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Abstract

This thesis consists of three chapters on economic development in sub-Saharan Africa. The first two chapters investigate financial inclusion in the region, specifically analyzing the impact of access to savings and credit through a digital financial tool called Mobile Money. The third chapter examines methods for making inferences using the Demographic Health Surveys (DHS) for rural West Africa.

For the past two decades, mobile money, a cellphone-based payment infrastructure, has been the key player in bringing financial services to the unbanked in developing economies. It provides a means for saving and has been widely used to make peer-to-peer (P2P) transfers, shown to be important in helping households deal with bad shocks. Recently, lenders in developing countries have used mobile money to extend digital credit loans to a wider population including the unbanked.

In Chapter 2, I use unique administrative data on mobile money transactions, to examine the impact of mobile credit on mobile money use. Using an event-study difference-in-differences approach, I observe statistically significant declines in P2P transfers in the first, 3 months following the initial take-up of mobile money loans. The most substantial impact occurs in the third month, with a 95% confidence interval indicating a 14% to 31% decrease in the number of transfers sent and a 16% to 34% decrease in the number of transfers received. This decline in the volume of P2P transfers made is associated with a decline of similar magnitude in the number of unique accounts with which transfers are made. This effect is solely driven by borrowers who become delinquent in repaying their loans. I argue that the results are driven by the repayment enforcement mechanism which allows garnishment of mobile money wallets, causing borrowers to avoid using mobile money until their debt is fully repaid.

In Chapter 3, I examine the role of mobile money as a savings tool in both formal and informal savings practices in Kenya. Using ownership of multiple SIM cards as an instru-

ment for M-Pesa savings, I find that M-Pesa savings have a statistically significant impact on ROSCA participation and bank savings. However, I find no evidence of an impact of M-Pesa saving on SACCO participation nor on savings done at home. Under the assumption of the usual exact IV exclusion restriction, I obtain a 95% confidence interval of 22% to 99% increase in ROSCA participation and a 20% to 75% increase in bank savings. The impact of M-Pesa savings on ROSCA participation is still statistically significant even when allowing for a violation of the exclusion restriction up to a direct effect of 6% (approximately 50% of the effect of a rural-urban dummy differential on ROSCA participation). Additionally, the impact of M-Pesa savings on bank savings remains statistically significant under violation of the exclusion restriction up to a direct effect of 5% (approximately 60% of the effect of a rural-urban dummy differential on bank savings).

Chapter 4, written in co-authorship with Aldo Sandoval Hernandez, uses data from Northern Nigeria and a linear model of mother's education predicting child's vaccination index to demonstrate the presence of spatial dependence in the Demographic Health Surveys and illustrate its importance for inference. We then review the performance of different methods of inference that account for spatial dependence within a Monte Carlo simulation experiment where outcomes are simulated to have the same spatial correlation structure as identified in the DHS data. We find heteroskedastic-robust standard error estimators as well as clustered standard errors with small clusters over reject the true null. Conley's (1999) estimator with a uniform kernel performs well at low-distance cutoffs but breaks down at longer-distance cutoffs. Bester Conley and Hansen (2011) clustered standard errors with large clusters defined by latitude and longitude coordinates perform well but can be conservative with 3 groups. Finally, clustered standard errors using Nigerian states perform surprisingly well and are less conservative than BCH with 3 groups.

Keywords

Mobile money, digital credit, savings, hypothesis testing, confidence interval

Summary for Lay Audience

My thesis is comprised of three chapters on economic development in sub-Saharan Africa. The first two chapters investigate financial inclusion in the region, specifically analyzing the impact of access to savings and credit through a digital financial tool called Mobile Money. The third chapter examines methods for making inferences using the Demographic Health Surveys (DHS) for rural West Africa.

Mobile money, a cellphone-based payment infrastructure, has played a crucial role in bringing financial services to the unbanked in developing economies over the past two decades. Initially introduced as a means of storing money electronically and providing a fast, cheap, and easy way to transfer money across distances, mobile money quickly gained traction. In regions where most individuals had limited access to financial services and relied heavily on informal transfers, it soon became a popular means for saving and making peer-to-peer (P2P) transfers. Building on its success, mobile money providers expanded their range of services beyond savings and P2P transfers to include a diverse set of other financial services. One of the most common of these new services was the digital credit product. Mobile money credit has since grown in popularity and is considered transformative for the credit market in developing countries.

In Chapter 2, I use unique administrative data on mobile money transactions from Ghana, to study the impact of mobile money credit on mobile money use. Several studies have shown that mobile money use, particularly for P2P transfers, has a positive impact on households. However, I observe statistically significant declines in P2P transfers in the first, 3 months following the initial take-up of mobile money loans. The most substantial impact occurs in the third month, with a 95% confidence interval indicating a 14% to 31% decrease in the number of transfers sent and a 16% to 34% decrease in the number of transfers received. This decline in the volume of P2P transfers made is associated with a decline of similar magnitude in the number of unique accounts with which transfers are made. This

effect is solely driven by borrowers who become delinquent in repaying their loans. I argue that the results are driven by the repayment enforcement mechanism which allows garnishment of mobile money wallets, causing borrowers to avoid using mobile money until their debt is fully repaid.

In Chapter 3, I examine the role of mobile money as a savings tool in both formal and informal savings practices in Kenya. Using ownership of multiple SIM cards as an instrument for M-Pesa savings, I find that M-Pesa savings have a statistically significant impact on ROSCA participation and bank savings. However, I find no evidence of an impact of M-Pesa saving on SACCO participation nor on savings done at home. Under the assumption of the usual exact IV exclusion restriction, I obtain a 95% confidence interval of 22% to 99% increase in ROSCA participation and a 20% to 75% increase in bank savings.

In Chapter 4, I focus on examining various methods of inference with the DHS data from rural West Africa. The DHS is an important source of data for empirical research across several countries. And just like in any study, there are likely to be unobservable factors that are correlated across observations, at least for those sufficiently close to each other. Researchers using DHS employ a variety of methods of inference to account for the possible spatial dependence, however, different methods of inference can produce substantially different results making it difficult for the researcher to choose an inference method. This chapter shows the results of a Monte Carlo simulation conducted using a model that is calibrated to match the DHS dataset from northern Nigeria to evaluate the performance of various methods of inference that allow for spatial dependence across observations.

Co-Authorship Statement

This thesis contains material co-authored with Aldo Sandoval Hernandez. All the authors are equally responsible for the work which appears in Chapter 3 of this thesis.

Dedication

To my late brother, Nana Banafo Cornelius, and my late grandmother, Helena Commey.

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Chapter 1

1 Introduction

This thesis consists of 3 chapters on economic development in sub-Saharan Africa. The first 2 chapters focus on financial inclusion. In particular, these chapters examine the role of mobile money as a savings tool and as a means of obtaining credit. The third chapter focuses on the methods of inference with the Demographic Health Survey (DHS) in the rural West African context.

Access to financial services as of 2012 was limited in developing economies. According to the World Bank Global Findex report, only 41% of adults in developing economies reported having access to a formal financial service, with the majority of the unbanked in sub-Saharan Africa Demirg uç-Kunt and Klapper (2012). Without access to formal financial services individuals and households relied on informal savings and credit tools as well as informal transfers to and from their friends and families.

In contrast to financial services, mobile phones were rapidly adopted in sub-Saharan Africa, driving the development of mobile money. Since its introduction in Kenya in 2007, mobile money has seen widespread use for transfers within social networks. Extensive research highlights its critical role in helping households share risk and has found mobile money savings to empower users, particularly women, to resist intra-household sharing pressures Jack and Suri (2014); Munyegera and Matsumoto (2016); Riley (2018, 2022). However, the impact of mobile money savings on existing financial tools remains unclear. Additionally, mobile money has recently expanded to include digital credit, revolutionizing access to credit by addressing key challenges faced by traditional providers Robinson et al. (2023). This expansion raises questions about whether extending services beyond transfers and savings will further increase mobile money usage and accelerate the digitization of payments. I address these questions in the first two chapters of my thesis.

Chapter 2 investigates the impact of mobile money credit on mobile money transfers. I employ a difference-in-differences design to estimate the impact of mobile money credit on mobile money transfers. I observe statistically significant declines in P2P transfers during the first, second, and third months after the adoption of mobile money credit with the magnitude of the decline increasing with relative time. In the third month post-adoption, I estimate a 95% confidence interval suggesting a 14% to 31% decrease in transfers sent and a 16% to 34% decrease in transfers received. This reduction in transfer volume is associated with a decline in the number of accounts used for transfers, also intensifying over time. The estimated 95% confidence interval indicates a 14% to 30% decline in the number of unique accounts transfers are sent to and a 17% to 34% decline in the number of accounts transfers are received from. Moreover, I find that the results are driven solely by loan adopters who are eventually delinquent in the repayment of a loan obtained within the period of observation.

Chapter 3 addresses the first question. In this chapter, I examine the interaction between mobile money savings and other financial tools. I investigate the impact of M-Pesa, the leading mobile money service in sub-Saharan Africa and the first of its kind in the region, on the usage of other financial services in Kenya. M-Pesa's widespread adoption in Kenya has been extensively documented by Jack et al. (2013). To investigate the influence of saving with M-Pesa on the utilization of various saving tools, I analyze data from a comprehensive panel survey of Kenyan households conducted by Suri (2017). Specifically, I focus on the most prevalent formal and informal savings tools within the dataset. The formal saving tools studied are banks and Savings and Credit Cooperatives (SACCOs), while informal savings tools studied are Rotating Savings and Credit Associations (ROSCAs) and savings kept at home. Using the instrumental variable approach I find a statistically significant positive effect of M-Pesa savings on ROSCA participation and bank savings that lie within a 95% confidence interval of 22% to 98% and 20% to 75% respectively.

Chapter 4, focuses on the broader issue of making inferences with one of the most commonly used datasets for studies on sub-Saharan Africa, the DHS. By collecting data on geographic locations, this dataset presents a unique opportunity to explore the role of spatial dependence across observations in the survey. In this chapter, a non-parametric test is used to demonstrate the existence of spatial dependence in the DHS using data from northern Nigeria and a linear model predicting vaccination index by mother's education. It also shows that various methods of inference with different tuning parameter choices produce substantially different results. Finally, using a Monte Carlo simulation experiment to evaluate the performance of various methods of inference that allow for spatial dependence across observations, recommendations are made for the use of the Bester et al. (2011) method of inference with 6 to 12 clusters defined by latitude-longitude strips. In the event that access to reliable data on geographic coordinates is lacking, the Bester et al. (2011) approach with states is a viable option specifically for the northern Nigeria context.

Chapter 2

2 Digital Credit and Digital Transfers: The Unintended Consequences of Mobile Money Digital Credit in Ghana

Mobile money, a cellphone-based payment infrastructure, has emerged as a catalyst for the digitization of payment systems across numerous developing economies (Demirgüç-Kunt et al., 2022).[1] Since its inception, it has garnered widespread adoption as a method for conducting transfers within one's social network and is also used to make retail payments (Suri, 2017). Extensive research underscores the pivotal role of these mobile money transfers in enabling households to insure against bad shocks (Jack and Suri, 2014; Munyegera and Matsumoto, 2016; Riley, 2018). However, despite the rapid proliferation of mobile money usage, cash remains the dominant payment mode, even for informal transfers. There is a growing acknowledgment of the necessity to diversify the array of financial services offered through the mobile money platform to fully realize the payment digitization agenda in developing economies. This diversification is widely believed to be a critical step in advancing the comprehensive digitization of payment systems in the region.

In 2012, mobile money first expanded its offering of financial services to include digital credit, ushering in a transformative era in the credit markets of developing countries. Mobile money's digital credit has the potential to revolutionize access to credit in an unprecedented manner. These credit products hold particular promise due to the widespread adoption of mobile money in the region, addressing two primary challenges faced by traditional credit providers. First, the issue of information asymmetry is mitigated by leveraging

[1] Digital payments include the use of a mobile money account, a debit or credit card, or a mobile phone or the internet to send money to relatives or friends or to pay bills make in-store or online merchant payments; paying utility bills; sending or receiving domestic remittances; receiving payments for agricultural products; or receiving wages, government transfers, or a public pension directly from or into an account.

novel data on cellphone usage, enabling lenders to assign credit scores even to individuals without a banking history. Second, the high administrative costs associated with traditional credit provision are effectively tackled by adapting the mobile money infrastructure for loan disbursement and repayment. However, like the introduction of any formal financial service, the interaction between mobile money digital credit and existing financial services remains ambiguous. In this study, I explore the impact of the adoption of mobile money digital credit in Ghana on the use of mobile money services.

The mobile money digital credit product I study, Qwikloan, is the first and most popular mobile money credit product in Ghana. It is operated by Mobile Telecommunications Network (MTN) which is the largest mobile network operator (MNO) in the country and which also has the largest share of the Ghanaian mobile money market.[2] The take-up of the Qwikloan product has been remarkable, with over 1 million accounts receiving loans within a year of its launch. The loan is advertised as an unsecured 30-day loan, ranging from 25 to 1,000 Ghana Cedis (GHS) that can be obtained within a few minutes via mobile money. It carries a 6.9% facilitating fee, with a 12.5% delay fee imposed on the remaining balance. The mobile money provider makes several efforts to maximize repayment including garnishing the delinquent borrower's mobile money wallet until the outstanding debt is repaid.

Ever since its introduction, the most frequent use of mobile money has been for interpersonal transfers referred to as peer-to-peer (P2P) transfers. The Financial Insight Survey conducted in 2014 with a nationally representative sample found that 96% of Ghanaian mobile money users adopted it to make P2P transfers. However, since its introduction, the digital credit feature on the platform has quickly gained popularity in Ghana as in other developing countries.[3] Digital credit products are expected to improve the lives of many by

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[2]Qwikloan was developed through a collaboration between Letshego (a non-banking financial institution previously known as Afb), MTN-Ghana a mobile money provider, and Jumo (a financial solutions company).

[3]Suri et al. (2021) documented a high take-up of M-Shwari digital credit in Kenya, and in Ghana, over 5 million loans were disbursed within the first year of the launch of Qwikloan.

expanding their access to credit and further integrating them into the financial system.

Examining how P2P transfers change in response to the adoption of mobile money loans will shed light on the role of digital credit in fostering the digitization of interpersonal transfers. Additionally, as P2P transfers represent the most widely used mobile money service, this study will also offer insights into the effects of mobile money loans and the utilization of mobile money at the intensive margin. While ideally, we would measure the effect on all transfers, data limitations prevent this. However, studies by Jack and Suri (2014), Riley (2018), and Munyegera and Matsumoto (2016) show a strong positive correlation between mobile money use and informal transfers, suggesting that the impact on P2P transfers is informative about the potential effect on informal transfers.

Studies on emerging digital credit in developing economies are limited and mostly investigate the direct impact on borrowers' welfare. [4] though Suri et al. (2021), Brailovskaya et al. (2021) and Björkegren et al. (2022) estimate welfare impacts along with the impact of total informal transfers. I add to these studies by analyzing the impact of mobile money digital credit on the use of mobile money for informal transfers in Ghana a country that relies heavily on informal transfers.

For my analysis, I use a unique administrative dataset from MTN of randomly sampled mobile money accounts active as of August 2021. The dataset includes all incoming and outgoing P2P transfers as well as Qwikloan transactions going as far back as January 2016. The data excludes accounts that became inactive before August 2021 which introduces survival bias into the analysis. I employ a difference-in-differences design to estimate the impact of these loans. In any given period, I define an account as treated if they make their first Qwikloan transaction in that period. I then assign as control the accounts that have the same qualifications as the treated group but only make their first Qwikloan transaction

[4] Brailovskaya et al. (2021) find no harmful effects though borrowers in Malawi are typically late in repayment while Suri et al. (2021) find they help households become resilient to bad shocks.

4 months later.[5] I estimate the effect of initial loan adoption by comparing the changes in mobile money usage between the treated group and the control group. This methodology identifies the average treatment effect of loan adoption under the assumption that changes in the outcomes of future loan adopters serve as a good estimate for the changes in the outcomes of the current loan adopters in the absence of loan adoption (parallel trends).

I observe statistically significant declines in P2P transfers during the first, second, and third months after adoption with the magnitude of the increasing with relative time. In the third month post-adoption, I estimate a 95% confidence interval suggesting a 14% to 31% decrease in transfers sent and a 16% to 34% decrease in transfers received. This reduction in transfer volume is associated with a decline in the number of accounts used for transfers, also intensifying over time. The estimated 95% confidence interval indicates a 14% to 30% decline in the number of unique accounts transfers are sent to and a 17% to 34% decline in the number of accounts transfers are received from. Moreover, I find that the results are driven solely by loan adopters who are eventually delinquent in the repayment of a loan obtained within the period of observation. I find no evidence of changes in the P2P transfers by adopters who are never delinquent in repaying a loan.

There are three possible explanations for why loan adoption could result in a decline in P2P transfers, particularly for delinquent borrowers. First, the incidence of bad shocks. Given that loan adoption is an endogenous decision, it is possible for loan adopters to be more likely to had experienced a bad shock which could decrease their ability to make transfers and even repay their loans. Second, loan adopters could be liquidity-constrained possibly due to their use of loans for lumpy expenditures or investments thereby decreasing their ability to make transfers. Lastly, delinquent loan adopters may avoid using their mobile money accounts to avoid any automatic deduction from their mobile money accounts in repayment of their outstanding debt. These mechanisms are not mutually exclusive.

[5] The qualifications are that the account owner must be 18 years or older and must have had an active mobile money account in the past 90 days

Under the assumption that borrowers of large amounts are likely to use their loans to make lumpy purchases, I explore the heterogeneous impacts of loan adoption by loan size. I find no difference in the response of the P2P transfers of borrowers of larger amounts and that of borrowers of smaller amounts. Without data on bad shocks, I investigate the role of bad shocks by comparing results with established results on the response of informal transfers to bad shocks from the literature on mobile money and show that the decline in P2P transfers is unlikely to be driven solely by bad shocks. I argue that delinquent borrowers decrease their mobile money activity to avoid automatic deductions from their money wallet. It is important to note however that bad shocks could increase the likelihood of delinquency such that the obtained result could be partly due to bad shocks and partly due to the fear of automatic loans deductions.

Though mobile money digital credit is expected to bring digital payment via mobile money, this study does not find that to be the case. Rather, I find that loan adoption leads to an unintended decline in mobile money activities. This study suggests that the penalties associated with delayed repayment cause borrowers to refrain from using their mobile money accounts when they have an outstanding debt. It is important to note that the survival bias introduced in the dataset by including only accounts that remain active at the time of extraction may result in an underestimation of the impact of loan adoption. One can reasonably assume that by excluding dormant mobile money accounts, I may be excluding delinquent borrowers who drop out of mobile money altogether to avoid loan repayment resulting in an underestimation of the impact of loan adoption on P2P transfers. Given the importance of access to mobile money P2P transfers for consumption smoothing, the obtained results suggest possible negative implications for the welfare of delinquent borrowers and members of their social network.

The remainder of this paper is organized as follows. In Section 2, I provide an overview of the literature related to this study, I describe the mobile money market in Ghana and provide background on the digital credit product in Section 3. Section 4 lays out the estimation strategy while Section 5 describes the data used in this study. Section 6 presents the main results of the study and Section 7 analyzes the potential mechanisms. In Section 8, I analyze a key identifying assumption (homogeneity). Section 9 provides concluding remarks are provided.

2.1 Related Literature

This study contributes to the literature on mobile money and digital banking. There is a large body of work on the impact of mobile money transfers however there are few studies on mobile money credit and digital credit. Suri et al. (2021) find a mobile money credit product in Kenya improved households' ability to cope with shocks without crowding out informal transfers while Brailovskaya et al. (2021) found no negative impact on the financial well-being of borrowers in Malawi and no evidence of loan substitution for existing sources of credit. Suri et al. (2021) and Brailovskaya et al. (2021) results may contrast the implications of this study, however, the context of their findings is important to understand as it may shed light on the different implications of those studies. The loan sizes in this study are larger than those of the studies mentioned. The average loan size conditional on taking a loan in this study is GHS 258 (US$51) which is 10 times that of Suri et al. (2021) (US$4.8) and about 9 times that of Brailovskaya et al. (2021) (US$5.7). In addition, the loan products in Kenya and Malawi studied do not garnish the mobile money wallets of delinquent borrowers, rather they make automatic deductions from separate savings accounts that are linked to their loan accounts.

This paper is also related to the literature on how the introduction of a formal financial institution affects social networks. Fernando (2021) study mobile-based agricultural extension services and find that while it reduces reliance on peers for agricultural advice, there is no negative impact on peer interaction, but rather, users find that their interactions in their social network are being prioritized. Comola and Prina (2021) also document a change in financial networks in response to access to savings accounts. Binzel et al. (2013) who show that formal financial access leads villagers to increase formal borrowing and reduce informal borrowing and gift exchange within the village, and that of Banerjee et al. (2021) who show access to formal credit to have a negative impact on willingness to demand and supply informal loans. Our results on decreased P2P transfers are indicative of a change in the channels with which transfers are made within social networks which also has implications for the cost and distance from which transfers may be made given that mobile money transfers facilitate cheaper and faster informal transfers for further geographic locations. Though this study does not capture the entire social networks of individuals or communities, in Ghana mobile money transfers are 60 percent of all transfers by the average individual. A decline in mobile money transfers could imply an overall decline in transfers within social networks.

This paper also contributes to microcredit literature on the effect of product characteristics. This research typically focuses on the response of loan repayment to different features of the loan product. Karlan et al. (2015) find that text message reminders reduce delinquency, Feigenberg et al. (2013) show that frequent microfinance group meetings decrease loan default while Field et al. (2013) find that giving a grace period for loan repayment increases default. Burlando et al. (2022) investigates the impact of the speed of digital loans on loan repayment and finds that doubling the delivery time decreases loan default. However, this study is directly related to the papers that analyze the impact of dynamic incentives which involve promises of future loans to secure current loans or exclusion from the credit market in the event of loan default. Karlan and Zinman (2009) finds that the promise of a new loan reduces defaults on the current one and Giné et al. (2010) shows that the threat of credit denial decreases default. However, the loan product in this study in addition to dynamic incentives includes an additional penalty for delayed repayment which is garnishing the mobile money account until the loan is repaid. This has the impact of decreasing the use of the mobile money platform for transfers by delinquent borrowers.

2.2 Background

In 2007, to encourage the digital financial service sector and promote cashless payment in Ghana, the Ghana Interbank Payment and Settlement Systems Limited (GHIPSS) was established by the Bank of Ghana to manage an interoperable payment system infrastructure for banks and other financial institutions. As part of its operations, GHIPSS developed a smart card e-Zwich for payments, which is connected to all financial institutions in the country. At the time, about 80% of the country's population was unbanked, so to encourage adoption, the requirement for obtaining an e-Zwich account was limited to just a thumbprint. The e-Zwich card functioned as a debit card without requiring the user to have a bank account. One could load cash onto their card at specific station points or could link their card to their bank accounts. The e-Zwich did not perform as expected due to various challenges with the adoption and use of the POS systems.

In 2008 the Ghanaian central bank introduced the Branchless Banking Guidelines to encourage deposit-taking financial institutions to extend financial services to the unbanked via branchless banking. To provide branchless banking services agents were needed to distribute limited stand-in banking services, so financial institutions partnered with mobile network operators who recruited vendors of their airtime as agents. The role of the telecommunication industry was restricted to only that of an agent, leaving the financial institutions as the sole providers of financial services. Since there are only a few MNOs and several banking institutions, MNOs were required by the Bank of Ghana to partner with at least three banking institutions to bring branchless services to the unbanked.

In this vein, MTN the largest mobile service provider in Ghana, partnered with nine banks and introduced mobile money services in Ghana in July 2009. All mobile money accounts created with MTN agents were linked to one of the nine partner banks. Each mobile money account opened with an MTN agent represented an account with one of the nine banks that the agent was assigned to. MTN heavily promoted the product and broadened its reach within the unbanked communities by extending its network of agents geographically. Within three months MTN had registered over 20,000 mobile money accounts. Other MNOs followed suit and partnered with other banks to provide their own mobile money services. Togo Cash was launched in 2010, Airtel Money in 2011, and Vodafone Cash in 2015. In 2017, the MNOs Airtel and Tigo merged and therefore merged their mobile money services. Despite the growing popularity of mobile money, the scale of the service was limited because operational decisions remained with the deposit-taking institution and these institutions had little incentive to invest in their branchless service due to the free rider problem associated with the many-to-many partnership with MNOs. The MNOs found themselves trying to convince multiple reluctant partners to make unanimous decisions regarding mobile money (Mckay and Zetterli, 2013).

In 2015, the Bank of Ghana updated the Banking Guidelines to include guidelines for electronic money (e-money) issuers and agents. The updated guideline introduced the status of Dedicated Electronic Money Issuer (DEMI) which when granted, allowed any organization to issue e-money. To get around the Branchless Banking Guidelines on the role of the telecommunication industry, MNOs obtained the DEMI status which allowed them to issue e-money without linking each mobile money account to a bank account. The telecommunications industry no longer served as agents for the banks, but rather, they became the principal in their relationship with customers, having their own clients and making their own operational decisions. New relations then formed between telecommunication organizations and specific banks where every e-money issued by the telecommunication company was backed by cash stored in an account with the partner bank.

With the e-money regulations in place, mobile money took off in Ghana at a rapid pace such that the country became the fastest-growing mobile money market in 2020. As of 2021 about 60% of adults in Ghana reported having mobile money accounts. While the mobile money markets in many sub-Saharan African economies are characterized by a significant gender gap, women in Ghana are just as likely as men to have a mobile money account as of 2021 (Demirgüç-Kunt et al., 2022).

When mobile money was introduced in Ghana it was marketed as a means of making transfers to friends, and relatives who live elsewhere within the country. It was therefore widely adopted for that purpose. It quickly became one of the most common ways of sending and receiving remittances (The Financial Inclusion Insights Survey, 2014). MNOs then started introducing other financial services over their mobile money platform. These services include loans, insurance, and pension products. One of the most successful mobile money products introduced in Ghana is Qwikloan which was introduced in 2018 through a partnership between MTN and Afb (later acquired and renamed as Letshego Ghana Savings and Loans) a credit institution that specialized in providing loans to government and quasi-government workers in Ghana. This mobile money digital loan comes on the heels of similar mobile money products introduced by peers in East Africa. Qwikloan is a 30-day unsecured loan facility created to help users access loans. The first loan obtained ranges from GHS 25 (US$ 5) to GHS 1000 (US$ 200). Over time, as an individual continues to repay their loan on time their credit limit can grow significantly. Each loan has an interest rate of 6.9% and any delayed payment results in an additional 12.5% penalty.

To be eligible for a loan one must be 18 years or older, a registered MTN customer, and must be an active mobile money user which means they must have sent or received a mobile money transfer within the past 90 days. In addition, one must meet the credit score criteria (i.e. having a credit score that exceeds the strict cutoff). Only one loan can be held at a time, and when the loan application is approved, the customer receives a text message indicating the principal amount, the repayment amount, the interest rate, and the due date. To repay the loan, a customer can manually transfer money to their loan account before the due date or wait till repayment is automatically deducted from their e-wallet on the due date or after (money will be automatically withdrawn from the mobile wallet until repayment is complete). In 2018, over a million customers adopted Qwikloan. According to the financial records of Letshego, a gross advance of GHS 229 million was made from Qwikloan in 2018 (US$ 45.8 million), GHS 182 million (US$ 36.4 million) in 2019, GHS 170 million (US$ 34 million) in 2020, and 375 million (US$ 75 million) in 2021.

2.3 Estimation Strategy

The main challenge in evaluating the effect of loan adoption on various outcomes of interest is estimating the counterfactual outcomes in the absence of loan adoption. I leverage the variation in the timing of loan adoption to construct a treatment and control group at each period to identify the counterfactual outcomes and estimate the treatment effect using a difference-in-differences event study approach. In this study, an account is considered as treated when it receives its first loan. The event-study approach evaluates the changes in outcomes within a 7-month window around loan adoption events.

This study relies on administrative data on mobile money transactions from January 2016 to August 2021 obtained from MTN which includes all P2P transfers made by sampled accounts and Qwikloan transactions. A detailed description of the data set is provided in Section (2.4). I aggregate the data for each account at the monthly level and each month corresponds to a cohort c of accounts that are assigned as treated or controlled based on their month of loan adoption. I define the treated group M_c in cohort c to include mobile money accounts that adopt Qwikloan in month c and the control group N_c to include active mobile money accounts in month c that adopt Qwikloan 4 months after month c.[6] The control account is defined in this manner to ensure they are comparable in observed characteristics as the treated accounts. To do this, the control accounts are selected to be

[6]This means that the control group in cohort c will be assigned as treated in cohort $c + 4$.

sufficiently close to the treated accounts in the loan adoption date yet sufficiently far apart in the adoption date to ensure a period where the control is not yet treated. I then create separate datasets for each cohort containing data on outcomes and characteristics of only the treated and control groups of that cohort.

Let Y_{it} represent the outcome of account i at time t. For each cohort, c, and for a given monthly lag τ, the effect of loan adoption τ months from the month of adoption is identified as

$$\mu_{c,\tau} = \underbrace{\mathbb{E}[Y_{i,c+\tau} - Y_{i,c-1}|i \in M_c]}_{\text{Change for treated}} - \underbrace{\mathbb{E}[Y_{j,c+\tau} - Y_{j,c-1}|j \in N_c]}_{\text{Change for control}}. \tag{2.1}$$

For each cohort corresponding to months from March 2018 to February 2021, the above treatment effect at each monthly lag from adoption $\tau \in \{-3, -2, 0, 1, 2, 3\}$ are estimated separately using the standard 2-by-2 difference-in-differences model comparing differences in outcomes a month before loan adoption and τ months after loan adoption.[7]. This estimation approach relies on the assumption that the changes in the outcomes of the control group are a good counterfactual for changes in the outcomes of the treated group, commonly referred to as the parallel trends assumption.

The treatment effect τ months after adoption within cohort c is estimated using the regression specification

$$Y_{it,c} = \alpha_{i,c} + \gamma_{t,c} + \mu_{c,\tau} D_{it,c}(t = c + \tau) + \varepsilon_{it,c} \tag{2.2}$$

where $Y_{it,c}$ is the outcome variable of interest for account i in cohort c at time t (measured in months), $D_{it,c}(t = c + \tau)$ is an indicator that account i in cohort c at time t was treated

[7]I exclude cohorts corresponding to December 2019 and April 2020 as the sample sizes become too small to obtain reliable estimates. The sample sizes are small due to the fact that very few loans were approved in April 2020 in response to COVID-related restrictions implemented at the time

τ months ago, and $\alpha_{i,c}$ and $\gamma_{t,c}$ are individual-cohort fixed effects and time-cohort fixed effects. This estimation strategy uses the period before adoption (i.e. $\tau = -1$) as the baseline such that the coefficient $\hat{\mu}_{c,\tau}$ in the regression is numerically equivalent to the sample analog of $\mu_{c,\tau}$ in equation (2.1). I estimate the treatment effects for cohorts representing months from March 2018 to February 2021 and for monthly lags K={-3,-2,0,1,2,3} separately, and the results are reported in section 2.7. I omit cohorts for December 2019 and April 2020 due to small sample sizes, which resulted from limited loan approvals amid COVID-related restrictions.

To summarize the treatment effects across cohorts at each monthly lag τ, I estimate a version of equation (2.2) pooled across all cohorts and specified as

$$Y_{it,c} = \alpha_{i,c} + \gamma_{t,c} + \sum_{\tau \in K} \mu_\tau D_{it,c}(t = c + \tau) + \varepsilon_{it,c}. \tag{2.3}$$

The model specification imposes the restriction $\mu_{c,\tau} = \mu_\tau$, that treatment effects are the same across cohorts. I allow the treatment effect to vary with time since adoption, τ.[8]

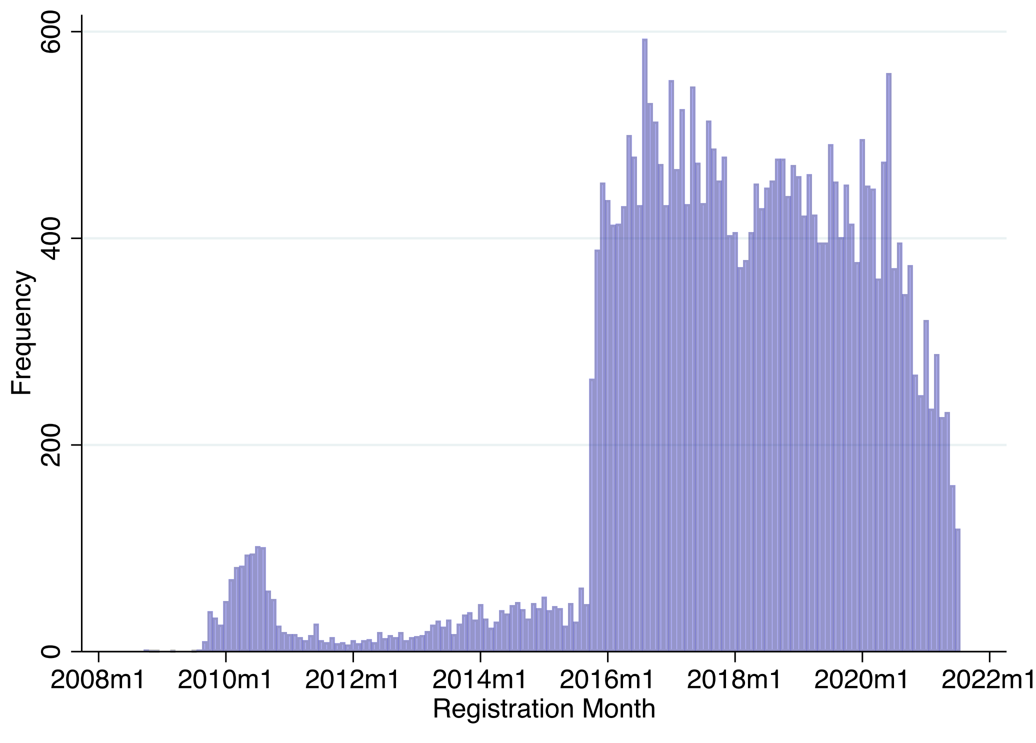
2.4 Data Description

From MTN I obtained two types of administrative datasets on 31,690 randomly sampled MTN mobile customers who were active users at the time of extraction in August 2021 and between the ages of 18 to 60 years in 2016. First, I obtained the Know Your Customer (KYC) dataset which includes information on the date of birth, gender, and the location of registration. Secondly, I obtained mobile money transactional data from January 2016 to July 2021, which provides information on mobile money P2P transfers, Qwikloan transactions, and transactions on other mobile money services including savings and pension. To compare the values of transfers and loans received over the years of observation to house-

[8]This model specification is commonly referred to as the stacked difference-in-differences specification.

hold expenditure I deflate the monetary value of mobile money transactions using annual CPI values from the World Bank.

Figure 2.1: Mobile Money Registration



It is important to note that each mobile money account is associated with a cellphone number. Figure 2.1 shows the enrollment for an MTN mobile money account within the full sample. It shows the distribution of account registration dates. There was a clear explosion in the enrollment for mobile money in the latter part of 2015 in our sample which coincides with the spike in mobile money adoption that occurred in Ghana at that same time resulting from a change in banking regulations that allowed MNOs in Ghana to fully invest in the expansion of mobile money services. Since the take-off in mobile money adoption in 2015, adoption remained high in the data sample also reflecting the persistent growth in mobile money adoption in Ghana as noted by the 2017 and 2021 Global Findex reports (Demirgüç-Kunt et al., 2022). The variation in adoption dates indicates variation in mobile money user experience in our sample. The average account in the dataset has been registered for mobile money services for about 4 years at the time of extraction. An additional feature of mobile money registration in the data sample is that early adoption is driven by male ownership while female account ownership takes off later such that by 2021, almost half of the accounts in our sample are female-owned. This trend aligns with the progression of the gender gap in mobile money account ownership in Ghana (Demirgüç-Kunt et al. (2022)).

By sampling active mobile money accounts as of August 2021, the dataset is characterized by survival bias which increases as one looks further back in time. Ghana's National Communication Authority permits MNOs to reassign a phone number and hence a mobile money account only after that number has remained inactive for half a year. In the case of phone numbers associated with mobile money accounts with pending loan repayments, the phone number can only be reassigned after 12 months. Individuals quit using their mobile money accounts for a myriad of reasons. Some mobile money users quit using their accounts over time to migrate to another mobile money provider or because they no longer require mobile network services[9]. Given that accounts may abandon their mobile money accounts to avoid repaying a loan, the survival bias in the estimation sample may bias an estimated effect of loan adoption on mobile money transactions towards zero.

I construct an estimation sample as described in Section 2.3 The estimation sample consists of mobile money accounts that were registered before 2017 and obtained an MTN Qwikloan between June 2018 and July 2021. It excludes accounts that make payments towards Qwikloan before they ever receive a loan which represents only about 5% of the full data sample. This action is considered an attempt to increase one's credit limit and a clear display of anticipatory behavior. These accounts are excluded due to the confounding effect of anticipatory behavior in identifying the treatment effects.[10]

[9]Some attrition may be due to users who migrate outside of the country or die.

[10]Recall the estimation strategy in this study defines the control group as accounts that will adopt the loan product in the future. Consequently, any anticipatory behavior might be misinterpreted as a treatment effect.

Table 2.1 shows the summary statistics from the full data sample in column 1 and our estimation sample in column 2. The full sample is relatively young, with approximately 55% of participants aged between 18 and 30 as of 2016. Gender balance is evident in account ownership within this sample. Regarding mobile money transfers, the average account in the full sample sent approximately 75 P2P transfers between 2016 and 2021, totaling about GHS 8,818 (US$1,763.6). Additionally, they received a total of 74 transfers, amounting to GHS 8,322.22 (US$1,664.4). On average, each account in the sample sent P2P transfers to approximately 15 unique accounts and received transfers from 15 unique accounts within the observation period. Furthermore, about a quarter of the full sample received digital loans, with the average account receiving approximately 2.4 loans totaling GHS 651(US$130.2).

Table 2.1: Summary Statistics from Administrative Data

	(1) Full Sample		(2) Estimation Sample		(3) Estimation Sample = non-estimation sample
	mean	sd	mean	sd	P-value
Panel A: Age group					
$18 \leq Age \leq 30$	0.55	0.50	0.58	0.49	0.00
$30 < Age \leq 45$	0.32	0.47	0.32	0.47	0.47
$45 < Age \leq 60$	0.13	0.33	0.09	0.29	0.000
Female	0.47	0.50	0.15	0.36	0.000
Panel B: MTN P2P Transfers					
Total value of P2P sent (GHS)	8817.78	34822.98	25810.11	63683.87	0.000
Total value of P2P received (GHS)	8322.22	19950.19	20800.67	32662.76	0.000
Total number of P2P sent	74.52	161.46	207.25	277.97	0.000
Total number of P2P received	73.60	136.94	158.80	218.51	0.000
Unique accounts P2P sent to	14.74	45.36	37.19	80.07	0.000
Unique accounts P2P received from	15.24	50.86	30.51	59.54	0.000
Panel C: MTN-Qwikloan					
Adopt Qwikloan	0.25	0.44	1.00	0.00	0.000
Total value of loans received	651.16	3092.68	3109.64	6520.62	0.000
Total number of loans received	2.44	6.11	10.43	9.65	0.000
Total	31690		3173		

The estimation sample differs from the full sample in several ways since by design accounts that obtain a loan are characteristically different from those that do not. This sample is slightly younger and male-dominated with only 15% of the estimation sample being female. This is a reflection of the existing gender gap in the usage of various mobile money services, despite the closing gender gap in mobile money account ownership in Ghana (Demirgüç-Kunt et al., 2022). In the full dataset, there is a 12.6% gender gap in the adoption of Qwikloan among account owners. Furthermore, accounts in the estimation sample send and receive substantially more P2P transfers than the average account in the full sample as shown in Panel B of column 2. The average account sent 207 P2P transfers worth GHS 25,810.11 (US$5,162.02) and received 159 P2P transfers worth GHS 20,800.67 (US$4,160.13). The average account in the estimation sample also sent and received P2P transfers to more accounts than the average account. They sent transfers to 37 unique accounts and received transfers from 31 unique accounts.

There are two reasons why the estimation sample displays more mobile money activity than the full sample. As mentioned before, more active mobile money accounts are more likely to be eligible for a loan. Secondly, the estimation sample selected was registered before 2017 meaning that on average the owners of these accounts have more experience as mobile money users than the owner of the average account in the full sample. The owner of an average account in the estimation sample has been a mobile money user for 2 years longer than the owner of the average account in the full sample who has only used mobile money for 4 years by the time of data extraction in 2021.

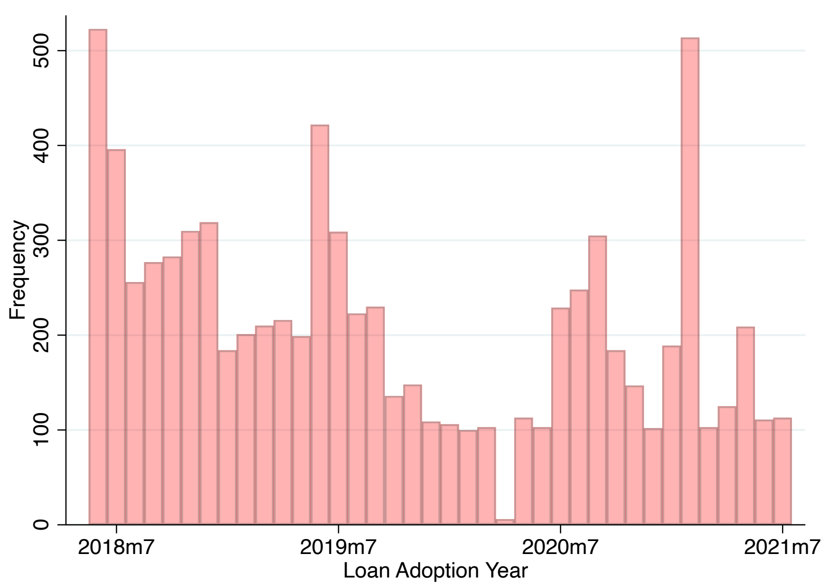
Finally, since all accounts in the estimation sample receive at least one loan during the period of observation, this sample on average receives more loans than the full sample. By July 2021, the owner of the average account in the estimation sample had received about 11 mobile money loans totaling GHS 3,109.64 (US$621.93) since the introduction of the Qwikloan in 2018.

To put these numbers into perspective, it is important to note that, according to the Ghana Living Standards Survey (GLSS 7) in 2017 the average annual household cash expenditure on food was GHS 6,015 (US$1,203), the cash expenditure on education was GHS 3,306 (US$661.2), and the cash expenditure on health was GHS 280 (US$56). This indicates that from the full sample, an average account within the span of 5 years sent enough transfers to cover a household's annual cash expenditure on food in 2017 and received almost as much in return. Most importantly the average loan amount in the full sample is more than 2 times the average annual household expenditure on health in 2017. Furthermore, the average account in the estimation sample obtained a loan value that is about 10 times the average annual cash expenditure on healthcare in 2017, about half the average household cash expenditure on food, and almost equal to the annual household cash expenditure on education.

Figure 2.2, displays a histogram of the month of adoption of Qwikloan within the full sample from June 2018 to July 2021. The figure displays a variation in the rate of adoption from June 2018 to July 2021. Over the period of observation, there have been spikes in adoption occurring in June 2018, June 2019, and February 2021. In figure 2.3 I show the number of loans that were taken each month by their repayment duration; repaid within 30 days (on time), repaid within 60 days, repaid within 90 days, and loans that had not been fully repaid by the 90 day mark after loan disbursement. Note that the loan take-up depicted includes new loan adoption and take-up by previous loan adopters. The drop in loans obtained in April 2020 coincides with the sharp drop in adoption in the same month. The dynamics in the loan take-up observed are consistent with the decline in the gross loan advances of Qwikloan between 2019 and 2020 and a resurgence in 2021 as indicated in the annual reports of Letshego. The data on loans obtained, therefore, is consistent with the dynamics in the demand for loans by the universe of MTN mobile money users.

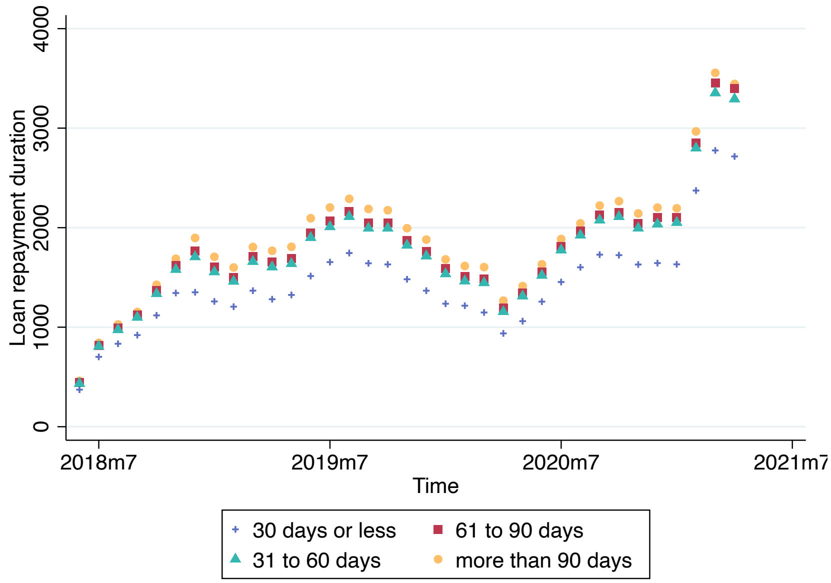
A persistent high repayment rate is an important feature of the data sample in this study as demonstrated in figure 2.3. The percentage of loans repaid within 30 days (on time) ranges between 67.16% to 88.8% with a mean of 75% of all loans taken from the introduction of the loan product being repaid on time. Rate of default defined as the percentage of loans that were not fully repaid within 90 days of disbursement ranges from 1.3% to 7.5%. These default rates are significantly lower than that of traditional loans in Ghana which is reported by the Bank of Ghana as 18%. The rate of default is also lower in comparison to the default rates of similar mobile money digital credit products in Kenya and Tanzania which reported delinquency rates of 50% and 56% respectively (Oppong, 2020). Though Oppong (2020) also reports significantly low default rates of digital loans dispersed in Ghana it is important to note that by sampling only active mobile money accounts, the default rate in the dataset may be biased downwards as loan defaulters may have become inactive mobile money users over the years.

Figure 2.2: Loan Adoption



The average account in the estimation sample received 1.18 loans in the month of adoption indicating that some loan adopters received more than one loan. Moreover, in any given month after the adoption month, 50% of account owners in the estimation sample received a loan (see figure A.1 in the appendix). The data therefore indicates a continued use of Qwikloan in the estimation sample which also reflects the high repayment rate that characterizes this dataset. Additionally, loans received in the months after adoption increased in

Figure 2.3: Loan take-up by repayment duration (June 2018-April2021)



size which is consistent with the fact that borrowers who repay their loans promptly have their credit limit increased as advertised by MTN.

2.5 Results

I begin the analysis by showing the results from equation (3.2) which are graphically depicted in figure 2.4. The figure illustrates the estimates of leads and lags that show the changes in the effects of loan adoption in the 7-month window around loan adoption. The figure presents the point estimates along with the 95% confidence interval of treatment effects.

While I find no evidence of an effect of loan adoption on the total value of P2P transfers made, I find that loan adoption decreases the number of transfers sent and received and the number of unique accounts with which transfers are made. The observed impacts of adoption on P2P transfers only become apparent after the first month of adoption and increase with time. On average, the number of P2P transfers sent decreases by 0.63 (16% of the baseline value) after a month of adoption while the number of transfers received decreases by 0.54 (17% of the baseline value) after the month of adoption. At the same time, after the month of adoption, the number of unique accounts to which transfers are sent decreases by 0.46 (16% of the baseline value) while the number of unique accounts from which transfers are received decreases by 0.4 (17% of baseline value).

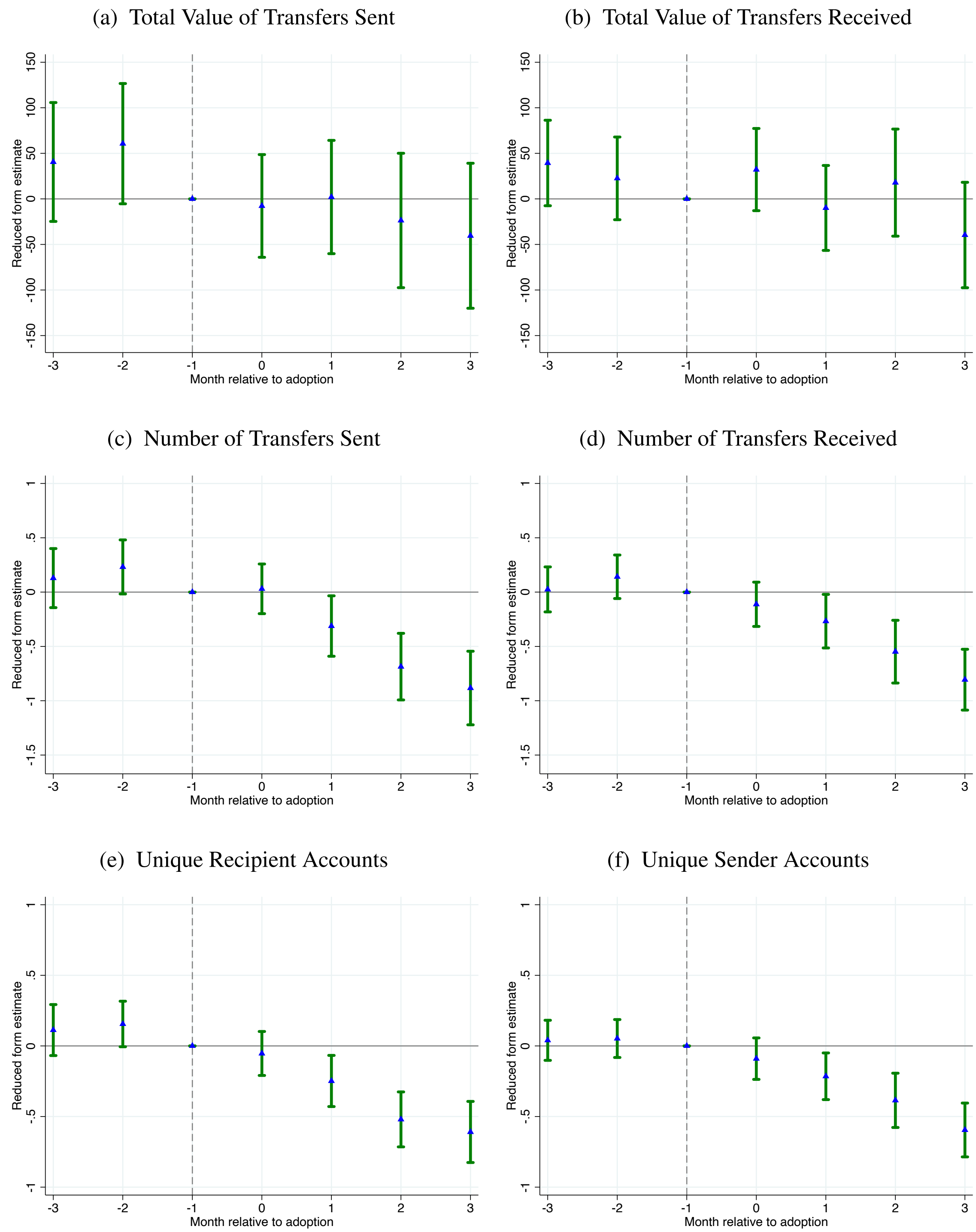
Estimates of leads presented in Figure 2.4 are statistically insignificant at the 5% level. This suggests no existing trends prior to loan adoption. Though it is possible in the setting of this study that borrowers believe that increasing their mobile money activity can manipulate their credit limit I find no strong evidence of this in the estimation sample. The lack of significant pre-adoption trends provides suggestive evidence of validity to the estimation approach.

The obtained results suggest that the adoption of Qwikloan negatively affects mobile money transfers. The majority of mobile money transactions are P2P transfers, as the Ghanaian mobile money customer mostly uses the platform to make P2P transfers. Over 80% of the transactions in the administrative data used in this study are P2P transactions. Therefore, a 16% decline in the P2P transfers indicates a 13% decrease in all mobile money transactions in the dataset.[11] This is striking because it contradicts the expectations of mobile money service providers and government regulators who anticipate that by widening its financial offerings mobile money will accelerate the digitization of payments in the country (Ministry of Finance Ghana, 2018). Mobile money so far has been the greatest contributor to e-payments in Ghana. According to the Payment System Report of the Bank of Ghana, mobile money overtook cheques to become the largest non-cash payment instrument in 2018 with 98.50 percent of non-cash retail payments made with mobile money.

To further understand the impact of loan adoption, I analyze its impact on the likelihood of conducting mobile money transactions. For brevity, the results are reported in the

[11] The dataset includes all mobile money transactions with the exception of cash-in and cash-out transactions.

Figure 2.4: Effect of Digital Credit Adoption on P2P Transfers



(a) Total Value of Transfers Sent

(b) Total Value of Transfers Received

(c) Number of Transfers Sent

(d) Number of Transfers Received

(e) Unique Recipient Accounts

(f) Unique Sender Accounts

Note: The Figure displays the main results of the event study analysis, with the blue triangles indicating the point estimates of μ_τ and the green bars representing the 95% confidence interval using standard errors that are clustered at the individual level.

appendix Figure A.2, but here I will summarize the main findings. I find loan adoption results in a decline in the likelihood of making any mobile money transaction including P2P transfers by 8% after the adoption month. This result is not exclusively driven by the decline in P2P transactions as the likelihood of conducting other mobile money transactions also decreases with loan adoption. It is however worth noting that during the month of adoption, there is a statistically significant increase in the likelihood of making any type of mobile money transaction. This effect reverses immediately after the month of adoption. What can be inferred from the results is that the adoption of Qwikloan decreased mobile money activity in the three months after adoption.

2.5.1 Possible Welfare Implications

To provide a definite answer on the welfare effects of the obtained results, it would be necessary to have information on the return of mobile money loans, the effect on individual and household consumption, and the extent to which mobile money loans replace or complement other sources of credit. Unfortunately, such information is not available. However, inferences can be made about the potential welfare implications of the results. Mobile money use has been shown to have a wide range of positive welfare effects for its users. For instance, it helps households insure themselves against bad shocks by facilitating remittances. As such, a decline in the use of mobile money could imply negative consequences for the welfare of households. However, without knowing the overall changes in all types of remittances it is difficult to interpret the impact on welfare implied by these findings. Moreover, in Ghana, where mobile money transactions are taxed, a decline in P2P transfers indicates a reduction in tax revenue.[12]

There are few studies that analyze the welfare impacts of mobile money loans and they

[12] In May 2022, the Ghanaian government introduced an e-levy of 1.5% on all mobile money transactions. Transactions that are less than GHS 100 are excluded from the e-levy. On the 11th of January 2023, the government reduced the e-levy to 1%.

have found mixed results. Suri et al. (2021) finds that they improve the resilience of eligible households while not substituting other forms of credit, Brailovskaya et al. (2021) find no negative impacts on the financial well-being of eligible mobile money users though most borrowers fail to repay on time. These studies also explored the net impact on aggregate measures of informal transfers which includes mobile money transfers and have found no substitution between informal transfers and mobile money digital credit. However Björkegren et al. (2022) find modest substitutability between digital credit and informal transfers in an RCT in Nigeria. This study however suggests at least a change in the composition of informal transfers but further studies will be required to know the overall effect of loan adoption on informal transfers. Recall that the size of loans in this study are larger than those previously studied and additionally, the loan repayment enforcement mechanism differs from that of those previously studied.

2.5.2 Heterogeneous Effects by Delinquency Status

The effects of loan adoption presented above are important as they indicate the overall impact of Qwikloan on loan adopters, however, different borrowers may reveal distinctly heterogeneous effects which may shed light on the mechanisms driving the overall results. I explore the differential impact of loan adoption for adopters who repay their loans on time and those who do not.

Qwikloan employs a repayment mechanism that allows the lender to make automatic deductions from the mobile money wallet of any delinquent borrower in repayment of the outstanding loan. As a result, any deposits made to the mobile money wallet of a delinquent borrower will be automatically deducted in repayment of their outstanding debt. Likewise, any incoming transfers made to their account will be automatically deducted to repay the outstanding debt. This creates an incentive for delinquent borrowers to halt their use of their mobile money accounts until they have fully repaid their debt. They may choose alternative tools for transfers and encourage their friend and families to send them transfers through alternative transfer tools. This behavior will be reflected in the data as a decline in P2P transfers and other mobile money transactions due to the adoption of the product.

To examine if the incentive created by account garnishing drives the negative response of mobile money transactions to loan adoption, I classify loan adopters into two groups based on whether they have ever delayed in repaying a loan within the month of adoption and the three months following adoption. I then analyze the treatment effects of loan adoption separately for adopters who are never delinquent and for those who are eventually delinquent within the time frame of the analysis.

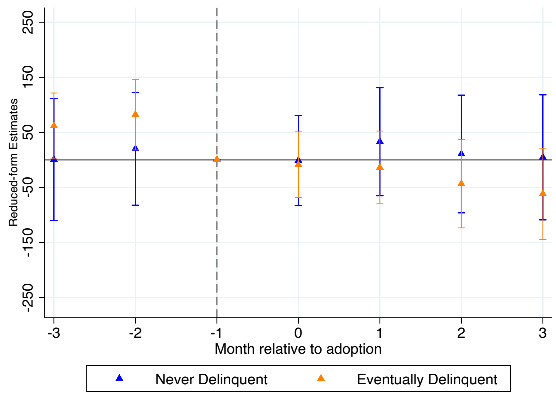
I provide results on the treatment effects of never-delinquent loan adopters and eventually-delinquent loan adopters in Figure 2.5. The analysis reveals striking results. I find that the decline in P2P transfers is entirely driven by adopters who are eventually delinquent. In the months following the adoption month, delinquent borrowers display sharp declines in the number of P2P transfers they sent and received, and the number of unique accounts to which they sent transfers and those from which they received transfers. I find no evidence of a change in P2P transfers by never-delinquent borrowers.

Eventually-delinquent borrowers on average sent 0.88 fewer transfers monthly and received 0.75 fewer transfers in return over the course of the three months following the loan adoption month. These changes in monthly transfers sent and received are equivalent to 23.5% of baseline levels of the number of transfers sent and 24% of the number of transfers received. The decrease in the volume of transfers made is associated with a decline in the number of unique accounts with which transfers are made. In the three months following the loan adoption month the number of unique accounts to which eventually-delinquent borrowers sent transfers decreased by 24.9% while the number of unique accounts from which they received transfers monthly also decreased by 23.2%.

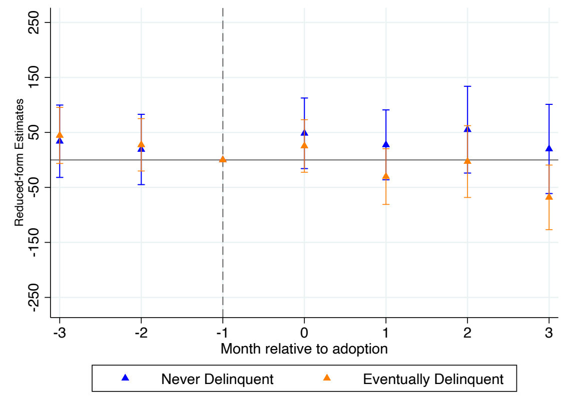
The results obtained are consistent with the narrative that the threat of account garnishing drives the negative relationship between mobile money transfers and loan adoption.

Figure 2.5: Effect of Digital Credit Adoption on P2P Transfers by Delinquency Status

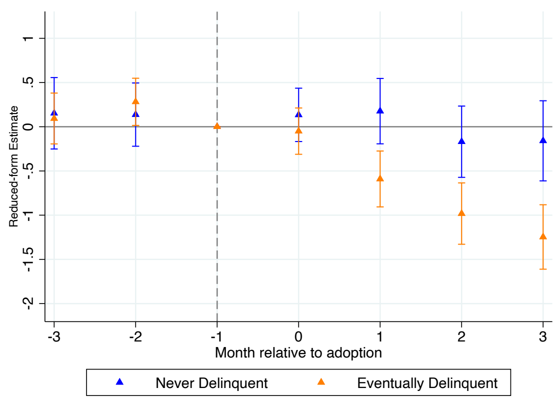
(a) Total Value of Transfers Sent



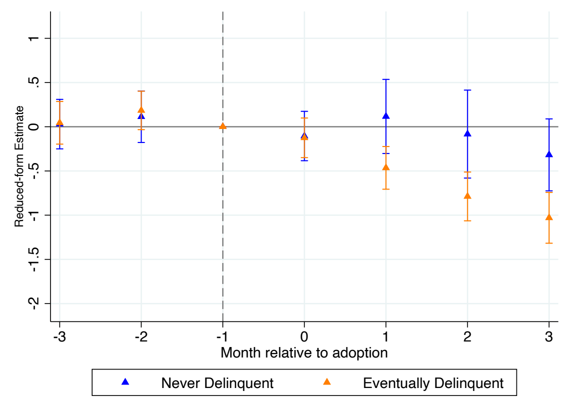
(b) Total Value of Transfers Received



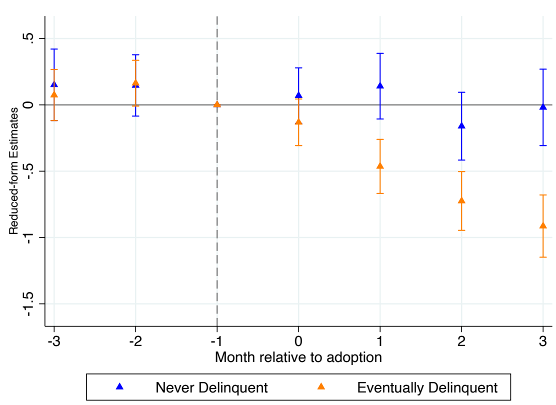
(c) Number of Transfers Sent



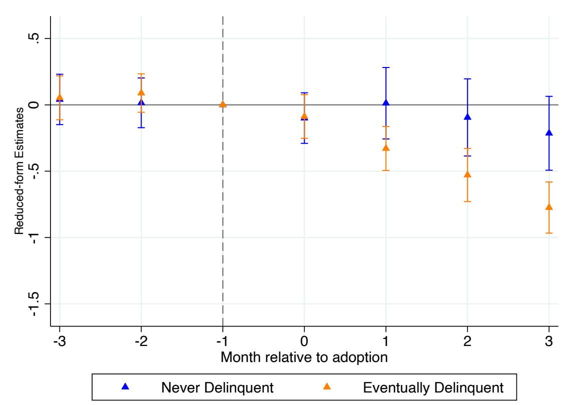
(d) Number of Transfers Received



(e) Unique Recipient Accounts



(f) Unique Sender Accounts



Note: The Figure displays the results of our event study analysis conditional delinquency status on all loans within the period of observation

Delinquent borrowers will avoid using their mobile money accounts to make or receive transfers. They may cease mobile money activities as any money in their mobile money wallet would be immediately collected until their debt is fully repaid.

Given this underlying mechanism, the estimated treatment effects will be an underestimation of the true impact of loan adoption on mobile money transfers because the accounts used in the analysis are mobile money accounts that were active in 2021, the time of data extraction. So, by excluding inactive mobile money accounts at the time of data extraction, the analysis does not include loan adopters who quit using their mobile money accounts altogether to avoid loan repayment. The analysis only includes mobile money accounts that become temporarily inactive as their owners avoid loan repayment.

2.6 Other Possible Mechanisms

There are other reasons why the adoption of Qwikloan may lead to a decrease in P2P transfers besides the loan repayment mechanisms, there are two main mechanisms that could be at play. First, bad shocks as an endogenous time-varying characteristic could be driving the results. Potential borrowers may adopt Qwikloan when they experience a bad shock and bad shocks can directly impact their ability to make financial transactions including making P2P transfers and repaying loans. If accounts in the treated group are more likely to experience a bad shock than accounts in the control group, then the control group no longer serves as a good counterfactual for the treated group presenting a challenge to the validity of the parallel trends assumption. Second, liquidity constraints associated with the use of loans could also be driving the results. If mobile money loans are used to make lumpy purchases or investments then the borrower may become temporarily constrained which may reduce their ability to make mobile money transactions. In this section, I examine the different potential explanations for the results obtained. These mechanisms in addition to the loan repayment mechanism may all be simultaneously at play and may be inseparable without data on the use of loans obtained.

2.6.1 Bad Shocks

Treatment in this study is defined by loan adoption, however, loan adoption is an endogenous decision determined by several time-varying and time-invariant characteristics. To handle the challenges of endogeneity, all analyses in this study control for individual fixed effects, however, due to data limitations I am unable to control for the relevant time-varying characteristics that could introduce endogeneity in the analysis. The main time-varying characteristic of concern that can drive both the adoption and the use of mobile money is the incidence of bad shocks. Though I do not have data on bad shocks I explore the possibility that the results obtained are driven by bad shocks.

Qwikloan is advertised as an instant loan that can be used to meet day-to-day needs and used in the case of emergencies. The use of Qwikloan for emergencies suggests that customers may only adopt the product when they experience a bad shock. This implies that the distribution of bad shocks in the treated group could differ from the distribution of bad shocks in the control group. The incidence of bad shocks can be expected to reduce one's ability to make transfers to her friends and family hence explaining how adoption may be correlated with a decline in various measures of P2P transfers sent. However, it is not clear how bad shocks may result in a decline in the number of transfers received and the number of unique accounts from which transfers are received. In the event of bad shocks, individuals typically receive assistance from their family and friends resulting in their receipt of more transfers than they typically would to smooth risk.

The response of incoming informal transfers to bad shocks is extensively documented in the economics literature. Genoni (2012) and Gertler and Gruber (2002) find that transfers from other households increase in response to health shock by a household member. In particular mobile money users are shown to receive more transfers in response to bad shocks. Jack and Suri (2014) study of the Kenyan mobile money market is the first to document the positive response of informal transfers to bad shocks of mobile money users. Similarly Riley (2018) finds the same response of transfers to rainfall shocks for mobile money users in Tanzania while Munyegera and Matsumoto (2016) demonstrates the same response for users in Uganda. Moreover, in the Ghanaian setting, Koomson et al. (2021) find that mobile money transfers increase in response to idiosyncratic shocks.

Given what is known about the response of informal transfers to bad shocks, particularly that mobile money users, one would expect that P2P transfers received if at all would increase in response to loan adoption if the results were driven by bad shocks. That is however not the case. With the exception of the likelihood of receiving P2P transfers increasing in the adoption month, I find no evidence of an increase in P2P transfers received before or after loan adoption. However, while it may seem unlikely, the potential influence of bad shocks on the results of this study cannot be entirely dismissed without access to data on such shocks.

Moreover, the incidence of a bad shock may cause borrowers to delay loan repayment which may then lead borrowers to avoid the automatic deduction of loans. This scenario indicates that an interaction between bad shocks and the repayment mechanism may drive the overall results and separating these effects will require detailed data on the incidence of bad shocks.

2.6.2 Lumpy Expenditure/Liquidity Constraint

Loans obtained could be used to make lumpy purchases like paying for children's education or investing in micro-enterprise activities. With their money tied up in an investment or a physical asset, the liquidity of borrowers may be temporarily limited hence reducing their capacity to make transfers to their friends and family. I explore the possibility that liquidity constraints created by the use of loans for lumpy expenditure may explain the effects of

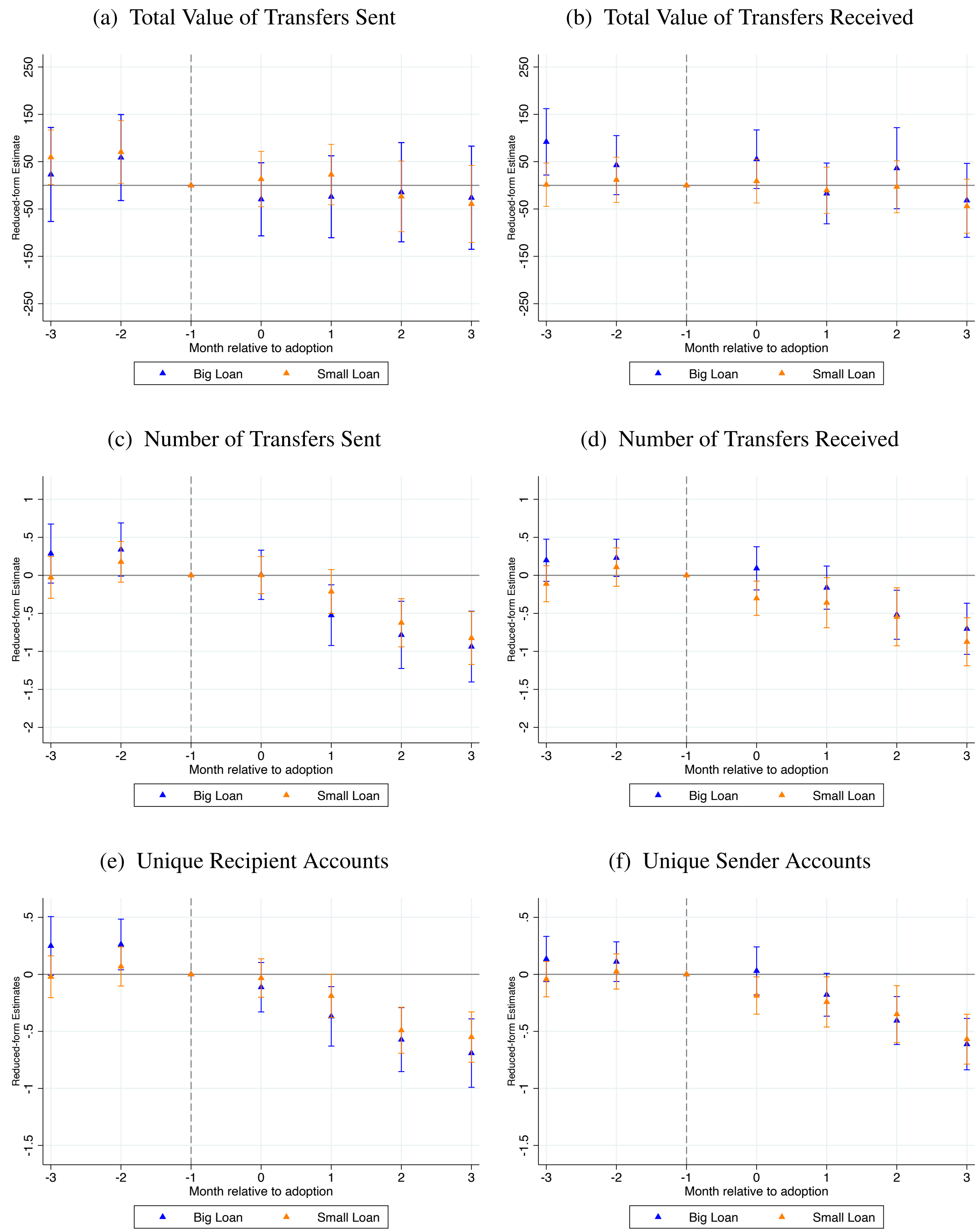
Qwikloan on informal transfers. While I do not have data on the use of the loans obtained, I capitalize on the size of the loans obtained as an indicator of their use. Smaller loans are more likely to be used for daily expenditures instead of lumpy purchases, while larger loans could be used to fund such expenditures.

The scenario described above implies a decline in transfers sent but makes no clear prediction on how informal transfers received may be affected. However one could think of different reasons why informal transfers may decline as well. For instance, if borrowers who make lumpy purchases are also the ones who tend to lend to their friends and family, then they may receive fewer transfers in return in response to the decline in their transfers sent.

To investigate the liquidity constraint channel that might explain the observed negative impact of Qwikloan on mobile money transfers I divide the treatment group into two groups defined by the size of the first loan obtained. I chose a benchmark of 60 GHS to define a loan as big or small. Borrowers whose first loan obtained was greater than 60 GHS (US$13) are classified as obtaining a big loan while those whose first loan was smaller than or equal to 60 GHS are classified as obtaining a smaller loan. The amount, 60 GHS, according to the GLSS 7 is about twice the daily income (which is 32.03 GHS) of the average individual in Ghana.

By conditioning the analysis on this classification of the size of the first loan we find that adopters who received a large initial loan respond in the same manner as adopters who received a small initial loan. Figure 2.6 displays the effect of Qwikloan adoption on mobile money transfers conditional on the size of the initial loan. The results are inconsistent with the hypothesis that liquidity constraint is the mechanism driving the main results of this study.

Figure 2.6: Effect of Digital Credit Adoption on P2P Transfers by Size of First Loan



Note: The Figure displays the results of our event study analysis conditional on the size of the first loan obtained. In each panel blue plots represents estimates for accounts that received a loan of value greater than 60 GHS, while orange plot represents estimates for accounts that received a loan of 60 GHS or less in value

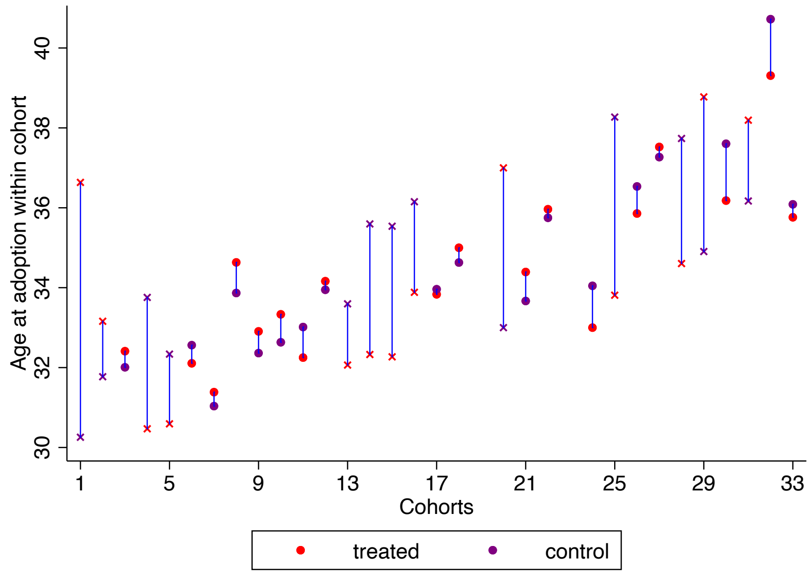
2.7 Homogeneous Treatment Effects Across Cohorts

One of the primary assumptions on which the validity of the results relies is the assumption of homogeneous treatment effects across different cohorts. To investigate the plausibility of this assumption, I estimate for each relative month after loan adoption the treatment effects separately for each cohort to obtain insight into the pattern of the effects of loan adoption across cohorts. It is possible for late adopters to differ from earlier adopters and for their differences to result in different magnitudes or even directions of the impact of loan adoption. I start with analyzing the age distribution across different cohorts. In Figure 2.7 I present the average ages at treatment of the treated and control groups of the different cohorts. Red markers represent the average ages of the treated group while purple markers represent the average ages of the control groups. Cohorts with statistically significant differences between the average ages of their treated and control groups are marked with stars and the vertical lines between markers represent the age gap between the treated and corresponding control groups of each cohort.

The average ages within cohorts range from 30.2 to 40.7 and Figure 2.7 shows a pattern of a slight increase in age with later adoption. It is possible that older loan adopters may respond differently to adoption than younger loan adopters would. This could be because older loan adopters may have more stable income sources, access to other forms of credit, or may have more social network members who depend on them. This could result in different treatment effect estimates for later adopters than earlier adopters. I investigate this possibility by separately estimating the treatment effects for each cohort.

Figure 2.8 shows the effect of loan adoption on P2P transfers for each cohort in the third month relative to loan adoption (95% confidence interval). The age composition of cohorts could potentially impact the response of each cohort to loan adoption, however, the Figure shows no clear pattern in the treatment effects across cohorts. For the number

Figure 2.7: Average Age by Cohort and Treatment Status



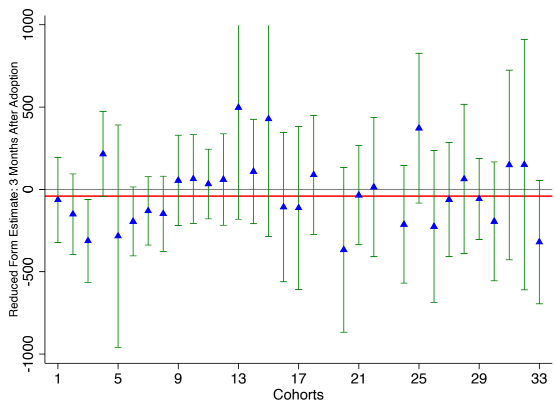
Note: Star markers represent the ages of cohorts with statistically significant differences in mean ages across treatment and control

of transfers sent and received and the number of unique accounts with which transfers are made, I estimate a sharp reduction in response to loan adoption for earlier cohorts and imprecise estimates for later cohorts. These are the main outcomes for which we find negative aggregate treatment effects. Despite the imprecise estimated treatment effects of most cohorts, almost all point estimates are negative. The results provide support for the homogeneity assumption made about the treatment effect across cohorts.

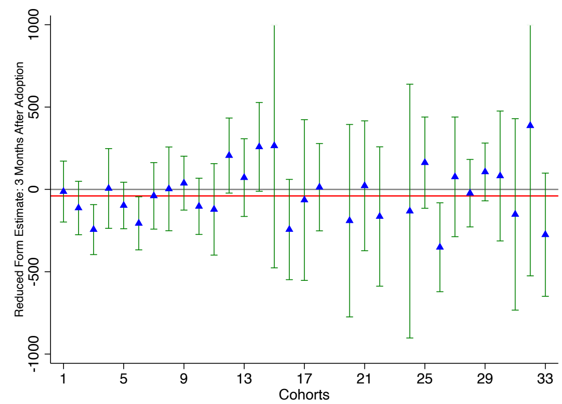
The same cohort analysis conditional on the delinquency status of loan adopters is presented in Figure A.4 in the appendix. The blue markers represent the treatment effects of never-delinquent adopters and the orange markers represent the treatment effect of the eventually delinquent adopters. The results also show no clear temporal patterns in the estimated treatment effects of loan adoption across cohorts of eventually delinquent adopters and never delinquent adopters. Estimates get noisier as sample sizes decrease with the decomposition of treatment groups into eventually delinquent and never-delinquent groups. Additionally, the estimated treatment effects of eventually delinquent adopters are mostly

Figure 2.8: Effect of Digital Credit Adoption on P2P Transfers by Cohort (τ = 3)

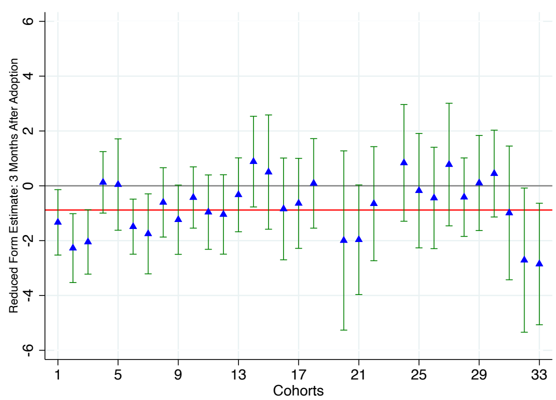
(a) Total Value of Transfers Sent



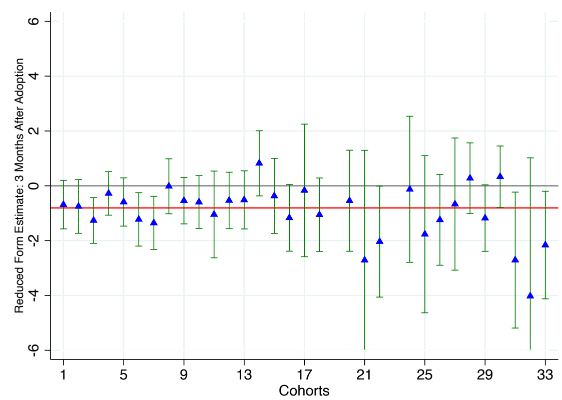
(b) Total Value of Transfers Received



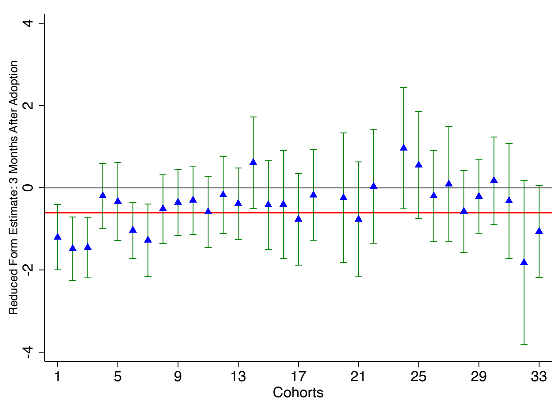
(c) Number of Transfers Sent



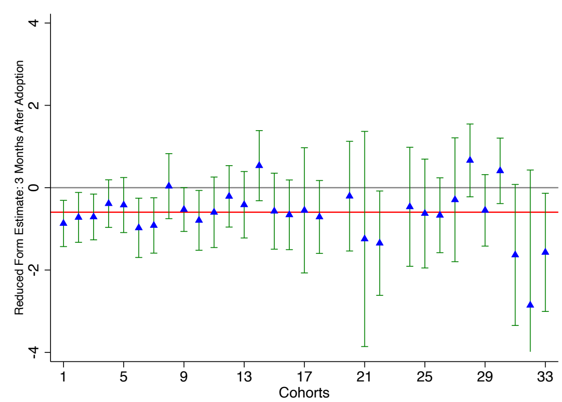
(d) Number of Transfers Received



(e) Unique Recipient Accounts



(f) Unique Sender Accounts



Note: The Figure plots estimates of the effect of loan adoption on each cohort three months after adoption. The blue triangle markers are the point estimates while the green bars are the 95% confidence intervals. Confident intervals without caps are truncated. The standard errors are clustered at the individual level. The red horizontal line depicts the aggregated treatment effects across cohorts obtained from equation (3.2).

below that of the never-delinquent adopters in Panels (c) to (d) which is consistent with the main results presented in Figure 2.5.

Finding no apparent pattern in the cohort-specific treatment effects provides support for the treatment effect homogeneity assumption. This indicates a low likelihood of bias in the estimated aggregated treatment effects obtained with equation(3.2). Furthermore, as depicted in Figure A.3 I find no evidence of heterogeneous effects by gender, though this could be due to the imprecise estimates of treatment effects for female account owners given the small sample size of female adopters in the estimation sample.

2.8 Conclusion

The prevailing belief suggests that expanding financial services on mobile money may result in increased digital payments in the developing world. To substantiate this notion empirically, I conducted an investigation into the impact of adopting mobile money digital credit on mobile money transfers in Ghana. Mobile money digital credit is one of the most widely adopted of the more recent mobile money offerings while mobile money P2P transfers are the largest contributor to digital payment in Ghana. Studying the impact of mobile money digital credit on P2P transfers sheds light on the role of the credit product in contributing to the cashless agenda of the country.

I find that loan adopters send and receive fewer P2P transfers to and from fewer mobile money accounts. This result is solely driven by eventually delinquent borrowers. This study suggests garnishing the mobile money wallet of delinquent borrowers as a mechanism to enforce repayment is at least partly responsible for the decline in P2P transfers of delinquent borrowers. This loan enforcement mechanism creates an incentive for delinquent borrowers to avoid using mobile money altogether until they are willing and able to repay their loans.

I explore three potential alternative explanations or considerations for my findings. Firstly, I address the survival bias introduced in my analysis by using retrospective data limited to active mobile money accounts in 2021. It's reasonable to anticipate that this bias might result in an underestimation of the negative impact of loan adoption on mobile money activity. Secondly, I examine the possibility of liquidity constraints resulting from loans being used for lumpy expenditures driving my findings. However, this theory fails to account for the decrease in P2P transfers received. Additionally, analyzing the initial loan size as an indicator of lumpy purchases reveals that both large and small loan recipients experience a similar decline in incoming and outgoing P2P transfers. Finally, I explore the most salient counter-story involving bad shocks. While bad shocks may prompt mobile money users to obtain loans, they do not justify the decrease in incoming transfers. In such instances, one would anticipate an increase in incoming transfers of mobile money users facing bad shocks.

The key takeaway from this study is that contrary to conventional wisdom, increasing the range of financial services on mobile money might result in a decline in platform usage. This unintended consequence could potentially reverse the positive strides made by mobile money over the years. Notably, the findings underscore the significance of the repayment enforcement mechanism, suggesting a potential retreat from platforms employing similar enforcement measures in the face of non-compliance.

An important caveat to this study is that I only observe mobile money activities on 1 out of 3 mobile money providers in Ghana, MTN. We therefore miss any substitution across mobile money platforms as a result of access to mobile money credit. However, MTN is the largest mobile money provider in Ghana with a market share of 80% (Ifeanyi-Ajufo, 2022), I, therefore, conjecture that the observed decline in mobile money transfers is not completely driven by this substitution across platforms.

Finally, another important caveat is that since the end of my study period (2021), Ghana's mobile money market has changed significantly. In 2022, the government imposed a tax on mobile money transactions collected through automatic wallet deductions, called the E-levy. Early studies indicate this tax reduces mobile money transactions, risking the reversal of gains in the sector (Anyidoho et al., 2023). The response to the E-Levy is expected to cause selection among mobile money users, potentially rendering this study's results inapplicable to the current market. However, the observed reduction in mobile money activities due to tax deductions aligns with our main explanation for the decreased participation: automatic wallet deductions decrease mobile money usage. This underscores the importance of understanding participation disincentives associated with mobile money platform characteristics/regulations.

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Chapter 3

3 Mobile Money Matters: Implications for Savings Behavior in Kenya

3.1 Introduction

Access to financial services in developing countries has historically been limited, but recent digital financial innovations have significantly improved accessibility. One such innovation is mobile money, a service provided by Mobile Network Operators (MNOs) enabling users to electronically store and transfer money to others. Mobile money has played a significant role in expanding access to financial services, especially in Sub-Saharan Africa, where account ownership has grown by 50% over the past decade (Demirgüç-Kunt et al., 2022). In the absence of traditional banking services, households in developing economies often resort to informal financial practices such as saving at home, participating in Rotating Savings and Credit Associations (ROSCAs), or relying on transfers within their social networks. Mobile money offers users a secure and cost-effective means to store funds and conduct quick transfers over long distances (Jack and Suri, 2014). In this study, I aim to examine the impact of saving with mobile money on households' utilization of existing saving tools.

Household income in developing economies is highly vulnerable to adverse shocks, underscoring the importance of access to financial services. Introducing new financial tools can have varying effects on the use of existing ones. The new financial tool may substitute for existing tools due to associated risks and costs, yet also complement them by enhancing effectiveness.[1] For instance, Banerjee et al. (2021) show that microcredit

[1] ROSCAs have inherent risks as recipients of earlier "pots" may fail to make subsequent contributions, and savings at home are subject to theft and draws from household members or relatives.

substitutes for informal credit obtained from one's friends and family in Bangladesh while Mobarak and Rosenzweig (2012) find that formal rainfall insurance with basic risks and informal insurance are complements in India .[2] The influence of new formal savings tools on existing ones remains uncertain. Mobile money, with its widespread accessibility and ease of use, presents an intriguing case study.

This study examines the impact of M-Pesa, the leading mobile money service in sub-Saharan Africa and the first of its kind in the region, on the usage of other financial services. M-Pesa's widespread adoption in Kenya has been extensively documented by Jack and Suri (2011).[3] To investigate the influence of saving with M-Pesa on the utilization of various saving tool, I analyze data from a comprehensive panel survey of Kenyan households conducted by Suri and Jack (2017). Specifically, I focus on the most prevalent formal and informal savings tools within the dataset.[4] The formal saving tools studied are banks and Savings and Credit Cooperatives (SACCOs), while informal savings tools studied are Rotating Savings and Credit Associations (ROSCAs) and savings kept at home.

In this study, I examine how a household's savings with M-Pesa influence its subsequent utilization of other saving tools by comparing the usage patterns of households that save with M-Pesa against those that do not save with M-Pesa. I employ a household panel from 2008 to 2010, to estimate an ordinary least squares (OLS) linear regression model that accounts for several observable factors that could impact a household's financial tool preferences.[5]

I observe a positive partial correlation between M-Pesa savings and both ROSCA participation and bank savings controlling for household characteristics.[6] However, the OLS

[2]Informal risk sharing that covers idiosyncratic losses enhances the benefits of index insurance.

[3]Within 4 years of its launch, 70% of adults in Kenya had adopted M-Pesa Jack and Suri (2014)

[4]Formal financial services as those regulated by institutions.

[5]OLS model employed controls for various household characteristics, including household wealth, rural residence, household composition by age and gender, as well as characteristics of the household head such as age, gender, education, occupation, and marital status.

[6]See footnote footnote 5 for a detailed description of the household characteristics included.

estimates obtained may fail to capture the causal relationship between M-Pesa savings and the studied outcomes as M-Pesa savings is an endogenous choice likely influenced by unobservable factors that also impact the use of other financial tools.

The main sources of endogeneity are related to the unobserved factors that generate a need for saving. For instance, households may decide to save in anticipation of a lumpy expenditure, such as school fees, funerals or festival-related expenditure, or the purchase of agricultural inputs. In Kenya, as in many developing countries, the cost of these items may be significant relative to household monthly income, and households often lack easy access to credit. As a result, households participate in savings groups like ROSCAs and SACCOs to gradually save for these large expenses or to obtain loans that they can repay through group contributions (Dupas and Robinson, 2013). This motive for saving, which is not observable, is also likely to increase household savings with M-Pesa.

To tackle the empirical challenge arising from the endogeneity of M-Pesa saving, I utilize the variation in the number of mobile SIM cards owned by households as an instrument. Specifically, I employ an indicator of multiple SIM card ownership as an instrument for M-Pesa saving. It is not uncommon for individuals in sub-Saharan Africa to own multiple SIM cards to access various networks for better connectivity. In this study's data, about 60% of households with multiple SIM cards reported doing so to access different networks, while 11.07% reported that the SIM cards were used by different household members. The need for better network connectivity may arise from poor network service or the importance placed on constant connectivity (by individuals who rely heavily on network connectivity). This need, however, is unrelated to the unobserved savings motives described earlier, making multiple SIM card ownership a suitable candidate for an exogenous instrument.

Ownership of multiple SIM cards is correlated with M-Pesa savings. I find a statistically significant partial correlation of 0.27 between owning multiple SIM cards and M-Pesa savings, controlling for all household characteristics included in the main model specification. A potential underlying mechanism driving this correlation is that individuals who have multiple SIM cards have more exposure to M-Pesa advertisements by virtue of possessing multiple contacts and possibly multiple cell phones. M-Pesa businesses frequently send out mass text messages to advertise their services. This practice increases the exposure of multiple SIM card owners to M-Pesa advertisements, as they are likely to receive promotional messages on each SIM card they own.

However, there is reason to believe that the usual IV exclusion restriction may not be perfectly satisfied. For instance, ownership of multiple SIM cards might be a signal of wealth not fully captured by the measure of household wealth available. Therefore, I consider the possibility of a violation of the exclusion restriction by employing the methods proposed by Conley et al. (2012). The idea of this approach is that with a prior on the magnitude of the direct effect of the instrument on the outcomes studied, the researcher can directly account for such a violation and make inferences on the treatment effect under said violation. I use this method to provide 95% confidence bounds on the estimated effect of M-Pesa savings under various magnitudes of the violation of the exclusion restriction, allowing the reader to understand the sensitivity of the results to these violations.

I first report the IV estimates under the assumption of exact exclusion restriction. I find a statistically significant positive effect of M-Pesa savings on ROSCA participation and bank savings that lies within a 95% confidence interval of 22% to 98% and 20% to 75% respectively. I then demonstrate that the findings are robust to violations of the exclusion restriction, even up to a 6% direct impact of the IV on ROSCA participation and a 5% direct impact on bank savings. A 6% direct effect of the IV on ROSCA participation is equivalent to half the impact of a rural-urban differential on ROSCA participation and to the impact of an increase in household wealth of more than 3 times the average household wealth. Similarly, a 5% direct impact of the IV on bank savings is equivalent to 60% of the impact of a rural-urban differential on bank savings and to the effect of an increase in household wealth by more than 2 times the average household wealth. These results indicate that the estimated impact of M-Pesa saving remains statistically significant even under substantial violation of the exclusion restriction.

This study builds upon earlier research on mobile money services which investigates how their interaction with existing financial tools affects users. Previous studies on mobile money have primarily focused on its role in savings and informal transfers (Jack and Suri, 2014; Mbiti and Weil, 2013; Morawczynski, 2011; Riley, 2019). Recent studies have used Randomized Controlled Trials (RCTs) providing mobile money accounts designated for specific purposes, coupled with varying interest rate incentives or automatic payment mechanisms (Aggarwal et al., 2018; Bastian et al., 2018; Batista et al., 2017; Blumenstock et al., 2018; Habyarimana and Jack, 2018; Lipscomb and Schechter, 2018). This body of literature has demonstrated that mobile money accounts effectively facilitate saving for business expenditures, school fees, health expenses, agricultural inputs, and unforeseen shocks. My findings are consistent with this body of work by demonstrating that household savings with M-Pesa increase participation in savings groups and banking.

The rest of this paper is structured as follows. Section 2 provides detailed information on the various financial tools in this study. Section 3 describes the data set used in this study and provides details of the features of the estimation sample. In Section 4, the empirical framework and estimation strategy are discussed in detail. Section 5 presents the findings from both OLS and IV analysis and explores the possible relaxation of the exclusion restriction of the IV. Finally, I conclude in section 6.

3.2 Financial Tools Background

According to the 2021 Global FinAccess Report, Kenya ranks among the most financially inclusive economies in sub-Saharan Africa, trailing behind Seychelles and South Africa. Between 2006 and 2021, access to a financial account at a formal financial institution or with a mobile money provider in Kenya surged from 27% to 83%.[7] Over the same period, the proportion of adult Kenyans not utilizing either formal or informal financial services dropped from 41% to 11.6% (Demirgüç-Kunt et al., 2022). The substantial increase in financial inclusion is largely attributed to the widespread adoption of mobile money. A third of the adults who reported having access to financial services relied solely on this platform.

In Kenya, formal financial services include traditional banks, microfinance institutions, and insurance companies, which offer various savings, credit, and insurance products and SACCOs.[8] Informal financial services, on the other hand, include savings done at home and saving groups like ROSCAs. Savings groups like ROSCAs and SACCOs pool funds among members, providing access to credit and savings opportunities. Beyond these financial services, saving at home sometimes referred to as "saving under the mattress," remains a prevalent informal financial practice. This study focuses on the most commonly used saving tools in Kenya; bank, SACCO, ROSCA, and home savings.

Access to banking services has demonstrated significant growth over the years in Kenya. Before the advent of mobile money in Kenya, access to banking services was limited, especially in rural areas. Traditional brick-and-mortar banks primarily served urban centers and wealthier individuals, leaving a significant portion of the population underserved or excluded from formal financial services. The 2021 Kenyan FinAccess household survey results indicate that mobile money and bank services providers recorded the highest proportion of usage at 81.4% percent and 44.1% respectively in 2021 (FSD Kenya, 2021).

A SACCO operates as a cooperative that encourages members to save at an interest rate and facilitates access to loans using the accumulated savings. Managed by an elected board of individuals, a typical SACCO accepts monthly savings from members and extends loans

[7] Formal financial services are services offered by institutions that are subject to government regulation.

[8] SACCOs are regulated by a government agency known as the SACCO Societies Regulatory Authority(SASRA).

up to two to three times their savings at favorable interest rates. Loan issuance is contingent upon the borrower finding another member to assume the debt obligation in case of default. The remaining pooled savings are invested in diverse securities, and profits are distributed among the members. SACCOs primarily come in two forms: employee-based SACCOs and agricultural-based SACCOs. SACCOs were established as part of governmental efforts to promote income-generating opportunities. According to FSD Kenya (2021), participation in SACCOs ranged from 9% to 13% from 2006 to 2021.

Like SACCOs, ROSCAs are saving groups where members contribute regular fixed amounts to a common fund, the "pot", which is then disbursed to each member in rotation. Depending on the order of receiving the "pot" a ROSCA can be a means of saving or obtaining credit. For the first recipient, it serves as a means of obtaining credit which must be repaid through subsequent contributions to the pot. For the last recipient, it strictly serves as a savings tool. For those in between, it serves as a mixture of both credit and savings. The nature of contributions provides a structure for its members to accumulate and access lump sums of money for various purposes and function as a commitment device, helping members safeguard their savings from impulsive spending (Ambec and Treich, 2007). Additionally, ROSCAs provide a secure space for women to safeguard their savings from spouses and potential theft (Anderson and Baland, 2002). They also offer insurance benefits, either by adjusting contributions based on members' needs or by allocating funds to address emergencies (Calomiris and Rajaraman, 1998).

Many individuals, particularly those in rural areas and low-income households, opt to keep their savings in cash at home due to limited access to formal financial institutions, lack of trust in banks, and cultural preferences. While saving at home provides a sense of security and control over one's finances, it also poses risks such as theft, loss, and claims from one's relatives and close friends. Despite these drawbacks, saving at home remains a common means of managing finances with 22.7% to 55.7% of adults in Kenya reporting using this method of saving between 2006 and 2021 (FSD Kenya, 2021).

Since the launch of M-Pesa in 2007, mobile money services have gained significant popularity in Kenya, allowing users to send, receive, and store money electronically using their mobile phones. Depositing funds is free, while other transactions like the transfer of funds and the withdrawal of funds attract a small fee. Transfers attract a fixed fee of 30 Kenyan shilling while withdrawals are charged according to a step function at a cost of 1-2%. While M-PESA is mostly used to make peer-to-peer transfers, it is also largely used to save. According to Jack and Suri (2011), about 79% of the early adopters of M-PESA, reported using it for saving.

3.3 Data and Summary Statistics

This study uses data from a comprehensive household panel survey spanning five rounds conducted across a large part of Kenya by Suri and Jack (2017) between 2008 and 2014. The northern and northeastern districts of the country were excluded from the sampling frame, due to limited cell tower and mobile money agent coverage at the start of the survey in these areas. Out of the remaining districts, 118 with at least one agent were randomly selected. In these locations were a total of 300 enumeration areas from which 10 households were sampled from each to partake in the survey.

The first round of the survey was conducted in September 2008. In the second round, conducted in December 2009, only 2017 households were re-interviewed, depicting a significant attrition rate. As such, a third round of the survey was conducted six months after the second round, in June 2010, with the aim of finding households that were missed in the second round. In this round, 1,595 of the original sample were re-interviewed, 265 of whom were not interviewed in 2010.

In this study, I use a panel of the 2,017 households from rounds 1 and 2 and add a second panel of the 265 households observed in rounds 1 and 3 but not in round 2. This strategy allows for the construction of a two-period panel of 2,282 households. From here on, I refer to round 1 as period 1 and refer to rounds 2 and 3 as period 2.

To conduct the empirical analysis, I use a sub-sample of households in the two-period panel that reported owning cellphones in the first period. This allows for an estimation of the impact of M-Pesa savings within households that meet the main criteria for opening an M-Pesa account, access to a cellphone.[9] This results in an estimation sample of 1704 households in the 2-period panel.

The surveys solicited information on household demographics, household wealth, and information on the use of financial services. In addition, detailed data on M-Pesa usage and cellphone usage is collected including the number of mobile SIM cards owned by a household. In Table 3.1 I report summary statistics on the data relevant to household financial decisions for the analysis sample. The share of households that saved with M-Pesa increased from 33% to 54%. While 63% of all households reported saving with bank accounts, about 73% reported saving money at home. ROSCA participation in households increased from 43% to 50% while SACCO participation decreased from 23% to 21%. Due to security concerns, data on the actual amounts saved with each instrument was not reported.[10]

3.4 Empirical Framework

The main aim of this study is to investigate how saving with M-Pesa affects households' saving behaviors. I specifically assess the impact of households' M-Pesa savings on their future utilization of ROSCAs, banks, SACCOs, and home savings.

[9] The other requirement for opening an M-Pesa account is having a valid identification document.

[10] Note the large increase in ownership of multiple SIM cards from period 1 to period 2 in Table 3.1. This is believed to be accurate as it is consistent with the evidence of growth in mobile subscriptions in Kenya in the late 2000s. For example, Aker and Mbiti (2010) documented a tripling in mobile subscriptions between 2006 and 2009.

Table 3.1: Summary Statistics

	Period 1		Period 2	
	Mean	SD	Mean	SD
Education of head (years)	7.962	5.633	8.294	5.049
Household size	4.224	2.146	4.302	2.241
Male household head	0.796	0.403	0.797	0.402
Married household head	0.751	0.432	0.727	0.445
Age of household head	41.508	13.925	42.702	13.829
Multiple SIM cards	0.089	0.285	0.570	0.495
Rural Dummy	0.314	0.464	0.322	0.468
Total wealth (KShs)	174,427	476,205	174,822	845,162
Saving Tools Dummies				
M-pesa	0.327	0.469	0.540	0.499
Bank	0.629	0.483	0.629	0.483
SACCO	0.230	0.421	0.210	0.408
Home	0.734	0.442	0.721	0.448
ROSCA	0.427	0.495	0.499	0.500
Head's Occupation				
Farmer	0.180	0.384	0.189	0.391
Public	0.041	0.199	0.041	0.197
Professional	0.236	0.425	0.236	0.424
Househelp	0.114	0.318	0.114	0.318
Business	0.171	0.377	0.171	0.377
Sales	0.112	0.316	0.111	0.314
Industry	0.021	0.144	0.022	0.147
Other	0.047	0.211	0.046	0.211
Unemployed	0.074	0.261	0.071	0.257

Note: Throughout, KShs refers to the local currency, Kenyan shillings. The exchange rate during this period was about KShs 75 = US $1.

3.4.1 OLS Estimation

I first estimate a simple OLS regression to examine the partial correlation between households' M-Pesa savings in period 1 and its use of the other saving tools of interest in period 2. I use the model specification

$$y_{i,t} = \alpha + \beta Mpesa_{i,t-1} + \theta X_{i,t} + \varepsilon_{i,t}, \tag{3.1}$$

where y_{it} is a dummy variable of household i's use of a particular financial tool in period t, and $Mpesa_{i,t}$ is an dummy variable that household i saves with M-Pesa in period t. I also include a vector of controls $X_{i,t}$ that could predict households' savings decisions. The control variables in this study include the educational level, age, gender, and marital status of the household head, as well as the household wealth measured in hundreds of thousands of Kenyan shillings. Occupational dummies(for farmer, business operator, public service, professional, househelp, business operation, sales, industry, and other occupations, with unemployed being the left out group) are also included, along with a dummy indicating the rural residential status of the household.

3.4.2 IV and Plausibly Exogenous Estimation

To address potential endogeneity concerns driven by unobserved factors driving households' need for savings, I utilize an indicator of the ownership of multiple SIM cards by households as an instrument for saving with M-Pesa.

I begin the analysis under the assumption of perfect exclusion restriction but due to the reasons described earlier, I go on to estimate the treatment effect of M-Pesa savings with violations of the exclusion restriction by treating the instrument as plausibly exogenous.

Plausibly Exogenous Instrument

I employ the methods of Conley et al. (2012) to investigate relaxations of the exclusion restriction of the instrumental variable. This method works with the assumption that the researcher has an idea about the magnitude of the violation of the exclusion restriction. I modify equation (3.1) to directly include the instrument with coefficients that are equivalent to the violation of the exclusion restriction such that

$$y_{i,t} = \alpha + \beta Mpesa_{i,t-1} + \theta X_{i,t} + \gamma SIM_{i,t-1} + \varepsilon_{i,t}. \tag{3.2}$$

where $SIM_{i,t-1}$, an indicator of multiple SIM card ownership, is the plausibly exogenous instrument. When $\gamma = 0$, the exclusion restriction is exactly satisfied. Large absolute values of γ indicate a large violation of the exclusion restriction. Suppose the true value of γ was known to be γ_0, then the estimation would proceed by transforming the outcome variable to remove the direct impact of the instrument, $SIM_{i,t-1}$, on the outcome, such that

$$(y_{i,t} - \gamma_0 SIM_{i,t-1}) = \alpha + \beta Mpesa_{i,t-1} + \theta X_{i,t} + \varepsilon_{i,t}. \tag{3.3}$$

We can then estimate the model using the IV approach.

Instead of assuming a particular value of γ_0, I conduct inference with this approach under the assumption that γ_0 lies within a range $[0, \bar{\gamma}]$. For different values of $\bar{\gamma}$, I create a grid of points in the range $[0, \bar{\gamma}]$ and allow γ_0 to assume each value on the grid. I then estimate equation (3.3) using the standard IV approach and obtain a 95% confidence interval for β, for each value of γ_0 on the grid, resulting in a set of γ_0-specific confidence intervals which are valid under the assumption that the true value of γ is γ_0. Finally, I take the union of the confidence intervals attained at each grid point which results in an estimate of the confidence interval of β under the assumption that $\gamma_0 \in [0, \bar{\gamma}]$. I display the results for a range of values of $\bar{\gamma}$ allowing readers to view the results under their own assumption of a reasonable value of $\bar{\gamma}$.

3.5 Results

In this section, I present the empirical findings from the methodologies outlined above. I first present the OLS estimates of the partial correlation between household savings with M-Pesa in period 1 and savings with ROSCAs, banks, SACCOs, and home savings in period 2, employing the basic specification outlined in equation 3.1. I then provide the instrumental variable results or the effect of M-Pesa savings on household financial choices under the assumption of perfect exclusion restriction of the instrumental variable. Following this, I present the results that allow for a violation of the exclusion restriction of the instrumental variable.

Table 3.2 presents the OLS estimates of the basic specification in equation (3.1). For each specification, the controls are as defined above, I do not report the estimated coefficients of the occupational dummies, and the robust standard error is reported in parenthesis. According to the OLS results, saving with M-Pesa is positively correlated with future participation in ROSCAs, and saving with a bank. However, I find no statistically significant partial correlation between M-Pesa savings and subsequent participation in SACCOs and savings done at home. The observed correlation between M-Pesa and bank saving and M-Pesa and ROSCA participation are all statistically significant at a 5% significance level. As indicated in Table 3.2, there is a 10% partial correlation between M-Pesa saving and ROSCA participation and a 17% partial correlation between M-Pesa saving and bank saving.

3.5.1 IV Estimates

The results displayed in Table 3.2 are unlikely to reflect the causal impact of M-Pesa savings as one may expect a potential correlation between M-Pesa savings and the error term

Table 3.2: OLS Regression Results

	(1) ROSCA	(2) Bank	(3) SACCO	(4) Home
M-Pesa	0.098***	0.169***	0.038	-0.041
	(0.031)	(0.028)	(0.026)	(0.028)
Education (years)	0.000	0.008***	0.001	0.001
	(0.003)	(0.002)	(0.003)	(0.003)
Age (years)	-0.001	-0.004**	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Gender	-0.097*	-0.027	0.032	0.046
	(0.057)	(0.050)	(0.046)	(0.051)
Married	0.041	0.111***	-0.040	-0.067
	(0.050)	(0.043)	(0.038)	(0.043)
Wealth (100,000 KShs)	-0.008***	0.013***	0.007**	0.002
	(0.003)	(0.002)	(0.003)	(0.002)
Male member (age) < 17	0.018	-0.034**	-0.001	-0.001
	(0.017)	(0.015)	(0.014)	(0.015)
Female member (age) < 17	0.005	-0.045***	-0.026*	0.020
	(0.016)	(0.015)	(0.014)	(0.014)
≥ 17 Male member (age) ≤ 39	0.015	0.018	-0.015	0.024
	(0.021)	(0.019)	(0.018)	(0.018)
≥ 17 Female member (age) ≤ 39	0.031	-0.001	0.023	-0.006
	(0.022)	(0.019)	(0.018)	(0.020)
Male member (age) ≥ 40	0.022	0.096**	0.074*	-0.053
	(0.045)	(0.038)	(0.038)	(0.037)
Female member (age) ≥ 40	-0.003	-0.019	0.028	-0.011
	(0.045)	(0.039)	(0.039)	(0.041)
Rural==1	0.054	-0.109***	0.051	0.044
	(0.041)	(0.038)	(0.033)	(0.035)
Observations	1704	1703	1703	1703
R^2	0.054	0.189	0.061	0.035

Heteroskedasticity-robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$\varepsilon_{i,t}$. As such, I instrument for M-PESA savings with an indicator of the ownership of multiple SIM cards by a household.

Appendix Table B.1 presents the first stage estimates of equation (3.1) controlling for the standard set of covariates described earlier. The Kleibergen-Paap F-test for weak instruments suggests that the dummy for multiple SIM card ownership is a strong instrument.

The IV estimates presented in Table 3.3 demonstrate a substantial rise in the probability of households engaging in ROSCAs as a result of saving with M-Pesa. Additionally, there is a significant increase in the likelihood of saving with a bank. To be specific, the estimated impact of M-Pesa savings on ROSCA participation lies with a 95% confidence interval of 22% to 90% while the impact of bank savings lies within the interval of 20% to 75%. [11] Consistent with OLS estimates, the IV estimates provide no evidence of an impact of M-pesa saving on a household's savings with SACCOs or savings kept at home.[12]

3.5.2 Plausibly Exogenous Instrument

Figure 3.1 displays the results of treating the instrument as plausibly exogenous, relaxing the exclusion restriction for the instrument. The figure displays the 95% confidence intervals using the union of symmetric γ_0-specific intervals with support restriction of the form $\gamma_0 \in [0, \bar{\gamma}]$. Panel (a) corresponds to ROSCA participation, while panel (b) focuses on bank savings as outcome variables. I only report the results for ROSCA and bank savings, as the standard IV estimates reveal no statistically significant impact of M-Pesa saving on

[11] The Anderson-Rubin weak instrument robust test aligns with the t-tests indicated in Table 3.3. The corresponding p-values for the test of zero slope for ROSCA participation and bank savings are 0.003 and 0.002, respectively.

[12] In appendix Table B.2 I explore whether the impact of M-Pesa saving is linked to prior usage of the financial tools under investigation. The analysis reveals statistically significant evidence of M-Pesa savings increasing both the take-up and the continued participation in ROSCAs while only increasing the continued use of bank savings. I observe a 20% to 40% transition out of ROSCA participation and bank savings respectively. Simultaneously, 40% of the estimation sample transitioned into ROSCA participation and bank savings.

Table 3.3: Impact of M-pesa saving in period 1 on use of financial tools in period 2 (IV estimates)

	(1) ROSCA	(2) Bank	(3) SACCO	(4) Home
M-Pesa	0.608***	0.475***	0.214	-0.172
	[0.196]	[0.141]	[0.191]	[0.194]
Education (years)	-0.004	0.005*	0.000	0.001
	[0.004]	[0.003]	[0.003]	[0.003]
Age (years)	-0.000	-0.004**	-0.003*	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]
Gender	-0.146**	-0.058	0.017	0.045
	[0.069]	[0.056]	[0.053]	[0.056]
married	0.052	0.138***	-0.023	-0.074*
	[0.058]	[0.047]	[0.041]	[0.043]
Wealth (100,000 KShs)	-0.009***	0.014***	0.006*	0.004
	[0.003]	[0.002]	[0.003]	[0.002]
Male member (age) < 17	0.026	-0.037**	0.002	-0.003
	[0.020]	[0.016]	[0.015]	[0.016]
Female member (age) < 17	0.028	-0.023	-0.026	0.017
	[0.020]	[0.018]	[0.017]	[0.017]
≥ 17 Male member (age) ≤ 39	0.028	0.031	-0.010	0.013
	[0.025]	[0.021]	[0.020]	[0.020]
≥ 17 Female member (age) ≤ 39	0.014	-0.013	0.012	-0.004
	[0.027]	[0.022]	[0.021]	[0.022]
Male member (age) ≥ 40	0.017	0.100**	0.103**	-0.066*
	[0.050]	[0.041]	[0.040]	[0.039]
Female member (age) ≥ 40	-0.036	-0.042	0.027	0.008
	[0.053]	[0.043]	[0.045]	[0.046]
Rural==1	0.110**	-0.078*	0.072*	0.035
	[0.050]	[0.041]	[0.038]	[0.041]
Observations	1,596	1,595	1,595	1,595
Kleibergen-Paap F statistic (critical value = 16.38)	26.979	26.970	26.628	26.998

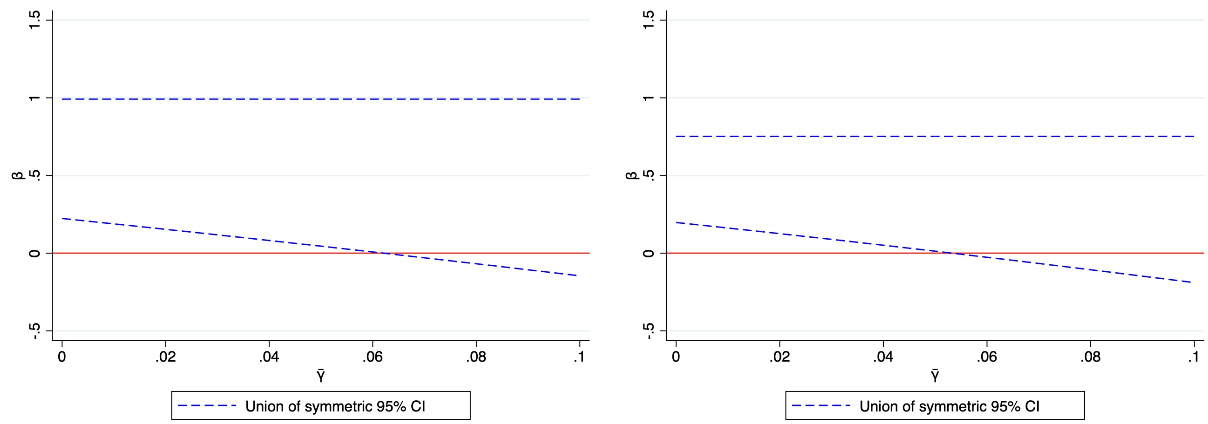
Heteroskedasticity-robust standard errors in brackets.

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

SACCO participation and saving at home.

Figure 3.1: Plausibly exogenous instrument $\gamma \in [0, \bar{\gamma}]$

(a) ROSCA (b) Bank



*Note: This figure shows the 95% confidence intervals for β under different violations of the exclusion restriction, indicated by $\bar{\gamma}$. The upper blue dashed line marks the higher end, and the lower blue dashed line marks the lower end of the confidence interval. At $\bar{\gamma} = 0$, the blue lines represent the standard confidence interval without exclusion restriction violations. As $\bar{\gamma}$ increases from left to right, the figure shows how the confidence interval changes as allowed exclusion restriction violations increase.

The results under the assumption of perfect exclusion restriction $\gamma = 0$ are given by intercept of the plots. As we move away from the intercept and $\bar{\gamma}$ increases, we get larger potential violations of the exclusion restriction and obtain wider confidence intervals. Eventually, the violation of the exclusion restriction gets large enough to lose statistical significance. Statistical significance of the impact of M-Pesa saving on ROSCA participation at the 5% level is lost by the time $\bar{\gamma} > 0.07$. In the same manner, the statistical significance of M-Pesa savings on bank savings is lost by the time $\bar{\gamma} > 0.06$.

For all values of $\bar{\gamma} \leq 0.06$, I observe a statistically significant impact of M-Pesa savings on ROSCA participation. A direct effect size of 0.06 represents a substantial violation of the exclusion restriction. In terms of ROSCA participation, this effect is equivalent to 50% of the impact of a rural-urban differential and the marginal effect of a change in household wealth by 667,000 KSh (average household wealth of the estimation sample is 174,822 KShs). Additionally, for all values of $\bar{\gamma} \leq 0.05$, I find a significant effect of M-Pesa savings on bank savings. Similar to the ROSCA participation case, $\gamma = 0.05$ represents a substantial violation of the exclusion restriction with regard to bank savings. This is equivalent to about 60% of the effect of a rural-urban differential on bank savings and the effect of a change in household wealth by approximately 357,000 KShs. Therefore, I argue that the estimated impact of M-Pesa saving on ROSCA participation and bank savings is robust to substantial violation of the exclusion restriction.

3.6 Conclusion

This study investigates how the use of M-Pesa for saving by households impacts their decision to save with other financial tools. To do that I focus on the four main financial tools used in Kenya i.e. banks, SACCOs, ROSCAs, and savings done at home. Leveraging household survey data from Suri and Jack (2017) and employing multiple SIM card ownership as an instrumental variable for M-Pesa saving, I find that saving with M-Pesa had a positive impact on households' savings with banks and ROSCAs. This result remains valid even with large violations of the exclusion restriction.

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Chapter 4

4 Inference with DHS Data for Rural West Africa

4.1 Introduction

Empirical studies on developing economies are often limited by the availability of reliable and comprehensive datasets. The Demographic and Health Surveys (DHSs) are perhaps the most important of such datasets. They have been used as a primary data source for over 6,000 journal articles.[1] The DHS are nationally representative household surveys collected by the United States Agency for International Development (USAID) and its country-specific partners. It constitutes a repeated cross-sectional data set that is collected from 87 low- and middle-income countries about every 5 years. Along with social and demographic data, the DHS includes a range of health measures for women, men, and children. This allows an exploration of the prevalence and trends of health behavior and economic measures within and across countries. Regardless of the study, there are likely to be unobservable factors that are correlated across observations, at least for those sufficiently close to each other.[2] This paper conducts a Monte Carlo simulation using a model that is calibrated to match the DHS dataset from northern Nigeria to evaluate the performance of various methods of inference that allow for spatial dependence across observations.[3,4]

Northern Nigeria serves as a compelling case study for examining inference with DHS

[1]Some examples of studies using the DHS are Acemoglu et al. (2014); Fenske (2013, 2015); Hjort and Poulsen (2019); Lowes and Montero (2021); Mamo et al. (2019); Osili and Long (2008). Refer to Table C.1 for a description of the studies mentioned.

[2]We could expect at a minimum that there will be a correlation across observations due to the geographic clustered sampling methodology.

[3]We apply to DHS the same methodology used by Conley et al. (2018) in a different data context.

[4]This study focuses on a linear model where child's vaccination index predicted by mother's education. However, we also find spatial dependence in residuals of other regressions not reported. Specifically, we find spatial dependence in residuals of linear models of child's Body Mass Index and female fertility (measured as the number of children born before age 25), predicted by the mother and woman's education respectively.

data. Northern Nigeria is reasonably representative of rural West Africa, an important region in which to study poverty and development.[5] This region is characterized by high levels of poverty, low educational attainment, and limited access to healthcare and infrastructure-common challenges across West Africa. In addition, social norms in northern Nigeria exhibit significant gender disparities with women and girls facing considerable barriers to education and economic opportunities. These gender disparities reflect those of West Africa and indeed all of sub-Saharan Africa.

It is important to properly account for spatial dependence when making inferences from data. The general issue is that the variance of estimated parameters with dependent data can be substantially different from that with independent data. In particular, there is a concern about positive spatial dependence which if unaccounted for could result in an underestimated standard error, inflated t-statistics, and spurious results.

There are two main methods commonly employed to address cross-sectional dependence in DHS data. These are standard errors commonly clustered using many small groups or Conley (1999) standard errors. Both methods require the researcher to make a choice of tuning parameters. When using clustered standard errors, the researcher must select a choice of clusters. When applying Conley (1999) errors, the researcher must select the kernel and the distance cut-off. However, different standard error estimators or different tuning parameters can produce substantially different results making it difficult for the researcher to choose a method for making inferences. The goal of this paper is to guide researchers in their choice of tuning parameters to best account for the cross-sectional dependence in rural West African DHS data.

We will also examine the large cluster /sample splitting methods by Ibragimov and Müller (2010) (IM) and Bester Conley and Hasen (2011) (BCH). BCH applies the standard

[5]Examples of studies on northern Nigeria include Udry (1990, 1994, 1995), Bakhtiar et al. (2022); Bastian et al. (2017); Carneiro et al. (2021); Dillon et al. (2011); Jaiyeola and Choga (2021); Okeke (2023); Okeke and Abubakar (2020).

cluster covariance estimator to a small number of large groups that are well-shaped (large interior relative to the boundary). BCH can be implemented using the cluster command in Stata. We construct large groups based on the latitude and longitude coordinates, treating these coordinates as Cartesian. For smaller numbers of large groups, we separate along longitudinal coordinates. For larger numbers of large groups, we separate by latitude and longitude into rectangles. Cao et al. (2021) provide an algorithm that can also be used to obtain well-shaped clusters. The IM approach constructs a set of cluster-specific estimates of a common parameter which are then treated as data points in a Gaussian location model with location equal to the common parameter. We employ the same constructed latitude-longitude clusters in implementing IM. The Cao et al. (2021) can also be used in implementing IM.

Our Monte Carlo simulation is based on a specific application using DHS data from northern Nigeria. The application we use is based on an empirical analysis by Fenske (2013) that investigates the relationship between vaccines and household characteristics. We focus on the effect of mothers' education on their child's vaccine outcomes controlling for a set of mother and child characteristics.

We begin by estimating a linear regression model using the DHS Child Recodes. This data has information on the children born to sampled women in the five years preceding the survey taking children as the observational unit. For our case study, we use the available sample (7,739) of oldest children under the age of 5 from the sixth round of northern Nigeria DHS data.[6] We report the standard errors using a set of available techniques that include clustered standard errors using small groups, Conley estimator with different cutoffs, and BCH estimates for different large cluster choices. We take the residuals from our case study regression and use non-parametric methods to describe the covariance structure within distance bins following Conley and Topa (2002) and Conley and Dupor (2003). We

[6]Northern Nigeria in this paper is defined as the North West and North East regions of Nigeria with the exception of Adamawa and Taraba states.

then estimate a parametric model of spatial dependence of error terms using the regression residuals. [7]

To estimate the DGP for our Monte Carlo simulation we use a linear model, our estimated means from the real data and the real data locations. We simulate new data points using a residual bootstrap, drawing error terms that follow a Gaussian distribution with the estimated covariance structure of the real data residuals process and adding these simulated errors to the estimated means.

We evaluate the performance of various inference methods for t-tests. For each simulated dataset, we estimate t-statistics using different estimators and calculate rejection frequencies when the null hypothesis is true. We then compare these rejection frequencies across different inference methods. In addition, for every simulation, we calculate the confidence intervals for each method of inference and investigate aspects of the confidence intervals across different inference methods (e.g. average confidence interval length).

We evaluate a set of inference methods with tuning parameters that are fixed across simulations. This includes Conley (1999) with uniform kernel and cutoffs set at various distances (100km,150km,200km,250km,300km, and 400km) and clustered standard errors at the DHS small cluster level (270 clusters). We also evaluate the performance of the BCH and IM inference methods with 3, 6, and 12 clusters.

Our Monte Carlo simulations show that the HAC estimator at short cutoffs, and BCH and IM with 6 and 12 clusters all perform well. Interestingly, when applied at the Nigerian state level, both IM and BCH perform reasonably well, with IM having a slightly better size and coverage. Therefore, for applications involving northern Nigeria data where reliable geographic coordinate data may be lacking, employing IM or BCH with northern Nigerian states is a viable inference method.

[7] We use the Bessel-Lommel function which has three parameters, is reasonably flexible, and allows for negative correlation. See section 4.4 for details. We also employ the exponential decay covariance function which only allows for non-negative spatial covariance.

4.2 Methodology

We analyze ordinary least square estimations of linear models using data from the sixth round of the DHS for northern Nigeria. The data is geographically cluster-sampled and includes anonymized geographic coordinates that are slightly dispersed from the center of the surveyed cluster. We therefore only have approximate coordinate locations.

We present results for vaccination index for children under the age of five, using data on the oldest child within this age group reported by each mother. The data reports whether a child has completed 9 different vaccinations against polio, tuberculous, diphtheria, tetanus, pertussis (DPT), and measles. The vaccination index represents the share of completed vaccines of the nine possible vaccines for children under five. We predict the vaccination index of each child with the key predictor being their mother's years of education along with other controls using the equation:

$$y_i = \boldsymbol{x}_i' \beta + \varepsilon_i. \tag{4.1}$$

Where y_i is a vaccination index, for individual i, ε_i is the error term, and x_i is a vector of characteristics that includes the treatment, mother's years of education, and other covariates which are mother's age, mother's age squared, child's age, child's age squared, child's gender, birth order, multiple births indicator, and an urban residential dummy.[8]

We focus on the OLS estimator of β which can be expressed as

$$\hat{\beta} = \left(\sum_{i=1}^{N} \boldsymbol{x}_i \boldsymbol{x}_i' \right)^{-1} \left(\sum_{i=1}^{N} \boldsymbol{x}_i y_i \right). \tag{4.2}$$

[8]This model specification follows that of Fenske (2013) though in their study they focus on the correlation between the total number of vaccines received and the presence or absence of a historical institution. Their model includes mothers' education in the form of educational attainment fixed effects.

If the data are weakly independent and usual regularity conditions are satisfied the large sample limiting distribution of $\hat{\beta}$ is Gaussian:

$$\sqrt{N}\left(\hat{\beta}-\beta\right) \xrightarrow{d} N\left(0, Q^{-1}VQ^{-1}\right)$$

where

$$V = \lim_{N\to\infty} \mathrm{Var}\left(\frac{1}{\sqrt{N}}\sum_{i=1}^{N} \boldsymbol{x}_i\varepsilon_i\right) \quad \text{and} \quad Q = \lim_{N\to\infty} \mathrm{E}\left[\boldsymbol{x}_i\boldsymbol{x}_i'\right].$$

Using a sample analog approximation of Q along with a consistent estimator $\widetilde{V}$ of V we get a typical large sample approximation of the distribution of $\hat{\beta}$

$$\hat{\beta} \overset{Approx}{\sim} N\left(\beta, \frac{1}{N}\left[\frac{1}{N}\sum_{i=1}^{N}\boldsymbol{x}_i\boldsymbol{x}_i'\right]^{-1}\widetilde{V}\left[\frac{1}{N}\sum_{i=1}^{N}\boldsymbol{x}_i\boldsymbol{x}_i'\right]^{-1}\right). \tag{4.3}$$

Using clustered covariance estimates for small clusters and the Conley (1999) approach corresponds to different choices of $\widetilde{V}$.

The covariance matrix $\widetilde{V}$ can be estimated as a weighted sum of sample autocovariance such that

$$\widetilde{V} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_N(i, j)\boldsymbol{x}_i\hat{\varepsilon}_i\boldsymbol{x}_j'\hat{\varepsilon}_j, \tag{4.4}$$

where $\hat{\varepsilon}_i$ is the OLS residual and $\omega(i, j)$ is a weight on the pair of residuals from observations i and j. For the same observations $\omega(i,i) = 1$, however, for distinct observations i and j, $\omega(i, j)$ can take various forms depending on the assumed nature of interdependence across observations.

A Conley (1999) covariance estimator uses weights that are dependent on a measure of distance $\delta(i, j)$ between observations i and j. The value of the weights depends on the kernel choice and the cutoff choice of the researcher. In this study, we focus on the uniform kernel applied with different cutoffs. For a given distance cutoff d, $\omega(i, j)$=1 if $\delta(i, j) \leq d$ and $\omega(i, j)$=0 if $\delta(i, j) > d$.

Clustered covariance estimators use a uniform weighting metric where $\omega(i, j) = 1$ if observations i and j belong to the same group along which the covariance matrix is being estimated and $\omega(i, j) = 0$ otherwise. The classical clustered covariance approach works with a large number of small clusters.

The BCH large cluster approach uses a small number G of large clusters that are required to be similarly sized and properly shaped (large interior relative to the boundary).[9] To get 3 clusters, we divided the data into equal longitude bins. For 6 clusters we divide the data into 6 equal longitude bins. To obtain 12 clusters, we further divide each of the 6 longitude bins into 2 equal parts by latitude coordinates. We manually check to ensure that each created groups have substantial interior observations compared to their boundary observations. The idea is that, with a fixed number of large groups, $\widetilde{V}$ is viewed as a random variable centered at V rather than a consistent estimator of V. The hope is that this approximation will better capture the reality when the covariance estimator is noisy. Under mild regularity conditions that include weak dependence, and homogeneity in regressor variances, the reference distribution of the t-statistic is based on a Student t distribution with $G - 1$ degrees of freedom. [10]

With the IM approach, the model parameters are separately estimated for each group, and the point estimates are used as data points to estimate a Gaussian location model. The point estimates of model parameters are then taken as the average of the group-specific-parameter estimates with the standard error of parameters being the sample standard de-

[9]Cao et al. (2021) show that such clusters can be defined using the k-medoids partitioning technique.

[10]The fixed G large group size limiting distribution of $\hat{t} = \frac{\sqrt{N}(\hat{\beta}-\beta_0)}{\sqrt{\hat{Q}^{-1}\widetilde{V}\hat{Q}^{-1}}}$ is approximately $\sqrt{\frac{G}{G-1}}t_{G-1}$.

viation of the group-specific-parameter estimates. Inference for t-tests is conducted using critical values based on Student t-distribution with $G-1$ degrees of freedom.[11]

4.3 Case study estimates

In our case study, we use the complete sample of the oldest children under 5 years of each mother from northern Nigeria, derived from the sixth round of the Nigerian DHS Child Recodes. This results in a sample size of 7,739. We focus on the effect of mother's years of education on the share of vaccines received by children.[12]

In Table 4.1, we present point estimates and half the length of the 95% confidence intervals for the model parameters from equation (4.1). The first column contains the OLS estimates of the model coefficients. The subsequent columns display half-lengths of 95% confidence interval of these parameters using different estimators. Mother's education, measured in the number of years of schooling, is our treatment effect of interest. Starting from column 2, moving from right to left, we show the confidence interval lengths estimated using White (1980) heteroskedasticity-robust standard errors, classical clustered standard errors at the small DHS cluster level, Conley (1999) standard errors with a uniform kernel and cutoffs set at 200km and 350km, and BCH standard errors with 3, 6, and 12 clusters.

The estimators that account for spatial dependence yield different estimates compared to the White (1980) heteroskedasticity-robust estimator. Specifically, relative to the White (1980) estimate, the clustered standard errors estimator at the district level produces a confidence interval that is 65% wider, while other methods of inference that account for spatial dependence range from 150% to 500% wider. In the case of a mother's education, none of the confidence intervals include zero, however, this is not always the case. For example,

[11]The limiting distribution of $\hat{t} = \frac{\sqrt{N}\bar{\hat{\beta}}}{s_{\hat{\beta}}}$ is the Student-t distribution with $G-1$ degrees of freedom.

[12]Summary statistics can be found in Table C.2.

in the case of the urban dummy coefficient, all the methods of inference that account for spatial dependence produce confidence intervals that include zero.

The results indicate a statistically significant positive but modest correlation between the number of years of education of a mother and the vaccination rate of their child. The average child in our data sample has received a third of the total vaccinations. The point estimate is 2.5% but the confidence interval varies by the method of inference ranging from [0.023, 0.027] to [0.0129,0.0371] a difference in ranges that could be important for policy decisions.

Table 4.1: Case Study Regression Results

	$\hat{\beta}$	Heteroskedastic	Cluster small DHS Clusters	HAC 100km	HAC 200km	HAC 350Km	BCH States	BCH 3	BCH 6	BCH 12
Mother's education	0.0250	0.0020	0.0033	0.0050	0.0062	0.0054	0.0072	0.0121	0.0077	0.0057
Mother's age	0.0087	0.0058	0.0063	0.0040	0.0054	0.0024	0.0054	0.0122	0.0069	0.0066
Mother's age squared	-0.0099	0.0090	0.0099	0.0040	0.0061	0.0035	0.0071	0.0064	0.0065	0.0059
Child's age	0.0753	0.0164	0.0161	0.0135	0.0103	0.0114	0.0124	0.0276	0.0131	0.0099
Child's age squared	-0.0158	0.0036	0.0034	0.0026	0.0026	0.0013	0.0028	0.0052	0.0029	0.0024
Child's gender	0.0083	0.0118	0.0129	0.0081	0.0092	0.0121	0.0092	0.0016	0.0139	0.0108
Birth order	-0.0009	0.0040	0.0047	0.0069	0.0079	0.0000	0.0087	0.0206	0.0084	0.0080
Multiple births	0.0553	0.0729	0.0708	0.0699	0.0690	0.0438	0.0758	0.2070	0.0786	0.0740
Urban	0.0449	0.0180	0.0376	0.0467	0.0384	0.0422	0.0501	0.0737	0.0665	0.0458
Constant	0.0159	0.0820	0.0904	0.0852	0.1072	0.0000	0.1009	0.2210	0.1233	0.1202
Observations	7,739									
R-squared	0.1460									

Notes: Data from the sixth round of the Northern Nigeria DHS survey. Northern Nigeria in this study includes only the North East and North West regions of Nigeria with the exception of Adamawa and Taraba states. States refers to the Nigerian administrative states. There are only 11 states in our data sample. See Figure C.1 for a map of the Nigerian states. This table includes point estimates and half-lengths of confidence intervals for different methods of inference.

We use the approximate geographic coordinates of the data observations and illustrate the covariance structure of the residuals. We construct non-parametric covariance estimates and test for spatial independence following Conley and Topa (2002) and Conley and Dupor (2003). First, we divide the range of distances into equally spaced bins. Within each bin, all cross-products of residuals of observations i and j whose distance apart $\delta(i, j)$ falls within the distance bin are averaged, and then this average covariance is divided by the sample variance to produce average autocorrelations which are plotted against the midpoint of the distance bin.

Figure 4.1: Average Residual Correlations by Distance

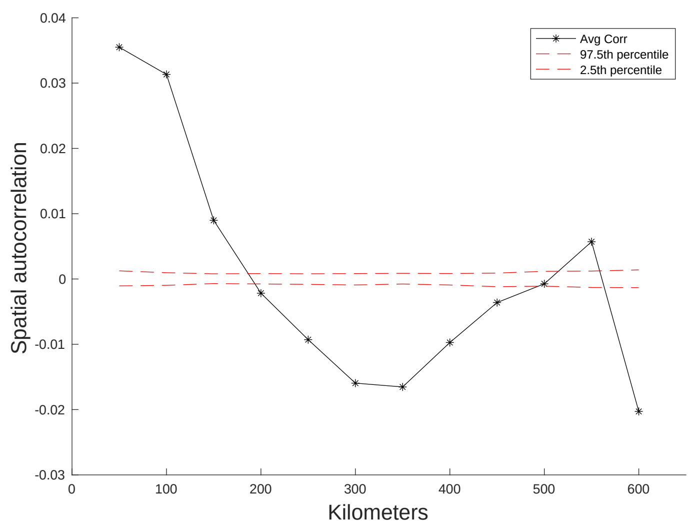
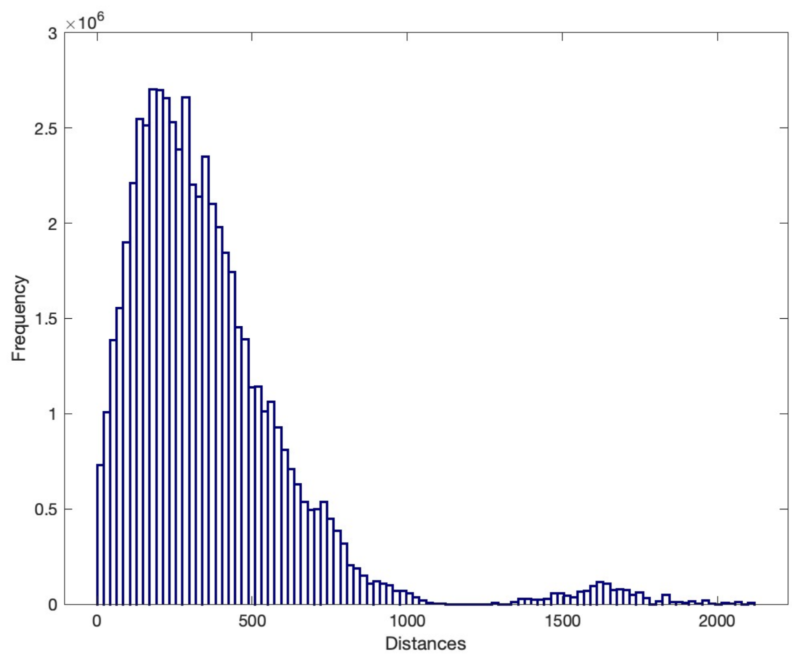


Figure 4.1 shows the estimated average autocorrelations of residuals obtained from equation (4.1). The average autocorrelation within each bin is marked with a star and plotted against the midpoint of the distance bins. We test the null hypothesis of spatial independence using a simulation procedure that re-estimates this autocorrelation for boot-

strap samples that impose the null hypothesis of spatial independence. Locations are taken as given and simulated residuals are constructed via iid draws with replacement from the empirical distribution of estimated regression residuals. We conduct a point-wise test of spatial independence by collecting simulated average correlations (under independence) at that distance using their 2.5th to 97.5th percentile to define an acceptance region. The red dashed markers indicate these percentiles of the reference distribution under independence. To conduct point-wise tests of independence we simply compare the stars to the dashed lines and reject the null for stars that lie outside the dashed lines.

It is important to note that there are two main reasons why the non-parametric test may reject the null hypothesis of spatial independence. One reason is that the true average spatial correlation may be non-zero. Another reason is that the sampling distribution under dependence is wider than the distribution under spatial independence.

Figure 4.2: Histogram of pairwise distances across observations



In Figure 4.1 we see positive estimated correlations for distances less than 175km that lie outside the acceptance region for independence. Our strong prior is that this is largely due to true positive spatial correlation because these are small distances. We also see a negative spatial correlation between 200km to 400km, which could be evidence of a true negative spatial correlation or could be due to noise or a bit of both. For the larger distances, we do not interpret the estimated spatial correlation as non-zero spatial correlation as it is quite likely to be noise. The noise in the estimated spatial correlation at large distances is reflected by sample size which can be seen in Figure 4.2.

4.4 Calibration and Simulation

We assume the distribution of the error term is multivariate Gaussian $N(0, \Omega)$. We parameterize the diagonal values of Ω to be σ^2. The off-diagonal entries of Ω, $Cov(\varepsilon_i, \varepsilon_j) = \Omega_{ij}$ are defined by

$$\Omega_{i,j} = f(\delta(i, j)), \tag{4.5}$$

where $\delta(i, j)$ is the great circle distance distance between locations of observations i and j. $f(\delta(i, j))$ is defined below.

We use the functional form of the Bessel-Lommel covariance function defined on $\mathbb{R}^2$ as:

$$f(\delta(i, j)) = \frac{\eta_0 \xi^2}{(2\pi)} \int_0^{\infty} dk \frac{k J_0(k\delta(i, j))}{1 + \eta_1 (k\xi)^2 + (k\xi)^4}, \tag{4.6}$$

with a vector of parameters is (η_0, η_1, ξ). The parameter η_0 is the amplitude coefficient, which determines the heights of the waves, and η_1 is the rigidity coefficient that determines how quickly the waves die out. ξ is the characteristic length that determines the width of the waves holding the amplitudes constant and therefore together with η_1 determine how the slope changes over distances.[13] $J_0(k)$, $k \in \mathbb{R}$ is the Bessel function of the first kind of order zero. We select the Bessel Lommel functional form because it is parsimonious and flexible enough to capture a wide variety of autocovariance functions.

We estimate the covariance function parameters (η_0, η_1, ξ) by least squares using pairs of distinct observations. In other words, we minimize

$$\min_{\{\eta_0,\eta_1,\xi\}} \sum_{i}^{N} \sum_{j \neq i}^{N} \left(\hat{\varepsilon}_i \hat{\varepsilon}_j - f(\delta(i,j))\right)^2 . \tag{4.7}$$

We use the sample variance of individual observations to estimate σ^2. We verify that the constraint that σ^2 is greater than $f\hat{(}0)$ was satisfied.

Our point estimates are $\hat{\eta}_0 = 0.0061$, $\hat{\eta}_1 = -1.8724$ and $\hat{\xi} = 75.8060$. In Figure 4.3 we plot our estimated covariance function normalized by the sample variance. Unsurprisingly, our estimated function agrees with the non-parametric autocovariance structure.

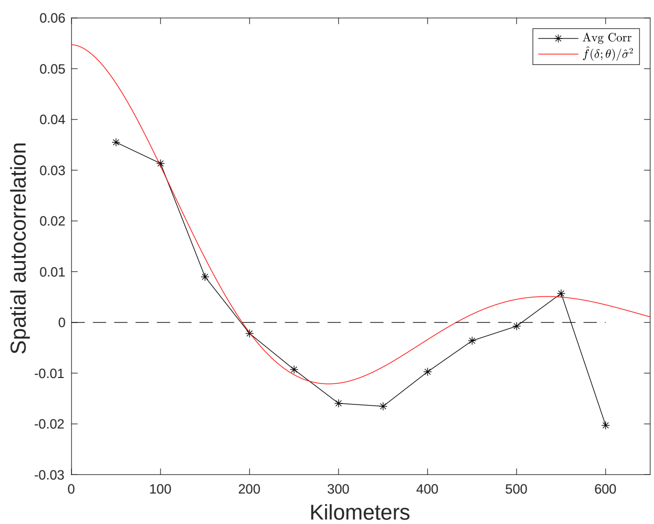
Note that the GPS data available represents the approximate center of a cluster of households therefore there is an inherent measurement error in our distances. This means we can not estimate the true autocovariance estimate function. What we estimate is an approximate autocovariance function that remains a plausible DGP for our simulation study. We argue that our estimated covariance function is an empirically relevant model for our DGP.

Simulation

To create a realistic scatter of observation locations, we modify the reported cluster coordinates. Observations within the same cluster are initially assigned the same coordinates, which is approximately the center of the cluster. To introduce variability, we jitter these coordinates within a radius equal to half the distance to the nearest reported cluster coordinate. This is done by adding independent draws from a uniform distribution on a circle with

[13]Refer to Hristopulos (2015) for a detailed description of the Bessel-Lommel covariance function.

Figure 4.3: Estimated Residual Correlation (Bessel-Lommel)



the estimated radius, resulting in an empirically relevant distribution of locations.

We generate 2000 simulated outcomes with the same sample size as our case study, 7,739 observations, using residual bootstrap. For each individual, we use the real characteristics $\boldsymbol{x}_{i,real}$ and the estimated $\hat{\beta}$ reported in Table 4.1. Letting $\hat{\Omega}$ be our estimate of Ω we draw a vector of errors $\{\varepsilon_1, ..., \varepsilon_{7739}\}'$ from a $N(0, \hat{\Omega})$. We proceed to generate outcomes using our linear model:

$$y_i = \hat{\beta}\boldsymbol{x}'_{i,real} + \varepsilon_i. \tag{4.8}$$

For each simulated data set we re-estimate our regression to evaluate different alternative methods of inference.

Two Alternate DGPs: Exponential Decay and Heteroskedasticity

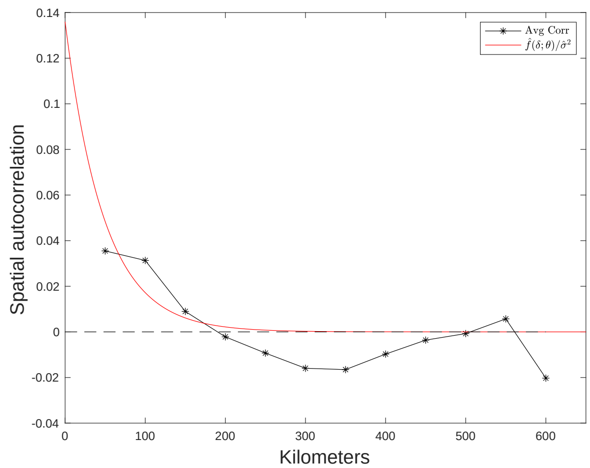
We also entertain two other specifications for Ω. Arguably, these specifications are not as well calibrated to the northern Nigeria data but they are potentially very relevant for applications in other places. First, we employ the exponential decay covariance functional form where the diagonal entries of Ω remain as the sample variance, and the off-diagonal entries of Ω are defined as

$$f(\delta(i, j)) = \lambda \exp\left(-(\tau\delta(i, j)\right), \tag{4.9}$$

with a vector of parameters (λ, τ). We estimate the covariance function parameters as above, using the pairs of distinct observations, and obtain $\hat{\lambda} = 0.0207, \hat{\tau} = 0.0095$. In Figure 4.4, we plot our estimated covariance function, normalized by the sample variance.

The final DGP we look at explores a model with heteroskedasticity by allowing the

Figure 4.4: Estimated Residual Correlation (Exponential Decay)



diagonal entries of Ω to vary by state while letting the off-diagonal entries take the exponential decay functional form specified as in equation 4.9. We reuse the estimates $\hat{\lambda}$ and $\hat{\tau}$ and the state-specific sample variances of residuals from equation (4.1). The state-specific sample variances differ from each other with the largest being 5 times that of the smallest variance.[14] We verify that all state variances exceed $\hat{f(0)}$.

We repeat the same style simulation described above by generating 2000 simulated outcomes of the same size of 7,739 as the estimation sample. In Table 4.3 and Table 4.4 we report the results from simulation with exponential decay DGP and the heteroskedastic DGP respectively.

[14]The state-specific variances are as follows; Bauchi= 0.081, Borno= 0.094, Gombe= 0.124, Jigawa= 0.056, Kaduna= 0.104, Kano= 0.073, Katsina= 0.072, Kebbi= 0.026, Sokoto= 0.032, Yobe= 0.084, and Zamfara= 0.042.

4.5 Results

Table 4.2 presents the rejection rates for t-tests at the 5% significance level for the Bessel-Lommel covariance DGP. It reports the mean and the 10th, 50th, and 90th percentile confidence interval lengths. Column 1 details the inference methods used in each row. Both inference methods that use heteroskedasticity-robust estimators and clustered standard errors with small DHS clusters show substantial size distortions with rejection rates of 18% and 12.2% respectively.

HAC estimators work well for smaller cutoffs below 200km with small size distortions and modest confidence interval lengths. However, they decrease in performance after the 200km cutoff. The source of under-performance is due to a combination of the existence of true negative correlations in simulated errors at distances between 200km and 450km, and noise. In extreme cases, this results in negative estimated variances, observed in 0.1% of simulations with a 250km cutoff, 1.7% of simulations with a 300km cutoff, and 7.6% of simulations with a 400km cutoff. [15] As the distance cutoff grows in this range there is a tendency for the variances to increase, and the typical HAC estimator (Conley, 1999) does not account for noise in estimated variances. This illustrates that researchers need to be careful when selecting the cutoff parameter for the Conley (1999) estimator.

The BCH approach with 3, 6, and 12 large clusters all perform well in terms of rejection frequencies, with rejection rates ranging from 3.6%, 5.0%, and 6.9% respectively. However, BCH with 3 clusters is quite conservative with large confidence interval lengths. The average length of confidence intervals produced using BCH with 3 clusters is at least 100% larger than the average confidence interval length of other small cluster approaches studied. This is because the test statistic associated with BCH with 3 clusters has 2 degrees of freedom. Amongst these choices, we recommend BCH with 6 clusters, but researchers willing

[15] The negative estimated variance can be avoided with different kernel choices but noise can not be avoided.

to compromise slightly on size (5.0% vs 6.9%) in exchange for a reduction in CI length (0.0068 vs 0.0055) might choose BCH with 12 clusters, or with the number of clusters in between 6 and 12.

Using BCH with clusters defined at the Nigerian state level works surprisingly well. It has a rejection rate of 6.6% and has an average CI length of 0.006 which lies between that of BCH 6 and 12. The 11 states that we use are not as well shaped as our constructed BCH clusters but most of them are approximately well shaped with small boundary vs interior.[16] These states in general are similar in population density as shown in Figure C.1. The outliers are Kano, Yobe, and Gombe with Kano having a population size of about 9 million while Yobe and Gombe have the smallest population size of about 2.3 million. The remaining 8 states have population sizes ranging from 3.2 to 6.1 million though the majority (75%) of these states have a population size of about 4 million (Nigerian National Population Commission, 2006). Evidently, most states are similar enough that the BCH approximation would work. Therefore in applications in northern Nigeria, where reliable data on geographic locations is unavailable, BCH with state clusters will be a reasonable alternative for inference. Note, however, that this might not work for other countries.

The IM approach yields results similar to the BCH approach. The estimator with 3, 6, and 12 large clusters performs well with respect to size, with rejection rates ranging from 3.4% to 6.1%. 12-cluster IM has the best size and the shortest average confidence interval. When applied at the state level in northern Nigeria, the IM approach proves effective just like BCH with states, resulting in a smaller size distortion and shorter average confidence interval than the 3- and 6-cluster IM approaches. Additionally, it outperforms the state-level BCH approach in terms of size and confidence interval length.

[16]The Nigerian states studied include Bauchi, Borno, Gombe, Jigawa, Kaduna, Kano, Katsina, Kebbi, Sokoto, Yobe, and Zamfara.

Table 4.2: Simulation Results (Bessel Lommel DGP): T-test rejection rates for 5% level tests and CI lengths

	Rejection Rate	Mean CI length	10 %tile CI length	50%tile CI length	90% tile CI length
Heteroskedastic	0.1800	0.0037	0.0033	0.0037	0.0041
Cluster (DHS cluster)	0.1220	0.0043	0.0035	0.0042	0.0051
HAC (100km)	0.0530	0.0053	0.0040	0.0051	0.0068
HAC (150km)	0.0430	0.0057	0.0041	0.0055	0.0076
HAC (200km)	0.0620	0.0054	0.0038	0.0052	0.0072
HAC* (250km)	0.0966	0.0048	0.0032	0.0046	0.0065
HAC* (300km)	0.1479	0.0043	0.0027	0.0042	0.0060
HAC* (400km)	0.1698	0.0040	0.0021	0.0040	0.0059
BCH (3)	0.0365	0.0123	0.0044	0.0113	0.0222
BCH (6)	0.0500	0.0068	0.0036	0.0064	0.0107
BCH (12)	0.0690	0.0055	0.0036	0.0052	0.0078
BCH (State)	0.0660	0.0060	0.0036	0.0055	0.0090
IM (3)	0.0340	0.0116	0.0040	0.0105	0.0207
IM (6)	0.0610	0.0058	0.0033	0.0055	0.0086
IM (12)	0.0490	0.0050	0.0035	0.0049	0.0067
IM (State)	0.0545	0.0053	0.0036	0.0052	0.0070

Notes: Results from 2000 simulations. HAC estimator refers to Conley (1999) estimator. HAC* indicates HAC estimators that resulted in negative estimated variances. Using a uniform kernel, the HAC can produce negative estimated covariances due to sampling error. The proportion of negative covariance produced by the HAC estimator with cutoffs at 250km, 300km, and 400km are 0.001, 0.017, and 0.076 respectively. The results reported with HAC* are only based on simulations that yielded positive covariances.

Alternate DGP Results

Simulations using exponential decay DGPs that assume both homoskedasticity and heteroskedasticity as described in section 4.4 produce results similar to the Bessel-Lommel DGP. Both the heteroskedastic-robust estimator and clustered standard errors with small DHS clusters show significant size distortions, again highlighting the significance of accounting for spatial dependence.

Inference methods that account for spatial dependence all perform well with reasonable tuning parameter choices. HAC estimators with distance cutoffs up to 200 km are effective but deteriorate past that point. We include simulation results for the same cutoffs as in Table 4.2 for comparability. However, in practice, a typical cutoff choice motivated by examining correlations in residuals just as is done in Figure 4.1, will lead researchers to use smaller cutoff choices. With small cutoffs, the HAC estimator is amongst the best.

BCH and IM applied to 3, 6, and 12 clusters show reasonable rejection rates (4.2% to 6.8%), though both produce wide confidence intervals with 3 clusters. Similar to the Bessel Lommel case, BCH, and IM applied to the northern Nigerian states perform surprisingly well in both homoskedastic and heteroskedastic exponential decay DGP cases. In the heteroskedastic DGP case, IM and BCH are close but IM has the advantage on every clustering level. It yields smaller size distortions with shorter average confidence interval lengths.

For these exponential decay DGPs, we recommend either HAC with 100km cutoff or IM inference approach with 12 clusters as they both perform well. Importantly, just as for the Bessel-Lommel DGP, if one does not have the coordinate location, state clustering works very well our recommendation is to use IM.

Table 4.3: Simulation Results (Homoskedastic Exponential Decay DGP): T-test rejection rates for 5% level tests and CI lengths

	Rejection Rate	Mean CI length	10 %tile CI length	50%tile CI length	90% tile CI length
Heteroskedastic	0.2630	0.0034	0.0033	0.0034	0.0035
Cluster(DHS cluster)	0.1265	0.0047	0.0042	0.0047	0.0052
HAC (100km)	0.0565	0.0053	0.0038	0.0052	0.0070
HAC (150km)	0.0590	0.0051	0.0034	0.0051	0.0072
HAC (200km)	0.0635	0.0050	0.0032	0.0049	0.0073
HAC* (250km)	0.0964	0.0046	0.0029	0.0045	0.0069
HAC* (300km)	0.1538	0.0043	0.0027	0.0042	0.0068
HAC* (400km)	0.1798	0.0039	0.0022	0.0037	0.0060
BCH (3)	0.0520	0.0109	0.0039	0.0103	0.0188
BCH (6)	0.0645	0.0069	0.0038	0.0067	0.0104
BCH (12)	0.0655	0.0061	0.0041	0.0059	0.0082
BCH (State)	0.0620	0.0062	0.0042	0.0060	0.0086
IM (3)	0.0535	0.0099	0.0036	0.0095	0.0171
IM (6)	0.0590	0.0059	0.0036	0.0058	0.0085
IM (12)	0.0555	0.0051	0.0038	0.0051	0.0067
IM (State)	0.0455	0.0054	0.0039	0.0054	0.0071

Notes: Results from 2000 simulations. HAC estimator refers to Conley (1999) estimator. HAC* indicates HAC estimators that resulted in negative covariances. Using a uniform kernel, the HAC can produce negative estimated covariances due to sampling error. The proportion of negative estimated variances produced by the HAC estimator with cutoffs at 250km, 300km, and 400km are 0.001, 0.009, and 0.019 respectively. The results reported with HAC* are only based on simulations that yielded positive covariances.

Table 4.4: Simulation Results (Heteroskedastic Exponential Decay DGP): T-test rejection rates for 5% level tests and CI

	Rejection Rate	Mean CI length	10 %tile CI length	50%tile CI length	90% tile CI length
Heteroskedastic	0.2445	0.0036	0.0035	0.0036	0.0037
Cluster(DHS cluster)	0.1215	0.0048	0.0043	0.0048	0.0054
HAC (100km)	0.0565	0.0054	0.0037	0.0054	0.0072
HAC (150km)	0.0610	0.0052	0.0036	0.0051	0.0074
HAC (200km)	0.0765	0.0051	0.0034	0.0051	0.0074
HAC* (250km)	0.1010	0.0047	0.0033	0.0046	0.0070
HAC* (300km)	0.1372	0.0044	0.0030	0.0043	0.0068
HAC* (400km)	0.1707	0.0040	0.0026	0.0038	0.0066
BCH (3)	0.0575	0.0110	0.0039	0.0103	0.0190
BCH (6)	0.0675	0.0070	0.0039	0.0067	0.0107
BCH (12)	0.0655	0.0062	0.0042	0.0060	0.0084
BCH (State)	0.0640	0.0063	0.0042	0.0061	0.0088
IM (3)	0.0560	0.0100	0.0036	0.0093	0.0171
IM (6)	0.0570	0.0060	0.0036	0.0058	0.0086
IM (12)	0.0580	0.0051	0.0037	0.0051	0.0067
IM (State)	0.0420	0.0053	0.0037	0.0052	0.0069

Notes: Results from 2000 simulations. HAC estimator refers to Conley (1999) estimator. HAC* indicates HAC estimators that resulted in negative covariances. Using a uniform kernel, the HAC can produce negative estimated covariances due to sampling error. The proportion of negative estimated variances produced by the HAC estimator with cutoffs at 250km, 300km, and 400km are 0.002, 0.012, and 0.020 respectively. The results reported with HAC* are only based on simulations that yielded positive covariances.

4.6 Conclusion

In this study, we evaluate the performance of a variety of inference methods using DHS data to guide researchers in addressing cross-sectional dependence in rural West African DHS data. We focus on heteroskedastic robust standard errors, classical small cluster standard errors, Conley (1999) standard errors, and large cluster standard errors by Bester et al. (2011) and Ibragimov and Müller (2010). Although many studies using DHS data report small clusters or Conley (1999) standard errors, these methods with different tuning parameters can lead to significantly different variances of model parameters. Additionally, newer inference methods might also produce substantially different variances, complicating the selection of appropriate tuning parameters for researchers.

To demonstrate the performance of the inference methods studied, we use northern Nigeria as a representative case study, focusing on a linear regression model where a child's vaccination index is predicted by the mother's education. We conduct Monte Carlo simulations with different DGPs that incorporate spatial correlation and heteroskedasticity in error terms. These simulations are calibrated to match the DHS dataset, aiming to imitate real DHS outcomes.

Our simulations reveal that heteroskedastic robust standard error and small cluster standard error estimators can perform poorly, exhibiting substantial size distortions. We also demonstrate that, for each DGP, the HAC estimator with a uniform kernel performs well at shorter distance cutoffs. BCH and IM approaches with 6 and 12 clusters have good size and confidence interval properties, however, IM is consistently a bit better. Finally, to our surprise, the large cluster estimators also perform effectively when applied at the northern Nigeria state level.

Across all DGPs, we recommend either HAC with a small (100km to 150km) cutoff or the IM approach with 12 clusters. For studies lacking reliable geographical coordinates, the state-level IM approach is our recommendation as it slightly performs better than BCH.

4.7 Future Work

In the future, we will examine an adaptive approach to choosing the tuning parameter for the Conley (1999) estimator for each simulation rather than using a fixed tuning parameter across simulations. We will do this by constructing distance bins based on potential distance cutoffs and estimating a non-parametric test statistic of spatial dependence at each potential distance cutoff. We can then sequentially test the hypothesis of spatial independence and select the first potential distance cutoff for which we fail to reject the null hypothesis.

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Appendices

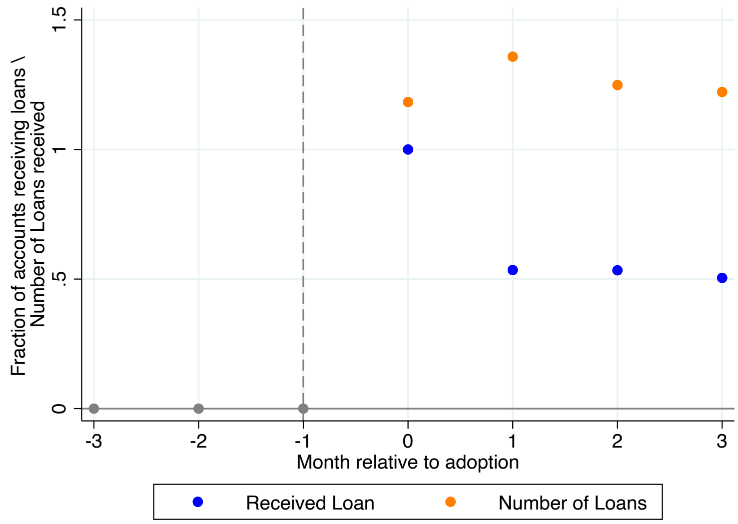
A Chapter 1

A.1 Chapter 1 Appendix

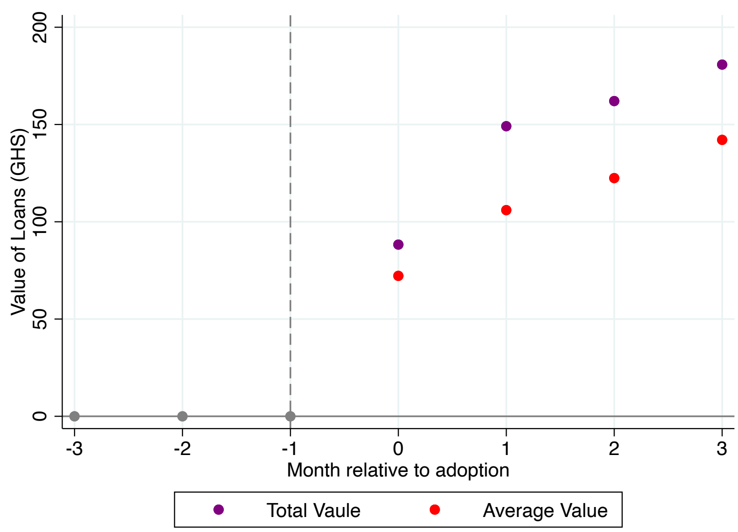
A.2 Plots

Figure A.1: Estimates of Loans Received by Adopters

(a) Received Loan/Number of Loans Received



(b) Value of Loans Received

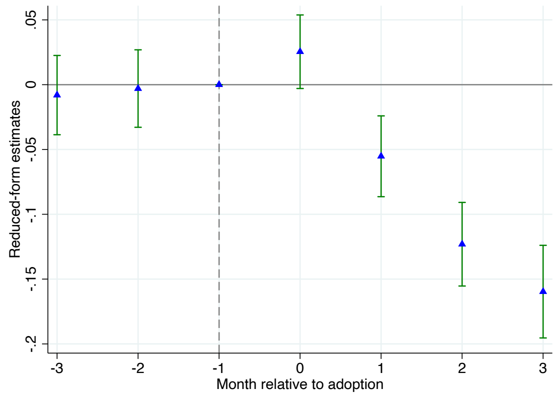


Note: The Figure displays estimates of loans taken by the average loan adopter. The average value of loans displayed in Panel (b) is conditional on receiving a loan.

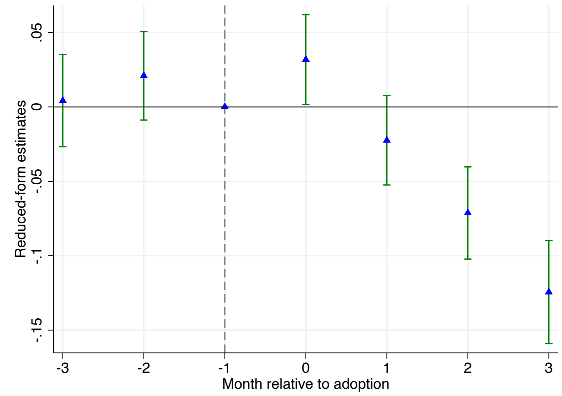
A.3 Tables

Figure A.2: Effect of Digital Credit Adoption on Mobile Money Usage

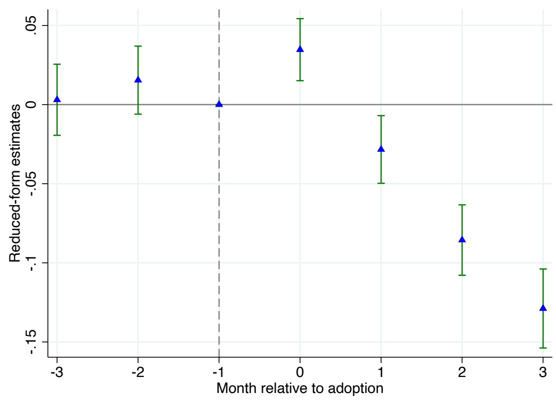
(a) Sent Transfers



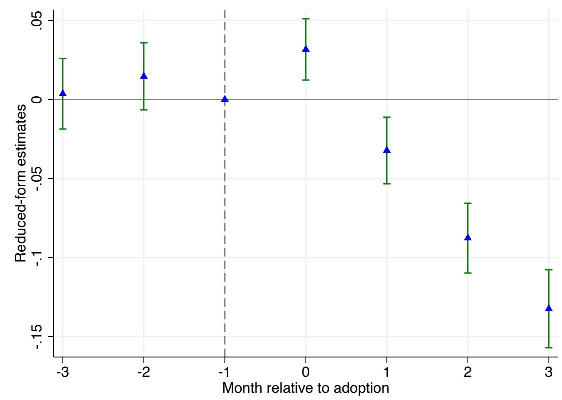
(b) Received Transfers



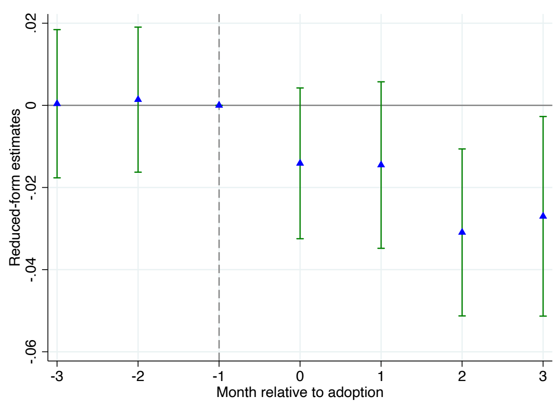
(c) Sent or Received Transfers



(d) All Mobile Money Transactions



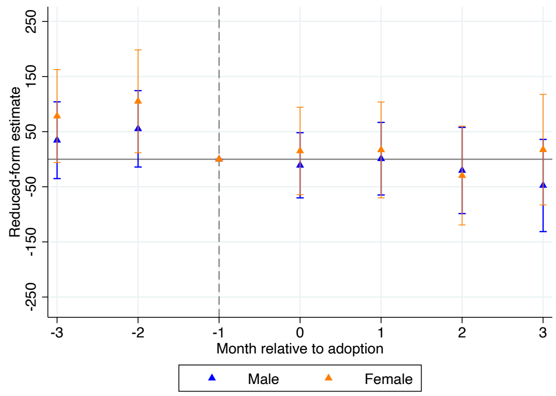
(e) Other Mobile Money Transactions



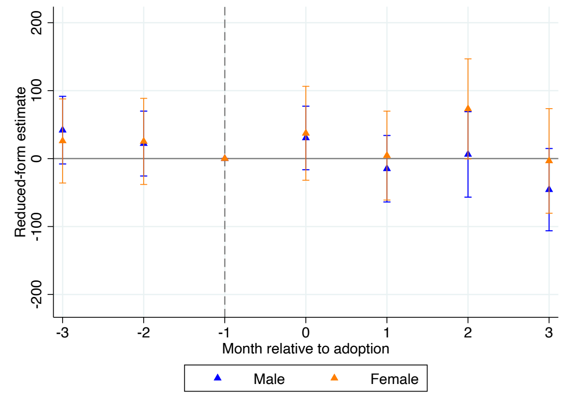
Note: The Figure displays the treatment effect on the likelihood of making a P2P transfer and other mobile money transactions, with the blue triangles indicating the point estimates of μ_τ and the green bars representing the 95% confidence interval using standard errors that are clustered at the individual level.

Figure A.3: Effect of Digital Credit Adoption on P2P Transfers by Gender

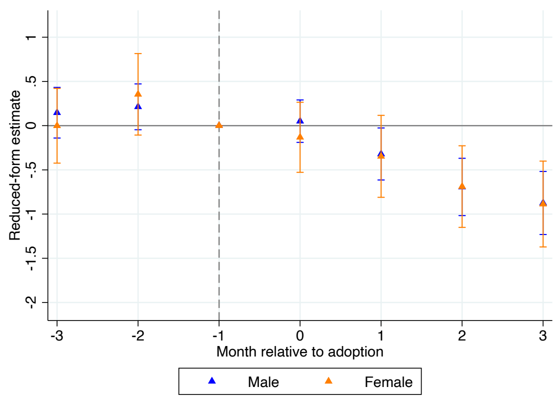
(a) Total Value of Transfers Sent



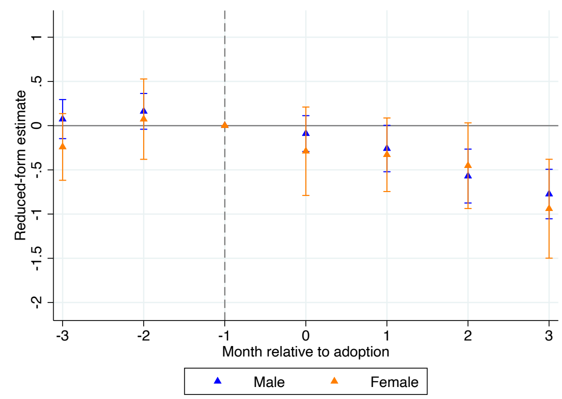
(b) Total Value of Transfers Received



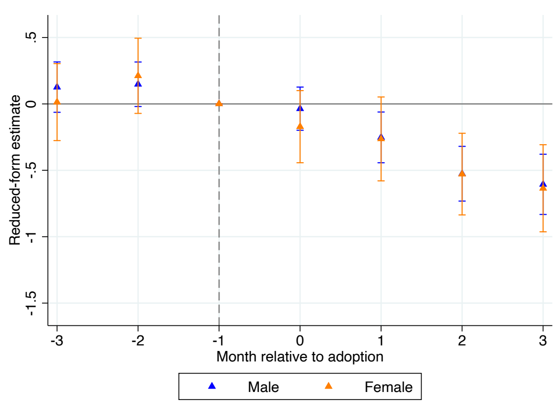
(c) Number of Transfers Sent



(d) Number of Transfers Received



(e) Unique Recipient Accounts



(f) Unique Sender Accounts

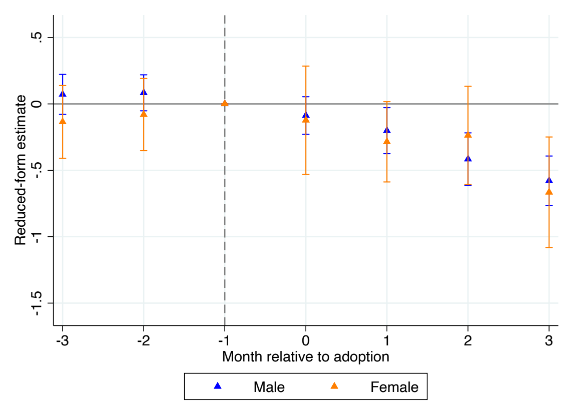
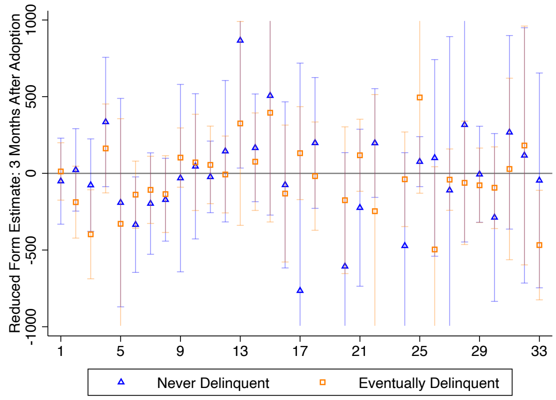
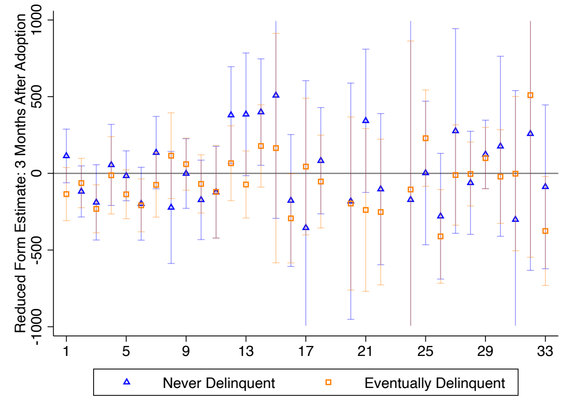


Figure A.4: Effect of Digital Credit Adoption on P2P Transfers by Cohort and Delinquency Status (τ = 3)

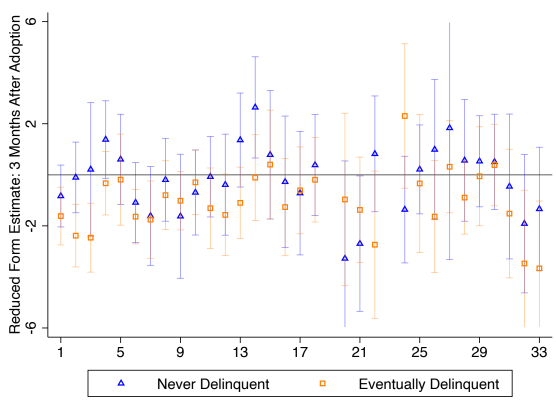
(a) Total Value of Transfers Sent



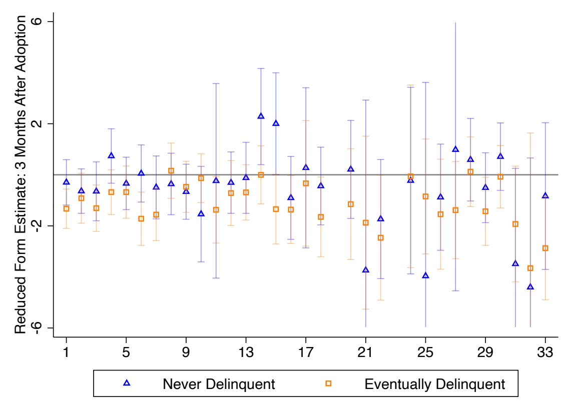
(b) Total Value of Transfers Received



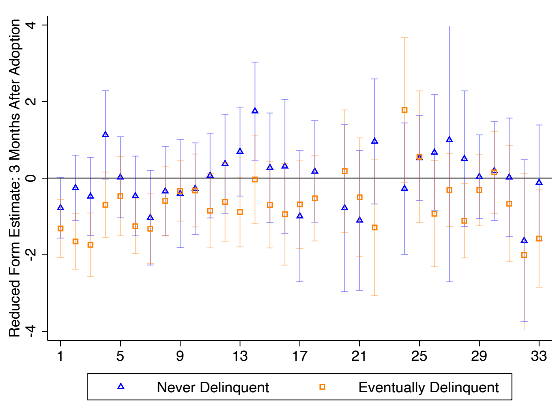
(c) Number of Transfers Sent



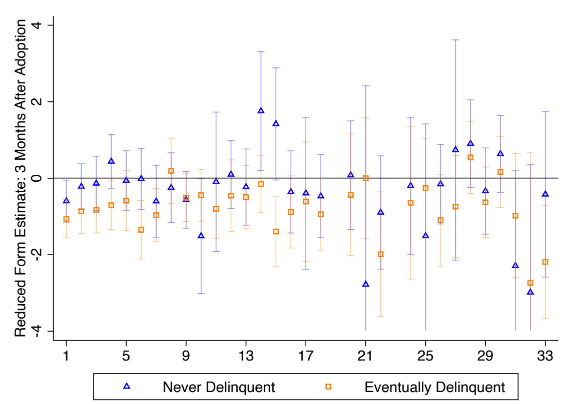
(d) Number of Transfers Received



(e) Unique Recipient Accounts



(f) Unique Sender Accounts



Note: The Figure plots estimates of the effect of loan adoption on each cohort three months after adoption. Confidence intervals without caps are truncated. The standard errors are clustered at the individual level.

Table A.1: Effect of Digital Credit Adoption on P2P Transfers

	(1) Total Value of Transfers Sent	(2) Total Value of Transfers Received	(3) Number of Transfers Sent	(4) Number of Transfers Received	(5) Unique Recipient Accounts	(6) Unique Sender Accounts
μ_{-3}	40.51	39.39	0.129	0.0248	0.112	0.0398
	(1.22)	(1.65)	(0.93)	(0.23)	(1.22)	(0.55)
μ_{-2}	60.62	22.53	0.232	0.141	0.155	0.0524
	(1.80)	(0.97)	(1.83)	(1.38)	(1.89)	(0.77)
μ_0	-7.739	32.17	0.0300	-0.112	-0.0534	-0.0901
	(-0.27)	(1.40)	(0.26)	(-1.08)	(-0.67)	(-1.20)
μ_1	2.048	-9.944	-0.312*	-0.268*	-0.248**	-0.215*
	(0.06)	(-0.42)	(-2.20)	(-2.13)	(-2.69)	(-2.55)
μ_2	-23.69	17.85	-0.686***	-0.548***	-0.520***	-0.385***
	(-0.63)	(0.60)	(-4.39)	(-3.72)	(-5.24)	(-3.93)
μ_3	-40.47	-39.67	-0.883***	-0.806***	-0.609***	-0.595***
	(-1.00)	(-1.34)	(-5.11)	(-5.65)	(-5.52)	(-6.12)
Constant	445.2***	389.7***	3.914***	3.227***	2.813***	2.311***
	(31.05)	(42.36)	(72.87)	(75.33)	(79.59)	(78.10)
Observations	35091	35091	35091	35091	35091	35091

t statistics in parentheses

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

Table A.2: Effect of Digital Credit Adoption on Mobile Money Activities

	(1) Sent Transfers	(2) Received Transfers	(3) Sent or Received Transfers	(4) All Mobile Money Transactions	(5) Other Mobile Money Transactions
μ_{-3}	-0.01	0.00	0.00	0.00	0.00
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
μ_{-2}	-0.00	0.02	0.02	0.01	0.00
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
μ_0	0.03	0.03*	0.03***	0.03**	-0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
μ_1	-0.06***	-0.02	-0.03**	-0.03**	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
μ_2	-0.12***	-0.07***	-0.09***	-0.09***	-0.03**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
μ_3	-0.16***	-0.12***	-0.13***	-0.13***	-0.03*
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Constant	0.72***	0.78***	0.91***	0.91***	0.11***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Observations	35091	35091	35091	35091	35091

Standard errors in parentheses

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

Table A.3: Effect of Digital Credit Adoption on P2P Transfers by Delinquency Status

	Never Delinquent						Eventually Delinquent					
	Total Value of Transfers Sent	Total Value of Transfers Received	Number of Transfers Sent	Number of Transfers Received	Unique Recipient Accounts	Unique Sender Accounts	Total Value of of Transfers Sent	Total Value of of Transfers Received	Number of Transfers Sent	Number of Transfers Received	Unique Recipient Accounts	Unique Senders Accounts
μ_{-3}	0.57	33.99	0.15	0.03	0.15	0.04	61.65*	44.55	0.09	0.04	0.07	0.05
	(56.51)	(33.56)	(0.21)	(0.14)	(0.14)	(0.10)	(30.53)	(26.02)	(0.15)	(0.12)	(0.10)	(0.08)
μ_{-2}	20.11	19.02	0.14	0.11	0.15	0.02	82.21*	27.50	0.28*	0.18	0.16	0.09
	(52.28)	(32.61)	(0.18)	(0.15)	(0.12)	(0.10)	(32.73)	(24.31)	(0.14)	(0.11)	(0.09)	(0.07)
μ_0	-1.07	48.43	0.13	-0.10	0.07	-0.10	-8.64	25.38	-0.05	-0.13	-0.13	-0.09
	(41.73)	(32.74)	(0.15)	(0.14)	(0.11)	(0.10)	(30.36)	(24.39)	(0.13)	(0.11)	(0.09)	(0.08)
μ_1	33.07	27.43	0.18	0.12	0.14	0.01	-13.74	-30.27	-0.59***	-0.47***	-0.46***	-0.33***
	(50.05)	(32.43)	(0.19)	(0.21)	(0.13)	(0.14)	(33.71)	(25.84)	(0.16)	(0.12)	(0.10)	(0.08)
μ_2	10.70	55.01	-0.17	-0.08	-0.16	-0.09	-43.42	-3.00	-0.98***	-0.79***	-0.72***	-0.53***
	(54.52)	(40.25)	(0.21)	(0.25)	(0.13)	(0.15)	(40.86)	(33.31)	(0.18)	(0.14)	(0.11)	(0.10)
μ_3	4.63	19.95	-0.16	-0.32	-0.02	-0.21	-61.60	-68.06*	-1.25***	-1.03***	-0.91***	-0.77***
	(57.94)	(41.38)	(0.23)	(0.21)	(0.15)	(0.14)	(42.25)	(29.98)	(0.19)	(0.15)	(0.12)	(0.10)
Constant	501.01***	418.05***	4.02***	3.30***	2.89***	2.35***	402.62***	375.74***	3.74***	3.12***	2.69***	2.25***
	(11.98)	(6.96)	(0.04)	(0.04)	(0.03)	(0.02)	(11.88)	(8.07)	(0.05)	(0.04)	(0.03)	(0.03)
Observations	21553	21553	21553	21553	21553	21553	28175	28175	28175	28175	28175	28175

Standard errors in parentheses

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

Table A.4: Effect of Digital Credit Adoption on P2P Transfers by Size of First Loan

	Never Delinquent						Eventually Delinquent					
	Total Value of Transfers Sent	Total Value of Transfers Received	Number of Transfers Sent	Number of Transfers Received	Unique Recipient Accounts	Unique Sender Accounts	Total Value of of Transfers Sent	Total Value of of Transfers Received	Number of Transfers Sent	Number of Transfers Received	Unique Recipient Accounts	Unique Senders Accounts
μ_{-3}	23.02	91.91*	0.29	0.20	0.25	0.13	59.44*	1.39	-0.03	-0.11	-0.02	-0.04
	(50.66)	(35.79)	(0.20)	(0.14)	(0.13)	(0.10)	(29.32)	(23.35)	(0.14)	(0.12)	(0.09)	(0.08)
μ_{-2}	58.71	42.72	0.34	0.23	0.26*	0.11	70.48*	11.67	0.18	0.11	0.07	0.03
	(46.33)	(31.83)	(0.18)	(0.12)	(0.11)	(0.09)	(33.82)	(24.42)	(0.14)	(0.13)	(0.09)	(0.08)
μ_{0}	-29.52	55.20	0.01	0.09	-0.11	0.03	13.26	8.88	0.00	-0.30**	-0.03	-0.19*
	(39.39)	(31.57)	(0.17)	(0.15)	(0.11)	(0.11)	(29.87)	(23.57)	(0.12)	(0.11)	(0.09)	(0.08)
μ_{1}	-24.09	-17.08	-0.52*	-0.16	-0.37**	-0.18	22.81	-10.48	-0.21	-0.36*	-0.19	-0.24*
	(44.15)	(32.72)	(0.20)	(0.14)	(0.13)	(0.10)	(32.55)	(24.98)	(0.15)	(0.17)	(0.10)	(0.11)
μ_{2}	-14.49	36.28	-0.78***	-0.52**	-0.57***	-0.40***	-23.38	-3.07	-0.62***	-0.55**	-0.49***	-0.35**
	(53.45)	(43.66)	(0.23)	(0.16)	(0.14)	(0.11)	(38.10)	(28.08)	(0.16)	(0.19)	(0.10)	(0.13)
μ_{3}	-26.11	-31.70	-0.94***	-0.70***	-0.69***	-0.61***	-39.29	-44.08	-0.82***	-0.87***	-0.55***	-0.57***
	(55.60)	(39.84)	(0.24)	(0.17)	(0.15)	(0.11)	(41.56)	(29.08)	(0.18)	(0.16)	(0.11)	(0.11)
Constant	560.68***	450.66***	4.50***	3.32***	3.21***	2.41***	337.74***	343.14***	3.28***	3.08***	2.38***	2.18***
	(12.63)	(8.23)	(0.05)	(0.03)	(0.03)	(0.02)	(10.84)	(7.01)	(0.04)	(0.04)	(0.03)	(0.03)
Observations	23751	23751	23751	23751	23751	23751	25977	25977	25977	25977	25977	25977

Standard errors in parentheses

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

B Chapter 2

In Table B.1 I report the first-stage regressions from the IV estimates presented in Table 3.3. Even though the same instrument is used, the estimation sample slightly differs across columns resulting in slightly different estimates.

Table B.2, illustrates the IV estimates of the treatment effect of M-Pesa savings conditional on the previous use of the financial tools studied.

Table B.1: First Stage Regressions of M-Pesa saving on multiple SIM card ownership

Second stage outcomes	M-Pesa			
	ROSCA	Bank	SACCO	Home
	(1)	(2)	(3)	(4)
SIMs	0.266***	0.266***	0.265***	0.266***
	[0.051]	[0.051]	[0.051]	[0.051]
Education (years)	0.007**	0.007**	0.007**	0.007**
	[0.003]	[0.003]	[0.003]	[0.003]
Age (years)	-0.001	-0.001	-0.001	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]
Gender	0.100*	0.100*	0.100*	0.100*
	[0.057]	[0.057]	[0.057]	[0.057]
married	-0.033	-0.033	-0.033	-0.033
	[0.049]	[0.049]	[0.049]	[0.049]
Wealth (100,000 KShs)	-0.003	-0.003	-0.003	-0.003
	[0.005]	[0.005]	[0.005]	[0.005]
Male member (age) < 17	-0.008	-0.008	-0.008	-0.008
	[0.017]	[0.017]	[0.017]	[0.017]
Female member (age) < 17	-0.042***	-0.042***	-0.042***	-0.042***
	[0.016]	[0.016]	[0.016]	[0.016]
≥ 17 Male member (age) ≤ 39	-0.045**	-0.045*	-0.045**	-0.045**
	[0.023]	[0.023]	[0.023]	[0.023]
≥ 17 Female member (age) ≤ 39	0.036	0.036	0.036	0.036
	[0.024]	[0.024]	[0.024]	[0.024]
Male member (age) ≥ 40	-0.038	-0.038	-0.038	-0.038
	[0.048]	[0.048]	[0.048]	[0.048]
Female member (age) ≥ 40	0.088*	0.088*	0.088*	0.088*
	[0.046]	[0.046]	[0.046]	[0.046]
Rural==1	-0.097**	-0.097**	-0.097**	-0.097**
	[0.041]	[0.041]	[0.041]	[0.041]
Observations	1,596	1,595	1,595	1,595
Kleibergen-Paap F statistic (critical value = 16.38)	26.979	26.970	26.628	26.998
R^2	0.063	0.063	0.062	0.063

Heteroskedasticity-robust standard errors in brackets. Estimation samples differ slightly across columns explaining the small differences in estimates across columns.
*** p<0.01, ** p<0.05, * p<0.1

Table B.2: Impact of M-pesa saving conditional on previous use of financial tools (IV estimates)

	$Y_{i,t-1} = 0$				$Y_{i,t-1} = 1$			
	ROSCA (1)	Bank (2)	SACCO (3)	Home (4)	ROSCA (5)	Bank (6)	SACCO (7)	Home (8)
M-Pesa	0.773***	-0.087	0.073	-0.500	0.430*	0.306**	-0.354	-0.021
	[0.290]	[0.981]	[0.187]	[0.393]	[0.238]	[0.122]	[0.490]	[0.240]
Education (years)	0.002	0.004	0.002	0.010	-0.007	0.004*	0.001	-0.001
	[0.005]	[0.012]	[0.004]	[0.008]	[0.006]	[0.002]	[0.006]	[0.003]
Age (years)	0.002	-0.004	-0.002	-0.006	0.000	-0.002	-0.008*	-0.000
	[0.003]	[0.004]	[0.001]	[0.005]	[0.004]	[0.002]	[0.005]	[0.002]
Gender	-0.146	-0.063	0.078*	-0.134	-0.117	-0.073	-0.076	0.104
	[0.108]	[0.106]	[0.043]	[0.125]	[0.091]	[0.058]	[0.107]	[0.063]
married	0.068	0.119	-0.075**	-0.036	0.051	0.132**	-0.027	-0.065
	[0.087]	[0.170]	[0.036]	[0.104]	[0.084]	[0.052]	[0.104]	[0.048]
Wealth (100,000 KShs)	-0.008**	0.040**	0.006*	-0.006	-0.007	0.008***	0.015	0.007**
	[0.004]	[0.018]	[0.003]	[0.008]	[0.007]	[0.002]	[0.011]	[0.003]
Male member (age) < 17	0.027	-0.026	-0.005	0.000	0.022	-0.022	0.007	-0.012
	[0.035]	[0.026]	[0.014]	[0.037]	[0.027]	[0.017]	[0.038]	[0.017]
Female member (age) < 17	0.003	-0.015	-0.011	-0.037	0.026	-0.017	-0.073	0.023
	[0.027]	[0.034]	[0.015]	[0.046]	[0.033]	[0.017]	[0.048]	[0.017]
≥ 17 Male member (age) ≤ 39	0.059	0.016	-0.007	0.056	0.002	0.022	-0.043	0.008
	[0.038]	[0.071]	[0.018]	[0.042]	[0.037]	[0.021]	[0.055]	[0.027]
≥ 17 Female member (age) ≤ 39	0.025	-0.027	0.025	-0.082	-0.020	-0.025	-0.004	0.007
	[0.039]	[0.046]	[0.019]	[0.054]	[0.038]	[0.024]	[0.056]	[0.028]
Male member (age) ≥ 40	0.003	0.051	0.039	0.095	-0.013	0.084*	0.156	-0.111**
	[0.072]	[0.087]	[0.037]	[0.098]	[0.071]	[0.044]	[0.113]	[0.048]
Female member (age) ≥ 40	-0.070	-0.060	0.025	0.077	-0.039	-0.014	0.151	-0.012
	[0.079]	[0.094]	[0.035]	[0.100]	[0.077]	[0.040]	[0.116]	[0.056]
Rural==1	0.233***	-0.114	0.026	-0.016	-0.022	-0.069	0.140	0.079
	[0.079]	[0.154]	[0.038]	[0.086]	[0.060]	[0.042]	[0.093]	[0.049]
Observations	937	480	1,217	406	659	1,115	378	1,189
Kleibergen-Paap F statistic (critical value = 16.38)	14.114	1.006	17.814	14.746	12.166	27.753	4.653	13.512

Heteroskedasticity-robust standard errors in brackets.

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

C Chapter 3

Table C.1: Summary of studies using DHS and the reported standard errors

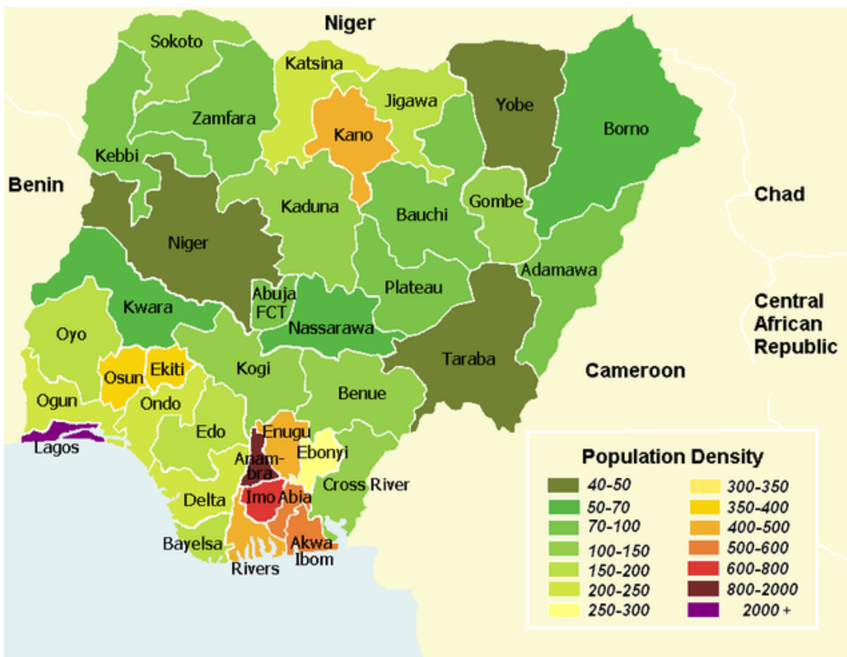
Authour(year)/Jouranl	Regression	Standard Error
Acemoglu et al (2014)/JPE	Weight for height/anemia/wealth on ruling families	clustered at chiefdom
Lowe and Montero(2021)/AER	Vaccination/blood test refusal on colonial medical campaigns	clustered at district or subdistrict
Brown et al (2019)/RESTAT	BMI/height for age/weight for height on wealth index	clustered(DHS survey cluster)
Osili, Long (2008)/JDE	Education/fertility on Universal Primary Education	clustered(year×state)
Hjort and Poulson (2019)/AER	Employment/education on internet access	clustered and Conley errors
Fenske (2013) /TEJ	Vaccination/polygamy on past polygamy or past slavery	clustered(DHS cluster), Conley errors
Fenske (2015) /JDE	Polygamy on years of education	clustered at colonial district
Mamo et al (2019)/JDE	Wealth index/infant mortality on mine discovery	clustered at region
De la Croix and Gobbi (2017)/JDE	Development on Population density	clustered(country) .

Table C.2: Summary Statistics of Case Study Sample

	(1)	(2)	(3)
	mean	sd	count
Vaccination index	0.330	0.317	7739
Mother's years of education	1.860	3.817	7739
Mother's age	28.838	7.631	7739
Child's age	2.615	1.292	7739
Female child	0.499	0.500	7739
Birth order	4.044	2.841	7739
Multiple birth	0.010	0.097	7739
Urban	0.221	0.415	7739
State==Bauchi	0.093	0.291	7739
State==Borno	0.047	0.211	7739
State==Gombe	0.080	0.271	7739
State==Jigawa	0.099	0.299	7739
State==Kaduna	0.078	0.268	7739
State==Kano	0.158	0.364	7739
State==Katsina	0.104	0.305	7739
State==Kebbi	0.085	0.279	7739
State==Sokoto	0.092	0.289	7739
State==Yobe	0.076	0.264	7739
State==Zamfara	0.090	0.286	7739

Notes: The sample includes only the oldest child of interviewed mothers in northern Nigeria.

Figure C.1: Nigeria population density by state



Source: Marcel Krüger

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