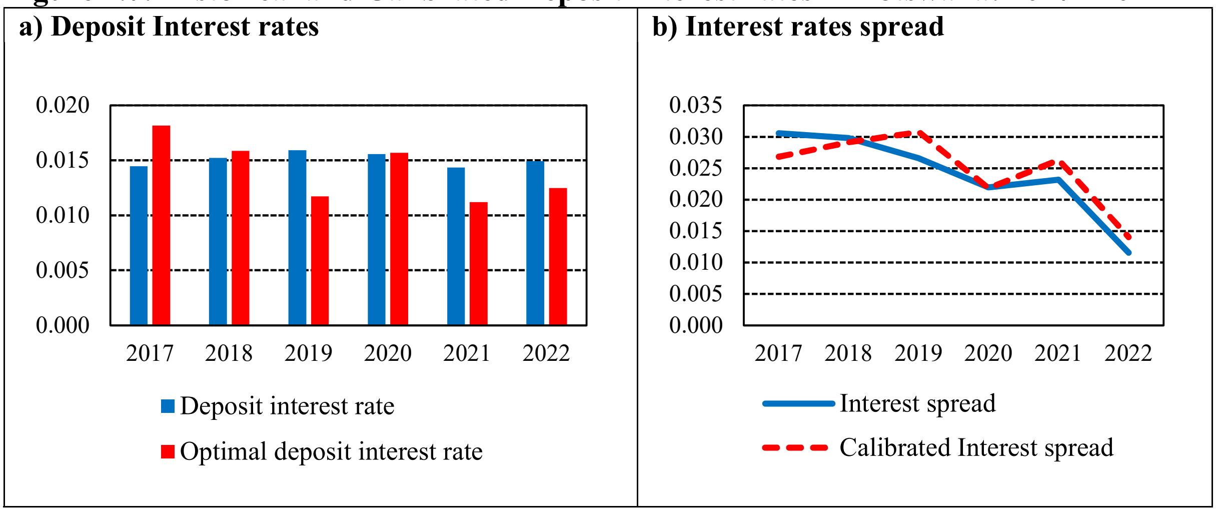
The ease of COVID-19 protocols in 2021 resulted in a significant fall of about 30% in B/H due to public concerns about the viral transmission from cash (notes and coins). On the other hand, we observed a surge in cashless payments, i.e., increase in Σ, between 2019-2021 mainly because of public concerns about the viral transmission from cash (notes and coins) and governments' pandemic relief packages delivered through cashless media. Further, post-COVID-19 in 2022, the ratio B/H was falling more than the ratio Σ, implying that non-cash transactions continue to be play a significant role in retail expenditures in Botswana.

4.6.3. Calibration Results

4.6.3.1. Calibration of Optimal Deposit Interest Rate

The calibrated deposit interest rate r_D^* is calculated by inserting data for H, v, r_E, r_L, γ, ϕ, Σ, and B^* into equation (4.18a). **Figure 4.7 (a)** compares the historical actual deposit interest rate r_D and calibrated or optimal deposit interest rate r_D^*. The results show that the calibrated deposit interest rate r_D^* is closer to the actual deposit interest rate r_D. We also observe that historical deposit rate for Botswana does not respond to cashlessness, viz., the deposit rate is more static regardless of decline in B^* particularly for the years 2019, 2021 and 2022. In contrast, for the same years, the calibrated deposit rate is consistent with our theory that increase in cashlessness leads to a fall in interest rate. In **Figure 4.7 (b)** we observe that the calibrated interest rates spread, $r_E - r_D^*$, mirrors the historical interest rates spread, $r_E - r_D$, between 2019 and 2022. This empirical evidence implies that to a large extent our model is successful in determination of optimal deposit interest rate.

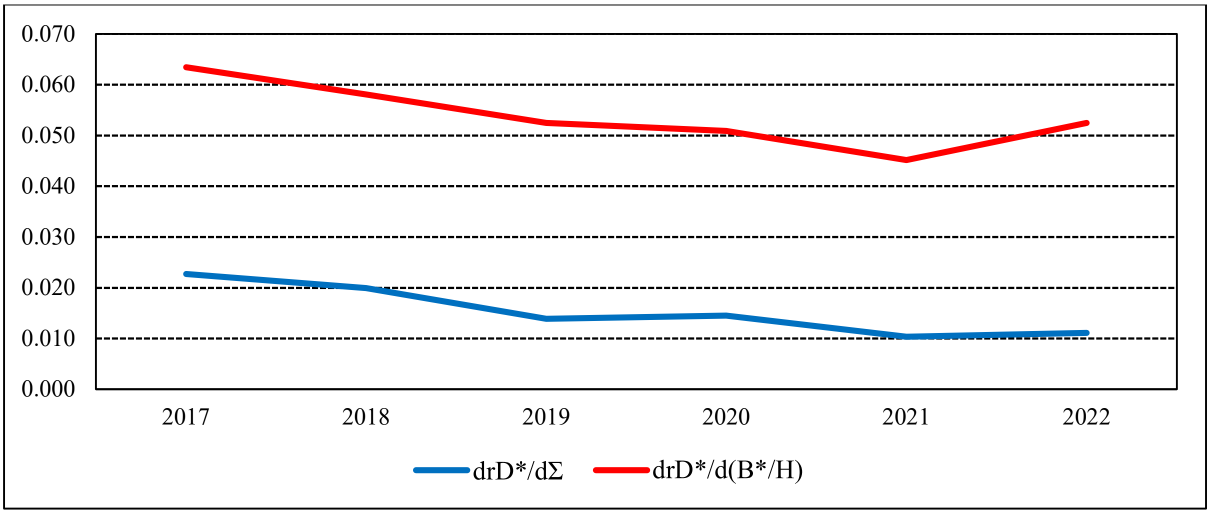
Figure 4.7: Historical and Calibrated Deposit Interest rates in Botswana: 2017 - 2022



Notes: The calibration of optimal deposit interest rate r_D^* is given by equation (4.18a)
Source: Author's computations

The results in **Figure 4.8** are based of theoretical results in equations (4.19a,b). These results show that the optimal deposit interest rates, r_D^*, is predominantly determined by a fall in ratio of optimal cash transactions balances to monetary base, B*/H, rather than a rising share of total non-interest bearing deposits to total deposits Σ. This provides conclusive evidence that changes in payments habits, viz. a fall in w_c^* due to switching away from cash which leads to a fall in ratio B*/H, and increase in ratio of non-interest deposits to total deposits Σ are the main contributing factors of optimal deposit interest rates.

Figure 4.8: Comparative Statics on Effects of Changes in Σ and B*/H on Optimal Deposit Interest Rate in Botswana: 2017 - 2022



Notes: The comparative statics $\frac{\partial r_D^*}{\partial \Sigma}$ and $\frac{\partial r_D^*}{\partial (B^*/H)}$ are obtained by inserting the historical data into equations (4.19a) and (4.19b), respectively.
Source: Author's computations.

4.6.3.2. Calibration of Implications of Policy Rate

Here we calibrate the theoretical **Results 4** and **5** that determine the implications for bank liquidity $\frac{dD}{dr_E}$ in (4.23) given the optimal adjustment by banks of the deposit interest rates $\frac{dr_D^*}{dr_E}$ given in (4.22). These results are shown in **Table 4.3**.

Table 4.3: Interest rate transmission mechanism on bank liquidity in Botswana

Year	Calibrated ΔB^* (%)	Official repo rate, r_E (%)	Lending rate, r_L (%)	Actual Δr_E (%)	$\frac{dr_L}{dr_E}$ (%)	$\frac{dr_D^*}{dr_E}$ (%)	$\frac{dD}{dr_E}$ P Million
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2017		4.50	6.88	-0.50	0.85	0.22	165.4
2018	-1.49	4.50	6.50	0.00			
2019	-20.61	4.25	6.40	-0.25	0.42	0.08	71.3
2020	-15.96	3.75	5.75	-0.50	1.29	0.35	369.2
2021	-16.93	3.75	5.25	0.00			
2022	-15.06	2.65	6.13	-1.10	-0.80	-0.17	-152.3

Notes: The empty cells are periods at which repo or policy rate r_E remained unchanged, e.g., 2018 and 2021.
Source: Author's computations

During the COVID-19 pandemic, in 2019-2020, the official money market/repo rate was cut by 50% basis points (**Table 4.3**, Column 4) and the model estimated the optimal adjustment in deposit interest rate was about 35% basis points increase (**Table 4.3**, Column 6). This results in turn leads to 16% decline in cash transactions balances (**Table 4.3**, Column 1) which potentially accounted for about P369.2 million expansion in deposits (**Table 4.3**, Column 7). This result is mainly attributable to significant uptake in cashless payments, and precautionary motives for holding cash during the pandemic. However, post COVID-19 in 2022, there was a further cut in repo rate of about 110% basis points which resulted in optimal adjustment in deposit interest rates by 17% basis points decrease which led to P152.3 million contraction of deposits.

4.6.3.3. Calibration of critical money market rate

In this subsection, we adopt the Markose and Loke (2003) theoretical 2% floor in the deposit rate to determine the critical official money market/repo rate[34]. Equation (4.18a) provides the bank's optimal deposit interest rate given the repo rate level, which can be used to evaluate the critical values for the official money market rate that will breach the 2% floor of the deposit interest rate. The critical money market rates r_E^* obtained from calibrated model of the banking

[34] Markose and Loke (2002) posits that the erosion of bank liquidity starts well before zero interest rate, while an incentive for cash economies ceases at deposit interest rates of 2% or below. Hence, once money market and lending rates fall to 2% or below, banks do not have any means for enhancing their liquidity by raising deposit interest rates.

sector are shown in column (3) of **Table 4.4**. The estimates of critical money market rates are based on the calibrated interest rate spread between money market and deposit rates $(r_E - r_D^*)$ at a given 2% floor of the deposit rate.

Table 4.4: Determination of critical money market rate (%)

Year	**Historical Money Market, r_E** (1)	**Optimal spread $(r_E - r_D^*)$** (2)	**Critical Money Market r_E^*** (3)
2017	4.50	2.68	4.68
2018	4.50	2.91	4.91
2019	4.25	3.08	5.08
2020	3.75	2.18	4.18
2021	3.75	2.63	4.63
2022	2.65	1.40	3.40

Notes: Column (3) is obtained by adding 2% to column (2), and column (2) is as plotted in **Figure 4.7(b)**
Source: Author's computations

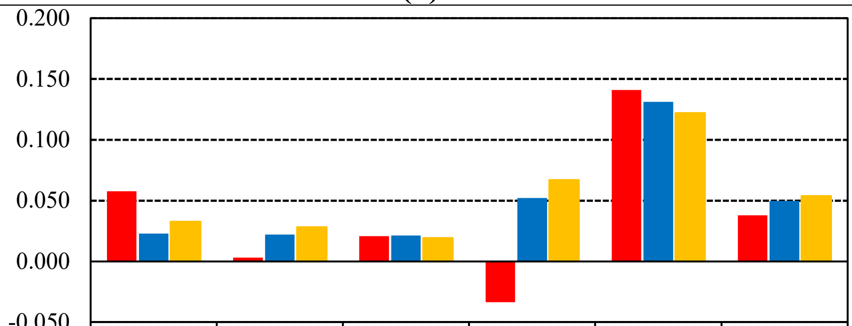
In **Result 2**, we have shown that banks consider the effects of payments innovations viz., B^*/H and Σ=TNIB/D, to optimally set the deposit interest rate given the money market rate. Hence, for years 2019 and 2021, we find that an economy with lower B^*/H has higher spread $(r_E - r_D^*)$. This implies that an economy with higher proportion of non-cash transactions (lower B^*/H) is more likely to have higher money market rates at which the deposit interest rates hit 2%. However, for a scenario where consumers stop to economize on cash balances, the demand for cash transactions balances B^* can increase resulting in decreased liquidity within the depository institutions.

During the COVID-19 pandemic of 2019-2020 in Botswana, deposits rise by 17.4%, and loans recorded lower growth of 4% (from 11.3% in 2019). In this period, nominal official money market/repo rates were cut by 50% basis points which were mirrored by the fall in deposit interest rates by 4% basis points to 1.56% in 2020. This finding implies that Botswana is still a cash economy because the deposit interest rates are below 2%. Therefore, it is vital for banks in Botswana to enhance their liquidity by raising their deposit interest rates above 2%.

4.6.3.4. Calibration of Inflation rates

The calibration of inflation rate given in equation (4.24) requires data for H, v, R, g, $\hat{\lambda}_c$, and T_c^*. **Figure 4.9** compares the historical inflation rate in Botswana for 2018-2022 with the actual inflation rates using empirical share of cash (w_c) and calibrated share of cash (w_c^*) transactions. The calculated inflation rates with w_c closely track the historical inflation rates from CPI. However, it is observed that calibrated inflation rate with w_c^* due to the changes in payment behaviour, viz., switching away from cash to cashless transactions, does slightly track the trend of the historical inflation rate in Botswana except for the year 2021. This finding highlights the importance of incorporating the technology driven changes in payment habits via the intensive margin changes into macroeconomic forecasting of prices.

Figure 4.9: Historical and Calibrated Inflation Rates (π) in Botswana: 2018-2022



	2018	2019	2020	2021	2022	Average Inflation (2018-2022)
π with calibrated weights w_c*	0.058	0.003	0.021	-0.034	0.141	0.038
π with actual weights w_c	0.023	0.022	0.021	0.052	0.131	0.050
π from historical CPI	0.032	0.028	0.019	0.067	0.122	0.054

Source: Author's calculations

Overall, the calibrated inflation rate is found to be lower than the historical inflation rates, particularly during the COVID-19 pandemic period (2019-2021) and this could imply that cashless retail expenditures contributed to a lower rate of inflation compared to the aggregate CPI rate for the economy as a whole. We find that on average the equilibrium inflation rate due cashlessness is around 3.8% which is lower than the 5.4% inflation for the entire economy. This result justifies our hypothesis that cashlessness which lead to a fall in transaction demand for cash due to substitution to electronic or mobile money innovations somehow negatively impact inflation. This observation is consistent with standard theory that high cashlessness is deflationary (Marimon *et al.* (1998); Markose and Loke (2002)).

4.7. Conclusion

This chapter examines the implications of cashless payments on monetary policy in Botswana by incorporating the micro-founded changes in payments habits in cashlessness. The general equilibrium model developed here considers the relationship between interest rates policies of a central bank and the role of banks in setting optimal deposit interest rates which are affected by the dynamics of switching away from cash to cashless payments by the households. We identify the two main factors of optimal deposit interest rates to be: the falling ratio of optimal cash transaction balances to monetary base, B^*/H, and the rising share of non-interest bearing deposits to total deposits, Σ=TNIB/D. Finally, we find that cashlessness which lead to a fall in transaction demand for cash due to substitutions to electronic or mobile money innovations somehow negatively impact inflation. The calibration results from the general equilibrium model have shown remarkable consistency with the observed empirical facts and trends of the Botswana economy. Therefore, it is crucial for central banks to consider the microfoundations of technology driven changes in payments habits in their pursuit of conducting monetary policy.

5. CONCLUSION

This thesis contributes to the ongoing literature on new payment technology adoption and its role in shaping financial inclusion, consumer payment behaviour, and macroeconomic policy. The research aims to operationalize the microfoundations of the adoption of mobile money, a network good, where the utility of its adoption increases in the number of adopters and analyses the implications of the resulting cashlessness on monetary policy. The analysis of this research utilizes both the theoretical and empirical models to demonstrate the significant role of network effects and switching cost in adoption decisions. First, chapter 2 focuses on the adoption of mobile money by applying a game-theoretic approach based on Myerson (1998) and the Binomial probability theory to quantify network effects. The study highlights that while mobile money can potentially transform Botswana's payment landscape, its adoption is hindered by strong incumbency effects from existing cash and bank-based payment systems. The empirical analysis employs 2017 and 2022 data from the Global Findex Survey for Botswana, and uses a Logistic Regression model to assess adoption determinants. The empirical results highlight that network effects have a positive and significant effect on mobile money adoption, with the dominance of conventional banking acting as a barrier to mobile money penetration.

The third chapter extends this analysis by investigating how the transition to cashless payments impacts the consumption allocation across different payments media. Using a framework inspired by Arrow (1964), the study show that the equilibrium portfolio weights for payment media align with aggregate consumption shares. The findings reveal that cash transactions decline as consumers adopt digital payment methods. However, bank cards remain the dominant non-cash payment method due to their strong network effects. Finally, fourth chapter mainly examines the importance of tracking the transition to cashless payments, as these changes affect the monetary base, inflation, and the banking sector's liquidity. In pursuit of this objective, we develop a general equilibrium model linking microfoundations of technology driven changes in payment habits toward digital money via the intensive margins to the above macroeconomic variables. The findings suggest that as digital payments gain traction, cash transactions will continue to decline, necessitating policy adjustments to ensure effective monetary policy. Additionally, lower inflation resulting from increased digital transactions offers potential benefits for macroeconomic stability.

In conclusion, this thesis offers valuable insights for policymakers, financial institutions, and mobile network operators seeking to enhance mobile money adoption and leverage its benefits for financial inclusion and macroeconomic policy. Future research could explore additional factors such as regulatory frameworks, and technological advancements, such as interoperability between mobile money and bank accounts, that may further influence the trajectory of mobile money adoption in Botswana and similar economies. Also, future research could extend the analysis by incorporating emerging alternative payment methods, such as Central Bank Digital Currencies (CBDCs) and cryptocurrencies. In future research, greater attention will be given to the supply side at the micro level, particularly focusing on the behaviour and dynamics of mobile money providers. Additionally, the role of the policy rate will be explicitly incorporated into the analysis.

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7. APPENDIX A

A1. Switching Costs

Table 1.1A: Payment instruments with service channels and cost elements for consumers

Payment Instrument	**Payment service channel**	**Cost element**
Cash	All channels[35]	Transaction time, Error costs, Theft Costs, Fraud costs, Holding costs, Production costs
	Point of interaction	Travel time
	Payment center	Waiting time
	Agent	Travel costs
	Branch ATM	Per transaction fees
Debit card Credit card Prepaid	All channels[36]	Transaction time, Reconciliation time, Error costs, Theft Costs, Fraud costs, Holding costs (in case of prepaid cards), Production costs, Periodic fees, Per transaction fees
	Point of interaction	Travel time
	Payment center	Waiting time
	Agent Branch ATM	Travel costs
	Internet/designated lines Telephone/mobile phone network	Communication costs
Mobile money	All channels[37]	Transaction time, Reconciliation time, Error costs, Theft Costs, Fraud costs, Periodic fees, Per transaction fees, Holding costs
	Point of interaction Telephone/mobile phone network	Communication costs
	Point of interaction Payment center Agent	Travel time Waiting time Travel cost

Source: World Bank (2016) "*Practical Guide for Measuring Retail Payment Costs*"

[35] These include point of interaction, payment center, agent outlet, branch, and ATM

[36] These include point of interaction, payment center, agent outlet, branch, ATM, Internet/designated lines, and telephone/mobile phone network.

[37] These include point of interaction, payment center, agent outlet, and telephone/mobile phone network.

Table 1.2A: Calibration of Switching costs

Population categories	Formula	Switching Costs
Banked with cellphone and with no mobile money	$ln(\tau_m)$ - $ln(\tau_b)$	-0.693
Financially excluded with cellphone	$ln(\tau_m)$ - $ln(\tau_c)$	-0.466
Banked with no mobile money and no cellphone	$ln(\tau_b)$	1.030
Financially excluded with no cellphone	$ln(\tau_c)$	0.802
Mobile money with cellphone	$ln(\tau_m)$	0.336
Mobile money with no cellphone	$ln(\tau_c)$	0.802

Notes: The average cost of using cash is τ_c = \$2.23, average cost of adopting a mobile money account is τ_m = \$1.40, and average cost of adopting a bank account τ_b = \$2.80. An agent who has a cellphone but is financially excluded or banked with no mobile money, always have a cost advantage or incentive to switch to adopt mobile money. Therefore, their cost advantage will be recorded as a negative value.
Source: Author's computations

A2. Utilities of Expected Network Effects used in the Regression Models

Table 1.3A: Calibration of Network effects

	General population network effects	Cohort network effects	Incumbent network effects
FE with cellphone	5.923	5.915	0.9845
FE without cellphone	0	0	6.9078
Banked-only with cellphone	5.923	5.915	-0.5206
Banked-only without cellphone	0	0	5.4027
Mobile money with cellphone	5.903	5.903	1.0051
Mobile money without cellphone	0	0	6.9078
Both accounts with cellphone	5.903	5.903	1.0051
Both accounts without cellphone	0	0	-0.5000

Source: Author's calculations based on **Table 2.5** formulas and data from 2022 Global Findex surveys for Botswana. These values are mapped with respect to the cohorts of the population in the cross-sections of the Global Findex Survey.

Goodness of fit and Model Selection Tests

Table 1.4A: Model Selection Criterion

	Model Selection Criterion		HL goodness of fit test	
MODELS	**AIC**	**BIC**	**χ^2**	**p-value**
Probit (1a)	1040.1	1118.6	8.66	0.3715
Logit1 (1b)	1039.8	1118.3	9.6	0.2943
Probit (2a)	577.9	656.4	33.29	0.0001
Logit (2b)	561.8	640.3	29.11	0.0003
Probit (3a)	107.6	186.1	0.55	0.9998
Logit (3b)	109.3	187.8	2.9	0.9405
Probit (4a)	92.3	175.7	1.44	0.9937
Logit (4b)	92.7	176.1	5.22	0.7337
Probit (5a)	104.3	182.8	0.46	0.9999
Logit (5b)	106.0	184.5	0.93	0.9986
Probit (6a)	90.0	173.4	1.47	0.9932
Logit (6b)	90.5	174.0	1.96	0.9823

Notes: The yellow shaded cells show the values of χ^2 which are statistically significant. If χ^2 is statistically significant we reject the null hypothesis of no difference between the observed and predicted probabilities, implying that the model does not fit the data well.
Source: Author's calculations

Table 1.5A: Test for Multicollinearity using Variance Inflation Factor (VIF)

Independent/Predictor variables	VIF for General Population case	VIF for Cohort case
Bank account	2.15	2.15
employed	1.21	1.21
Female	1.07	1.07
Age squared	20.97	20.97
Age	1.66	1.66
Income quintiles	1.15	1.15
Education	1.74	1.74
General population	8.44	
Cohorts		8.41
Incumbent	12.68	12.67
Switching costs	3.42	3.43

Notes: The yellow shaded cells show all values where VIF>10 which is an indication of collinearity.
Source: Author's calculations

Table 1.5A: Marginal effects estimated from the Logit model of Mobile Money Adoption with Network Effects and Switching Costs

SCENARIOS/MODELS VARIABLES	**(1)** Mobile Money	**(3)** Mobile Money	**(4)** Mobile Money	**(5)** Mobile Money	**(6)** Mobile Money
Bank account	0.202***				
	(0.0250)				
Cellphone	0.0618				
	(0.0457)				
Employed	0.0906***	0.0287**	0.0101	0.0285**	0.0101
	(0.0267)	(0.0118)	(0.00826)	(0.0116)	(0.00818)
Female	0.00188	0.0212*	0.00776	0.0212*	0.00780
	(0.0261)	(0.0123)	(0.00835)	(0.0123)	(0.00837)
Age Categories					
25-34	-0.00600	-0.0198	-0.0221*	-0.0199	-0.0221*
	(0.0356)	(0.0156)	(0.0121)	(0.0155)	(0.0120)
35-44	0.00283	-0.0135	-0.0215	-0.0135	-0.0213
	(0.0400)	(0.0183)	(0.0135)	(0.0180)	(0.0134)
45-54	-0.125**	-0.0253	-0.0277**	-0.0251	-0.0272**
	(0.0513)	(0.0273)	(0.0140)	(0.0267)	(0.0138)
55-64	-0.0857	-0.0128	0.000978	-0.0129	0.00120
	(0.0603)	(0.0257)	(0.0239)	(0.0250)	(0.0238)
65+	-0.114*	-0.0467*	-0.0373**	-0.0448*	-0.0364**
	(0.0583)	(0.0246)	(0.0188)	(0.0235)	(0.0182)
Income Quintiles					
Second 20%	0.0593	0.000850	0.0102	0.00122	0.0104
	(0.0467)	(0.0190)	(0.0161)	(0.0184)	(0.0160)
Middle 20%	0.0595	0.00514	-0.00163	0.00541	-0.00140
	(0.0445)	(0.0184)	(0.0156)	(0.0180)	(0.0155)
Fourth 20%	0.115***	0.00330	0.000409	0.00290	0.000319
	(0.0439)	(0.0161)	(0.0123)	(0.0158)	(0.0122)
Richest 20%	0.195***	0.0128	0.0100	0.0125	0.00996
	(0.0449)	(0.0178)	(0.0152)	(0.0175)	(0.0152)
Education					
Secondary	0.138***	0.0138	0.00352	0.0131	0.00351
	(0.0343)	(0.0180)	(0.0113)	(0.0173)	(0.0111)
Tertiary	0.166***	0.0209	0.0106	0.0196	0.0103
	(0.0503)	(0.0201)	(0.0109)	(0.0192)	(0.0108)
Coats					
Switching Costs		0.343***	0.210***	0.322***	0.200***
		(0.0386)	(0.0443)	(0.0373)	(0.0426)
Network effects variables					
General Population network effects for mobile money		0.0550***	0.0253***		
		(0.00532)	(0.00537)		
Network effects for Incumbent Money			-0.0163***		-0.0155***
			(0.00191)		(0.00182)
Cohort network effects for mobile money				0.0528***	0.0246***
				(0.00523)	(0.00530)
Observations	1,000	1,000	1,000	1,000	1,000

Notes: Values in the parentheses are standard errors. ***, ** and * indicate that the corresponding coefficient is statistically significant at 1 percent, 5 percent, and 10 percent, respectively.
Source: Author’s computations using Global Findex survey (2017)

8. APPENDIX B

B1. Imputing Household Consumption for quintiles using the Household Expenditures Survey, and Global Findex Survey

The annual household consumption across different population cohorts (h ={financially excluded, banked only, mobile money, and both account holders}) and quintiles (q = {poorest, second, middle, fourth, and richest}) are computed as follows:

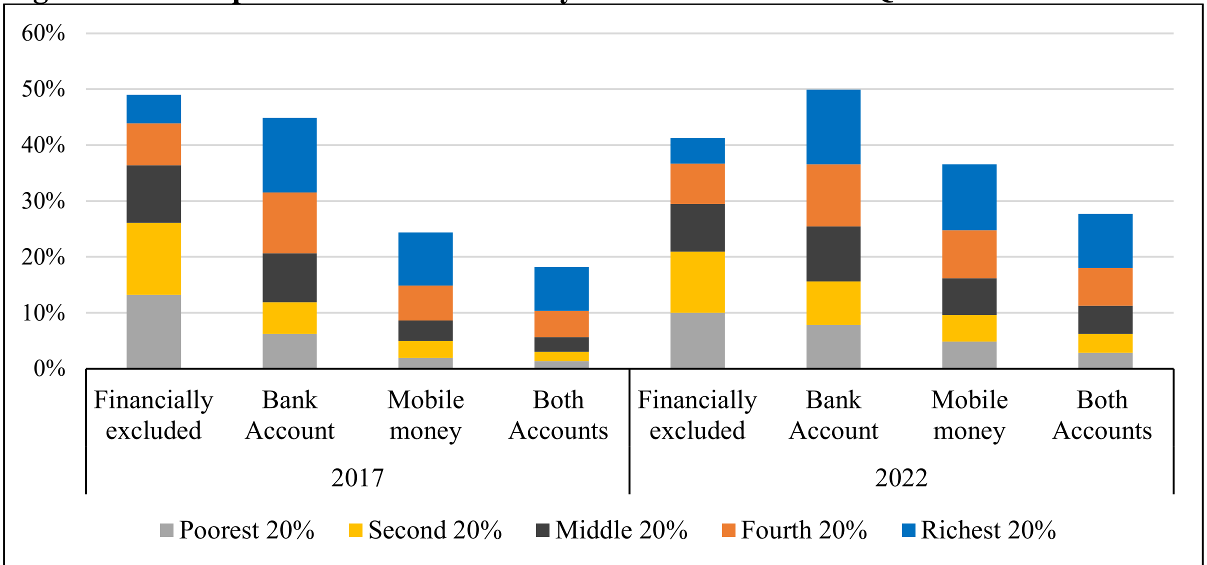
Household consumption for cohort h following the Global Findex Survey is calculated as:

$$C_{it}^{h} = 12\sum_{i=1}^{N} z_{iq}^{h}\, C_q = 12[z_{i,poor}^{h} C_{poor} + z_{i,second}^{h} C_{second} + z_{i,middle}^{h} C_{middle} + z_{i,fou}^{h} \quad C_{four} \quad + z_{i,rich}^{h} C_{ric}\ ]$$

where z_{iq}^{h} is the number of households i in quintile q and belonging to cohort h, and C_q is the average monthly household consumption for each quintile. So annual data requires multiplication by 12.

The Global Findex survey categorises the population into cohorts and income quintiles (**Figure 1.1B**). We then use the Household Expenditure Survey to generate the average monthly expenditure values for each quintile (**Table 1.1B**), and map this information into the Global Findex survey to estimate how much each cohort consumes on an annual basis.

Figure 1.1B: Proportion of Households by Cohorts and Income Quintiles in Botswana



Notes: Income quintiles is a measure of income distribution whereby households are divided into five groups with an equal number of people according to their disposable income. The first quintile represents the lowest or poorest 20% of income earners, and the fifth quintile represents the highest or richest 20% of income earners.
Source: Authors computations from Global Findex Surveys.

Table 1.1B: Average Monthly Household Consumption Expenditure (in Pula) in Botswana

	BMTHS 2015/16		
Quintiles	**Minimum**	**Maximum**	**Mean**
Poorest 20%	312.33	802.87	582.42
Second 20%	803.02	1373.55	1073.53
Middle 20%	1374.03	2312.68	1802.24
Fourth 20%	2314.79	4503.56	3250.58
Richest 20%	4504.84	475218.30	12114.48
Total			**3927.43**

Notes: Pula (BWP) is Botswana's official currency, and an exchange of GBP1 is approximately BWP16.
Source: Author's calculations from Household Income and Expenditure Surveys known as Botswana Multi-Topic Household Survey (BMTHS, 2015/16).

We, therefore, combine the results in **Figure 1.1B** and **Table 1.1B** to calculate each household's annual average consumption expenditure conditional on their cohort and quintile.

B2. Data Sources for Macroeconomic Variables used in Figure 3.2

Summary of Variables: Definition and Sources

Variables	Definition	Statistical Source
Cash Use		
Cash-based consumption	Household consumption minus cash payment substitutes, such as EFTPOS and Mobile money, to household consumption.	BoB, Botswana's Mobile Network Operators, and own calculations
Cashless Transactions		
Mobile Money at POS	The value of mobile money transitions at the point of sale.	Botswana's Mobile Network Operators
Bank cards at POS	The value of bank (both debit and credit) card transactions at the point of sale.	BoB
Other Variables		
Household consumption	Household final consumption of goods and services.	BoB

Source: Author's elaborations.