Back to bank: digital currency, deposits' substitution and credit[*]

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Abstract

We study the consequences of substitution between cash and digital currency on banks' lending behavior. Leveraging an unexpected tax on Mobile Money in Uganda and using an exclusive dataset on the universe of mobile money transactions, we show a drop in mobile money usage and an increase in the flow of bank deposits and ATM withdrawals. The high turnover of new deposits helps us uncover unique insights into banks' hedging against liquidity risk: we show a general decrease in loans' repayment terms, and a transfer of rent from high-risk borrowers lacking credit history to low-risk borrowers. Consequently, the latter group experiences relatively higher loans and lower interest rates.

Keywords: Mobile Money, Financial Inclusion, Digital Currency

JEL Codes: G21, E41, O11

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1 Introduction

The dynamic landscape of digital payments is undergoing a transformative phase, with implications reaching far beyond transactional convenience. Within this context, we explore the intricate interactions between digital and traditional payment systems, focusing on the repercussions for bank lending and financial inclusion.

A pivotal catalyst for our investigation is the ongoing debate on the potential introduction of Central Bank Digital Currencies (CBDCs), with raising questions about the ambiguous effects on the credit market (Andolfatto (2021), Agur et al. (2022)). The global interest in CBDCs highlights the need for empirical investigations into their potential repercussions on the banking sector. While theoretical frameworks, as exemplified by Chiu et al. (2023), offer diverse perspectives on the consequences of CBDC introduction, empirical validations remain scarce.

Our research aims to bridge this gap. We exploit an unexpected tax on Mobile Money introduced by the Ugandan government in July 2018 to study how a shock to the cost of digital currencies induces substitution with cash and bank deposits, eventually affecting banks' liquidity and credit provision.

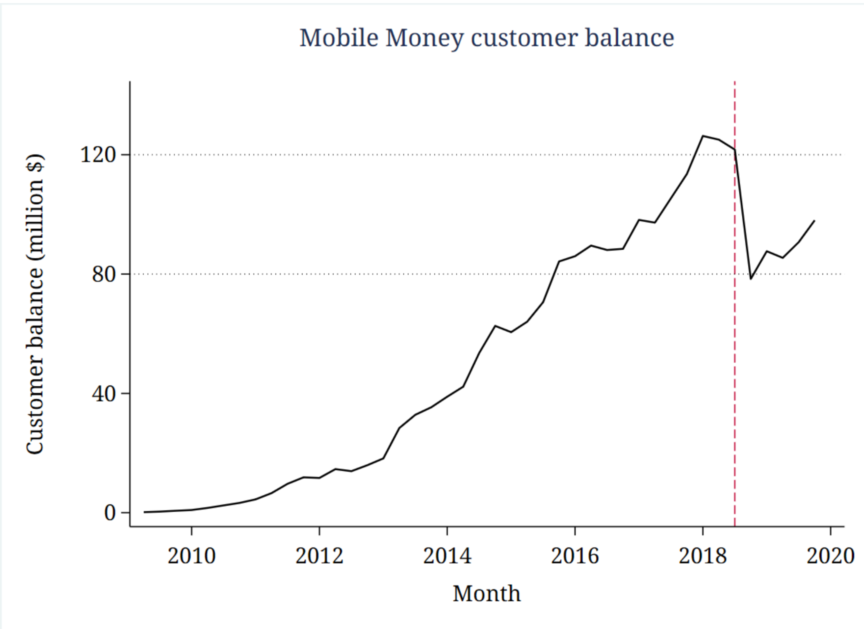
From a policy perspective, we also provide empirical evidence on the unintended consequences of digital currency taxation in developing countries (Okunogbe and Tourek, 2024). Indeed, the palpable tension surrounding Mobile Money taxes across African nations[1] underscores a broader concern about the trade-offs inherent in the adoption of digital currencies. Mobile money has emerged as one of the most widespread digital payment systems (Demirguc-Kunt et al., 2018), and its diffusion resulted in tangible changes in various economic and financial indicators like risk-sharing (Jack and Suri (2011); Blumenstock et al. (2016)), remittances (Riley (2018); Aker et al. (2020)), lending (Suri et al., 2021) and savings (Breza et al., 2022), among others. Despite these significant developments, research on the functioning and regulation of this technology

[1] In the last few years, taxes on mobile money transactions have increasingly been implemented in various African countries, with Uganda, Zimbabwe, Côte d'Ivoire, Kenya and the Republic of the Congo having implemented this tax prior to the Covid pandemic in 2020, while Tanzania, Cameroon and Ghana have done the same since.

remains limited (Brunnermeier et al., 2023).

Positioning Mobile Money in competition with both cash for transactions and bank deposits for money storage, our conceptual framework elucidates its comparative advantages. Factors such as accessibility, cost-effectiveness, and ease of account opening underscore the potential dominance of Mobile Money in specific contexts. The Mobile Money tax introduced by the Ugandan Government in July 2018 affected the convenience of Mobile Money with respect to other systems, resulting in an abrupt drop in its usage. In Figure 1 we show that in the first quarter following the tax users withdrew the equivalent of 40 million US $ from the Mobile Money network. With our analysis, we support evidence that this money was (partly) moved to the banking sector for its storage as deposits, inducing a positive liquidity shock to banks, that influenced their lending behavior.

Figure 1: Mobile Money customer balance



Notes: This figure plots the quarterly customer balance of mobile money, expressed in US $. It represents the value of mobile money detained by users.

As outlined in our model in Online Appendix C - Theoretical Framework for currency substitution, the tax-induced shock triggers a shift in payment systems usage, depending on users' responsiveness to the increased cost of digital currency. To empirically investigate the outlined mechanisms, our research leverages an exclusive dataset on the universe of Mobile Money transactions in Uganda, allowing us to track individual users. We employ a quasi-experimental design, leveraging the temporal variation introduced by the Mobile Money tax and the variation at geographical level coming from the heterogeneous access to Mobile Money alternatives, proxied by the density of ATMs. Difference-in-differences and event-study approaches form the backbone of our empirical methodology.

We exploit the same identification to provide evidence of increased bank deposits and cash usage in districts where access to banks is made easier by the pervasiveness of ATMs. We show that the mobile money tax triggers the adoption of a new bank-related technology, banking agents, that facilitates the deposit of cash and we provide evidence that bank deposits grow through this new technology. These results are in line with previous literature on complementarity of network technologies, such as Crouzet et al. (2019). Our results on increased ATMs withdrawals and cash issuance support our hypothesis that mobile money competes with bank deposits for money storage and with physical cash for payments.

Eventually, we leverage the transition from mobile money to bank deposits and its subsequent positive impact on bank liquidity to examine its effects on the credit market. Our study unveils novel insights into the lending behaviors of banks amidst increased deposit volatility. Despite observing heightened deposit flows and ATM withdrawals post the tax implementation, our evidence reveals no significant change in the overall deposit stock at the bank level. This suggests the precarious nature of the newfound liquidity, which banks cannot depend on for long-term and secure credit.

The data indicates a widespread reduction in the repayment term of new loans, reflecting the imperative for banks to cope with the continual cash withdrawals. Additionally, there is a discernible shift in rent from high-risk borrowers lacking credit history to low-risk borrowers with established credit records. These findings imply a shift in banks' strategies as they hedge against the risk of liquidity shortages. The anticipated outcomes encompass varied effects on banks, resulting in modified credit provision and potential rent transfers to specific borrower subgroups (Agarwal et al. (2018), Beck et al.

(2018)). We exploit the methodology proposed by Khwaja and Mian (2008) within our difference-in-difference setting to isolate the bank lending channel.

Our research project intersects with multiple literature streams, each offering valuable insights into the multifaceted dimensions of digital payments, banking competition, and financial inclusion.

The recent surge in Central Bank Digital Currencies (CBDCs) research, exemplified by Chiu et al. (2023), Andolfatto (2021), and Agur et al. (2022), offers varied perspectives on the potential impact of CBDCs on financial sector competition. Concerns about disintermediation raised by Keister and Sanches (2023) underscore the critical backdrop for our study on real-world consequences (Meaning et al. (2018), Brunnermeier et al. (2019), Brunnermeier and Niepelt (2019), Piazzesi and Schneider (2020), Duffie (2019), Sockin and Xiong (2023)). While the extensive theoretical literature has no clear agreement on the effects of the introduction of CBDCs, we try to provide empirical evidence to fill this gap.

Exploring the evolving FinTech landscape, Buchak et al. (2018) and Erel and Liebersohn (2022) examine technology's role in traditional banking decline and FinTech's response to financial service demand. These insights contextualize the coexistence of digital and traditional payment systems (Beaumont et al. (2022), Ferrari et al. (2010)).

In the literature on the economic effects of instant payment systems, Parlour et al. (2022), Di Maggio and Yao (2021), and Babina et al. (2022) link payment systems to lending decisions and financial inclusion. This stream of literature enriches our understanding of the interconnectedness of digital payments and broader financial services (Higgins (2020), Bachas et al. (2018), Duarte et al. (2022), Sarkisyan (2023), Balyuk and Williams (2021), Dubey and Purnanandam (2023), Bian et al. (2023), Dupas et al. (2018)).

Drawing parallels with the literature on demonetization, our investigation into the Mobile Money tax-induced shock finds resonance with studies exploring policy changes that induce shifts in currency use. Chodorow-Reich et al. (2020) examine the consequences of demonetization, noting relative reductions in economic activity and shifts towards alternative payment technologies. Similarly, Crouzet et al. (2019) document how a cash contraction spurs the adoption of new payment technologies.

The extensive literature on the effects of Mobile Money provides a foundational understanding of its role in financial inclusion and transactional behavior. Pioneering studies by Jack and Suri (2011), Jack et al. (2013), and Jack and Suri (2014) highlight the transformative impact of Mobile Money on access to formal financial systems. Our research builds on this foundation, acknowledging the dual role of Mobile Money as both a facilitator of financial inclusion and a potential disruptor of traditional banking systems (Suri and Jack (2016), Suri (2017), Suri et al. (2021), Brunnermeier et al. (2023)).

The literature on liquidity, credit supply, and the impact of shocks on financial markets offers a theoretical and empirical foundation for our exploration. Khwaja and Mian (2008), Limodio (2022), and Choudhary and Limodio (2022) delve into the intricacies of liquidity shocks and their effects on credit provision. These insights inform our investigation into how shocks to the cost of digital currency might influence banks' credit supply. Choudhary and Jain (2022) study the distributional impacts of bank credit rationing. We differentiate from this paper showing the effects of volatile liquidity on credit.

Eventually, a rich body of literature explores the relationship between information asymmetries, credit provision, and the implications of data portability in the financial sector. Agarwal et al. (2018), Banerjee et al. (2021), and Beck et al. (2018) provide insights into the benefits of data portability and its role in enhancing credit provision. Our research contributes to this discourse by examining how shifts in payment systems might influence established relationships between banks and borrowers (Berlin and Mester (1999), Sette and Gobbi (2015)).

The rest of the paper is as follows. Section 2 offers details about the institutional aspects of the Ugandan mobile money tax, and provides an insight on a new bank-related technology, banking agents, that allow easier access to banks' services. Section 3 describes the data we use, comprehensive of a unique dataset on individual transactions of the whole Ugandan population of Mobile Money users, a dataset on individual banking agents, a dataset on the Central Bank's issuance of cash at local level, and a dataset on the universe of loans granted by private banks. Section 4 provides evidence on the substitution of Mobile Money with traditional payment and money storage systems. In Section 5 we show the effects of the Mobile Money tax induced positive liquidity shock to banks on the credit market. Section 6 concludes.

2 Institutional framework

In this section we provide insights on the Ugandan mobile money market and the introduction of the tax, which was unexpected by the public. We also give details about banking agents, a new bank-related technology that facilitates cash deposits. Indeed, this technology had a pivotal role in driving the shift from mobile money to bank deposits: while banking agents had never taken over before the introduction of the tax, the increased cost of mobile money spurred their adoption.

2.1 Mobile Money Tax

Mobile money services were first introduced in Uganda by MTN in 2009 and, since then, the sector has seen significant growth. During the first year of operation, the number of registered accounts grew to 770,000 and the total value of transactions amounted to approximately UGX 133 billion (US$ 36 million) over the year.

After MTN, other mobile network operators (MNOs) soon introduced similar services. Within a decade, the number of registered, active accounts had surpassed 16 million and the total annual value of transactions had grown to UGX 73 trillion (US$ 20 billion). [2]

Figure B.1 in Online Appendix B: Additional Figures reports the number of mobile money users and the volume and value of mobile money transactions in Uganda over the last 12 years. This growth is due, in part, to the accessibility of mobile money, enabled through a national network of roughly 212,500 registered mobile money agents who are markedly more prevalent than more traditional financial service providers, such as commercial banks.[3]

[2]Source: Bank of Uganda, 2021

[3]Surveys have indicated that whereas 54% of the population had a mobile money point-of-service

As the sector, and its turnover, has grown, governments are increasingly viewing mobile money as a convenient tax handle. This is especially true for governments facing pressures, both domestic and external, to increase domestic revenue mobilisation and reduce the reliance on aid and borrowing to fund public services. The resulting tax measures are often controversial and have drawn sharp criticism from those who fear that they will undermine the growth of nascent digital finance sectors and the development gains that (digital) financial inclusion is claimed to enable.[4]

Uganda presents an interesting case study of this trend. On 1 July 2018, the government introduced an especially contentious new tax of 1%[5] on the value of all mobile money transactions, aimed at mobilising more revenue from the telecommunications and financial sectors (Lees and Akol, 2021).

The mobile money tax legislation was initially drafted such that every stage of a mobile money transfer was taxed – depositing, sending, receiving, and withdrawing the money. These were identified as separate, and thus individually taxable, transactions. In effect, one transfer between two users might have been taxed up to four times.

Uganda currently has the foundations of a strong, well-structured system for policy development, providing for an orderly progression from an idea for change to the implementation of a final tax measure (Wales and Lees, 2020). Tax policy development in Uganda follows a series of distinct phases, closely linked to the annual budget cycle, as illustrated in Figure B.2. However, unanticipated expenditure requirements, and the rejection of several revenue-raising tax proposals, created pressure to find new sources of revenue late in the budget cycle. This led to surpass the standard steps required by the Ugandan legislation for law promulgation. These resulted in the introduction of a Mobile Money tax strongly advised by Ugandan President Yoweri Museveni[6]. The faster than usual process for the approval of this tax led to a lack of widespread citizen engage-

within one kilometer of their home, just 16% per cent of the population had a point-of-service for a traditional bank (Bank of Uganda 2017).

[4] See link

[5] After widespread public outcry and significant challenges in implementation, the tax rate was adjusted to 0.5 % and restricted to withdrawals in November 2018.

[6] The President wrote on his blog that the informal sector is “never taxed” and a tax on mobile money would ensure a “modest contribution”

ment and the tax proposal seemed largely absent from the general public discourse at the time. Indeed, the tax was unexpected by citizens, and as an indication of this, Figure B.3 shows Google search interest from Uganda in the terms "tax" and "mobile money" throughout 2018. Search interest for "tax" and "mobile money" peak in the week starting 1 July 2018.

The introduction of the mobile money tax triggered immediate public outcry, with concerns about double taxation, financial inclusion, job losses, and the impact on the poor. Civil society, journalists, students, and activists organized protests, gaining international media attention.[7] In response, the President requested Parliament to amend the tax on July 12. Cabinet limited the tax to withdrawals, halving the rate. Despite delays, the Finance Committee supported the amendment for budgetary reasons. The Amendment Bill was implemented on November 17, following a series of events detailed in Figure B.4. As shown in Figure 1, the tax had a huge impact on the usage of mobile money.

2.2 Agent Banking

In July 2017 (one year before the mobile money tax), Bank of Uganda passed a new regulation aimed at establishing a new tool through which commercial banks can operate: Agent Banking[8]. Agent banking is a banking model that involves the use of third-party agents, such as retail shops, to provide banking and financial services on behalf of traditional banks. This approach is particularly relevant in regions with limited access to physical bank branches, as it enables financial institutions to expand their reach and offer their services to underserved or remote areas. In Uganda, agent banking has gained momentum in recent years as a means to enhance financial inclusion and improve access to banking services, especially in rural and underserved areas. Agent banking services typically include cash deposits, cash withdrawals, balance inquiries, fund transfers, utility bill payments, and sometimes even account opening. The key fea-

[7] A public opinion survey of nearly 3,000 people conducted in the second week of July found that 98% of respondents did not support or were strongly opposed to the mobile money tax (Whitehead, 2018).

[8] The Financial Institutions (Agent Banking) Regulations, 2017

ture of Agent Banking is that it does not require the opening of a bank account in order to perform operations such as depositing, withdrawing or transferring money. When depositing money, for example, the banking agent releases a receipt to the customer, who will use it to withdraw the money later on. While this tool has been long used by banks, in 2017 it was formalized through the creation of an inter-banks agency. The Agent Banking Company (ABC) was established in 2017 by Uganda Banker's Association (UBA) the umbrella organization for commercial banks in Uganda and Eclectics a pan-African technology company. Similar to the Mobile Money model, Agent Banking empowers commercial banks to appoint agents to provide banking services such as deposits, withdrawals and more on their behalf. Agents can be the local shopkeeper, kiosk owners, supermarket attendant or anyone in your community who has been authorized by your bank. The financial services currently offered through the ABC platform include cash deposits, cash withdrawals, bill payments and money transfers. The platform enables commercial banks to enhance customer experience, reduce the cost to serve and increase coverage while avoiding duplication of investment and effort. As at the end of 2021, there were 22 commercial banks with 20,108 agents enrolled on the platform. Between 2018 and 2021, agents on the platform cumulatively processed over 12 million transactions worth $ 4.3 billion.

In the analysis, we show the spur of banking agency after the introduction of the Mobile Money tax. We claim that this shock to the cost of digital currency triggers the adoption of this new banking-related technology that drives the registered increase in the flow of bank deposits.

3 Data

This section describes the datasets employed in the analysis.

1. Mobile Money transaction data. We have access to the universe of mobile money transactions from one of the two major companies in Uganda. MTN and Airtel share the mobile money market equally, have similar coverage and set extremely similar prices

on mobile money transactions. We expect no major differences in individual level usage between the two comapnies, indeed it is estimated that at least 30% of the Ugandan population with access to a a mobile phone has a SIM subscription with both operators.[9] For the only year 2018, we have access to more than 50 million transactions, divided by person-to-person transfers (P2P), cash-in (deposits) and cash-out (withdrawals). We are able to access both the sender, the receiver or the mobile money agent identifier, hence allowing us to reconstruct the whole network of mobile money transactions. We have access to the type of transaction, to its value in Ugandan Shillings (UGX), to the fees applied on the transactions, as well as on the time and day it was performed.

2. Mobile Money user location. Out of the 5.5 million mobile money users active before the introduction of the tax, we are able to identify the district of residence for a random sample of about 1.5 million users. This allows us to present evidence of heterogeneity in mobile money usage elasticity between different district, depending on local characteristics.

3. Issuance of physical cash. The Central Bank of Uganda has also provided daily data on the issuance of cash by local private banks' branches for the years 2017-2022. Bank of Uganda has 10 offices spread throughout the Ugandan territory. Each of these offices provide cash on a daily basis to the major branch of private banks present in that area. We hence have a bank-location panel of cash issued. We use these data as a proxy of cash demand at the local level. Indeed, the only reason why banks issue physical cash is to meet the demand of depositors withdrawing money.

4. Credit registry loan-level data. Our study employs detailed data on the commercial and household lending activities of banks. Uganda has a fully functional and comprehensive credit register that is maintained by the private credit bureau Compuscan Uganda CRB Ltd. under the supervision of the Bank of Uganda. The credit register collects data on all new originated loans based on monthly reports from all commercial banks, microfinance deposit-taking institutions, and other credit institutions. We have access to the full dataset covering the period 2017-2023. For each granted loan we are able to identify

[9]National IT Survey Uganda (NITA), 2018. See link.

both borrower-specific and loan-specific variables. We observe: i) the nature of the borrower, wether individual or business; ii) the type of loan (secured or unsecured); iii) the credit risk of the borrower); iv) the purpose of the loan (business, mortgage, school loan, house restructuring, land purchase); v) for credit to individuals, we are able to identify the income of the borrower and her professional activity; for businesses, we are able to identify the sector of activity; vi) for all borrowers we identify the district of residency; vii) the day on which the loan was granted; viii) the rate of repayment as stated on the day of the granting; ix) the term/maturity of the loan.

5. Bank-level data on deposits. The Bank of Uganda provides monthly data on private institutions deposits. We are able to identify different types of deposits (demand, saving and time deposits).

6. Agent Banking Company individual agent's data. The Bank of Uganda has provided the details of deposits and withdrawals for each banking agent. We aggregate data at the district level. Data are available since April 2018.

7. Ugandan National Panel Survey. We employ household-level panel microdata from the Uganda Bureau of Statistics. These data provides information of a wide range of topics on households' income, savings, entrepreneurial activity, mobile money usage.

8. Geographical data on urban development and nighttime light intensity. We exploit the dataset introduced by Cattaneo et al. (2021) to create a district's measure of urban development.

9. Individual Bank's ATMs and branches location. We obtained data for the location of all ATMs and branches of each bank. We exploit these data to create a district-level proxy of access to mobile money substitutes, namely bank deposits and cash. We will use this measure in our identification strategy presented in Section 4

4 Results on Mobile money and bank usage

We develop our analysis adopting two main empirical approaches. For our main results, we first develop an event study design meant to test for pre-trends and to investigate the dynamics of the treatment effect. Second, we implement a difference-in-differences specification using two-way fixed effects regressions. Our main assumption is that individuals substitute mobile money with other means of payment and money storage (namely cash and deposits) depending on the conveniency or the easiness of access to them. We rationalize these results through a simplified model of currency choice in Online Appendix C - Theoretical Framework for currency substitution. For our identification strategy, we employ a quasi-experimental design, leveraging the temporal variation introduced by the Mobile Money tax and the variation at geographical level coming from the heterogeneous access to Mobile Money alternatives, proxied by the density of ATMs.

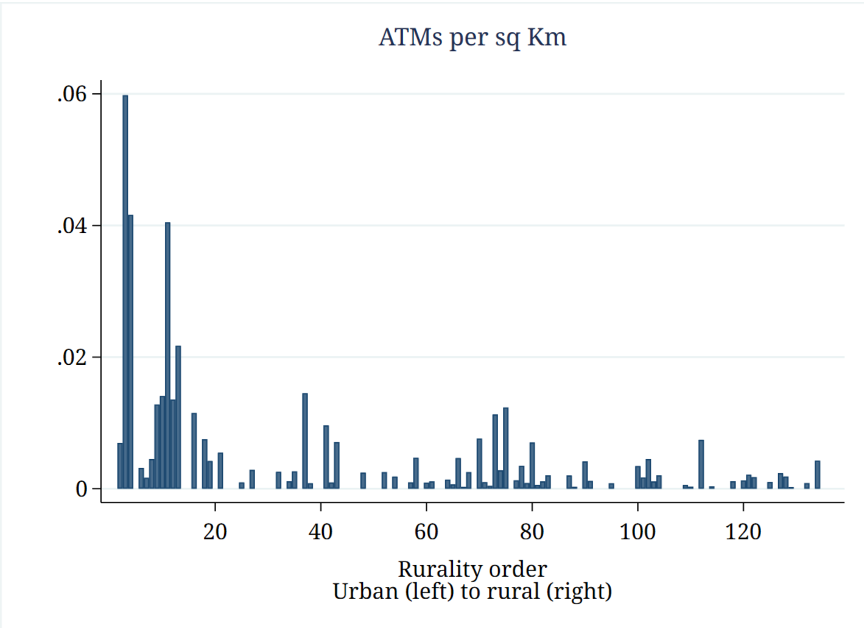
In the first subsection we hence provide evidence that mobile money usage dropped for individuals residing in districts where access to banks is made easier by a higher density of ATMs. In the second subsection, we show that the take up of a new technology (agent banking) that facilitates bank deposits is significatively starker in those same districts. In the third subsection we shift our analysis at the bank level. Indeed, those financial institutions who detain a higher share of the ATMs market register a higher increase in customers' cash withdrawals and in the take up of agent banking. In the fourth subsection we provide evidence that the request for cash becomes higher in districts with more access to ATMs. These pieces of evidence suggest that mobile money is substituted by banks' deposits for money storage and by cash for transactions.

4.1 Mobile Money

Our assumption is that mobile money users are differentially affected by the introduction of the tax depending on the possibility of access to other means of payments. We exploit the density of ATMs in a given district as measure of access to mobile money alternatives.

At the intensive margin, i.e. conditional on keeping using Mobile Money, the drop in the growth of value transacted is of more than 10% for individuals in those high-ATM-density districts. In Online Appendix A: Additional Tables, we show results on the the extensive margin and document a generalized drop in mobile money usage. We show that users in districts with high ATM density are about 13% more likely to perform at least one transaction after the introduction of the tax. We explain this difference between intensive and extensive margin with the fact that high ATM density areas are more likely to be urban areas. Indeed in Figure 2 we show high correlation between ATM density and the rurality index as defined by Cattaneo et al. (2021). These areas are the ones with more economic opportunities: we are hence not surprised that people might perform at least one mobile money transaction even after the introduction of the tax.

Figure 2: ATM density and urban development



Notes: This figure plots the number of ATMs per squared kilometer over the order of the district's rurality index as proposed in Cattaneo et al. (2021). More urban districts show a higher density of ATMs.

The difference-in-differences design we exploit is the following:

$$Y_{idt} = \alpha_i + \gamma \text{Post Tax}_t + \beta \text{Post Tax}_t \times \mathbf{I}[\text{High ATM density}]_d + \epsilon_{idt} \tag{1}$$

where we define individual i in district d in the pre or post policy period defined by t. The dummy $\mathbf{I}[\text{High ATM density}]_d$ indicates whether the individual resides in a district in the upper quartile of the ATM density distribution. We assign to each user the ATM density (calculated as number of ATMs over the districts area) of the district where she resides. We define $\mathbf{I}[\text{High ATM density}]_d$ as a dummy indicating whether the users i in district d is in the highest 25 percentile of the users' distribution of ATM density. We use the subscript d as there are no users in the same district assigned a different value of the dummy variable.[10] We interact it with a post tax dummy. We include individual FEs, α_i. The Post Tax$_t$ dummy accounts for time FEs.

We collapse data over four months before and after the introduction of the tax (respectively February, March, April and May, and August, September, October, November). We do not include June and July due to the serious limitations of the observations in those months, as several glitches made it impossible to the mobile money company to collect the data. However, even including the available data from those two months, the results remain qualitatively similar. We are hence using two observations for each user: at time 0 (before the tax) and at time 1 (after the tax). This allows us to ease the interpretation of results.

We instead use the following event study approach for the intensive margin analysis:

$$Y_{idt} = \alpha_i + \alpha_t + \sum_{\tau=1,\tau\neq 5}^{T} \beta_\tau \text{Month}_\tau \times \mathbf{I}[\text{High ATM density}]_d + \epsilon_{idt} \tag{2}$$

where we use May as the baseline category and exclude June and July from the analysis. In this case, we use observations at the monthly level. We control for individual α_i and time (month) α_t fixed effects.

4.1.1 Intensive margin: individual level

While the extensive margin provides a measure of the likelihood of remaining in the mobile money network, it is relevant to study the extent to which the technology is used by customers in the post-tax period. We here presents results of the same specification of Eq. 2, using as outcome variable the individual's average daily amount of a given type of transaction, the number of times and the share of days in which that type of transaction was performed in a given month. We express all outcomes in log. We however restrict the sample to those users that perform a given type of transaction both in the pre-tax and the post-tax period. The coefficient γ hence estimate the effect of the tax on individuals

[10] Similar results are obtained if we we assign to each user the urban index of the district where the individual resides as defined by Cattaneo et al. (2021). Indeed, there is a high correlation between urbanity index and ATM density.

in low ATM density areas, for only those individuals that keep using mobile money for performing transactions of a given type. The β coefficient estimates the differential effect on users in high ATM density districts that keep using mobile money after the tax. Long story short, zeros are hence excluded. Table 1 present the results on the log average daily value of transactions. We hence interpret the coefficients as percentage change. We also show results for an additional measure, net deposits, i.e. the difference between deposits and withdrawals. This measures the money that a given individual deposits in the mobile money network net of the money she withdraws. Since the difference between deposits and withdrawals can take negative value, we cannot log transform the outcome variable: we hence standardize it, and the interpretation changes accordingly. Again, we do not include time fixed effects in order to show the generalized negative impact of the tax on mobile money usage. As before, the Post Tax$_t$ dummy represents the time fixed effect.

Table 1: Intensive margin: performed transactions

	Sent	Received	Deposits	Withdrawals	Net
	(1)	(2)	(3)	(4)	(5)
Tax dummy$_t$	-0.689***	-0.607***	-0.662***	-0.256***	-0.035***
	(0.006)	(0.004)	(0.003)	(0.002)	(0.000)
Tax dummy$_t$ × High ATM density$_d$	-0.103***	-0.117***	-0.040***	-0.060***	-0.004***
	(0.009)	(0.007)	(0.004)	(0.003)	(0.001)
User FE	Yes	Yes	Yes	Yes	Yes
N. of users	142522	225365	585690	691428	768061
Obs.	285044	450730	1171380	1382856	1536122
Adj. R sq.	0.438	0.349	0.407	0.448	0.225
Mean Dep. Var. High ATM	2900.033	2497.483	5883.921	5804.549	-220.917
Mean Dep. Var. Low ATM	2253.829	1849.746	4292.215	4178.469	-171.947

Notes: In this table, we use the specification presented in Eq. **??** and we show how mobile money users in high ATM density districts respond to the introduction of the mobile money tax at the intensive margin, relatively to users in low ATM density districts. High-ATM-density users transact between 4% and 12% less with respect to low-ATM-density users, after the tax. We estimate the effect on the sample of users that performed transactions of a given type before and after the tax. Column (1) show the effects on the amount of mobile money sent, column (2) on the amount received, column (3) on the amount deposited, column (4) on the amount withdrawn. For columns (1)-(4) outcome variables are the log of the average daily amount. In column (5) we use as outcome variable the standardized value of the difference between deposits and withdrawals. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

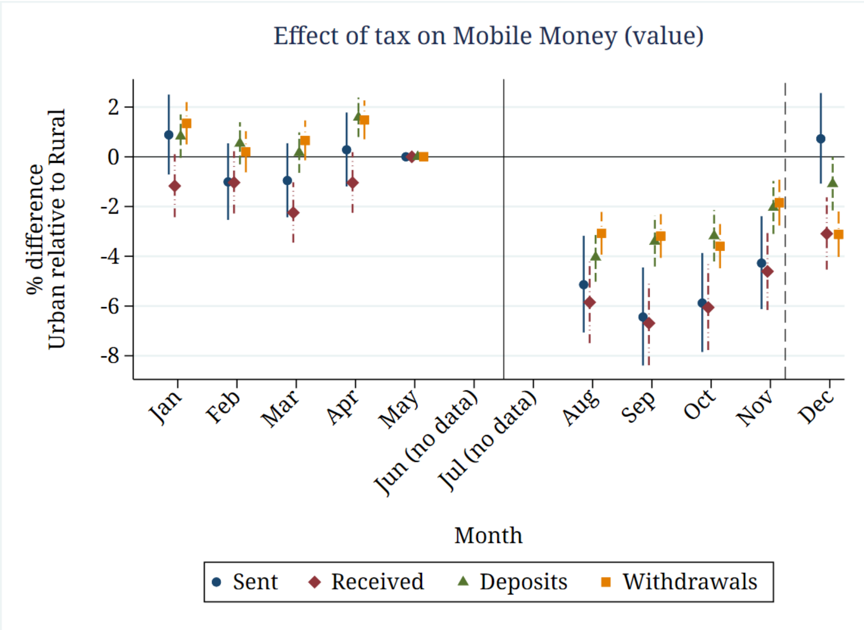
Table 1 shows that, conditional on keeping performing a transaction, high-ATM-density users reduce the average amount transacted daily by between 4% and 12%. These results are further confirmed in Online Appendix A: Additional Tables, Tables A.2 and A.3, where we present results for the daily average number of transactions and for the share of days in which a type of transaction is performed. High-ATM-density users decrease significatively their usage at all levels.

We complement the analysis on the intensive margin adopting a difference-in-differences and an event study approach using monthly level data at the individual level. So, in this case, t will identify a month. In Online Appendix A: Additional Tables, Tables A.4, A.5 and A.6 we respectively show the results for the average daily value of transactions in a month, the log average daily number of transactions in a month, and the share of days in which a transaction is performed in a month. In practice, we are exploiting Eq. 1 without collapsing observations over two periods pre and post policy.

Below, in Figure 3 we show results for the event study on the log average daily value transacted in a month.

These two last specifications come with no ease interpretation. Hence, it is worthwhile to spend a few words describing the structure of the dataset and the meaning of the estimated coefficients. Also in this case we are estimating the intensive margin, this means that we observe no value (missing) for when no transaction is made by the user. Users can however potentially transact every month. The first issue hence derives by the fact that users might be different in the timing of their transactions (i.e. user i might transact in April and August, while user j might transact in May, September and November). Including individual fixed effects hence controls for patterns of transactions: we are hence estimating the effect within individuals that make transactions in the same months. Months fixed effects instead clear out month specific differences. For the difference-in-differences, the β represents the average effect of the tax on otherwise similar high-ATM-density users with respect to low-ATM-density users. The β_τ's in the event study, instead, represent the average difference in the outcome of otherwise similar high-ATM-density users with respect to low-ATM-density users within a given month, with respect to the reference month, which is May. Figure B.5 also shows results for the average number of transactions and the share of days. In both figures, we already express the y-axis in percentage change.

Figure 3: Differential effect of the tax on users in high ATM density districts



Notes: This figure plots the coefficients β of the event study described in Eq. **??**. We use as outcome variable the log of average daily value of mobile money transactions in a month at the individual level. We differentiate between type of transactions. We already express the y axis in terms of % change. We use May as the baseline month. Data for June and July are excluded due to issues with data collection. Standard errors are clustered at the individual level, and the figure reports 95% confidence interval.

4.1.2 Survey data

To further confirm our previous results, we analyzed data from the Ugandan National Panel Survey (UNPS). The UNPS is carried out by the Ugandan Bureau of Statistics over a twelve-month period (a "wave") on a nationally representative sample of individuals/households, for the purpose of accommodating the seasonality associated with the composition of and expenditures on consumption. The UNPS set out to track and interview more than 5'000 individuals.

We employ data from the 2018/2019 wave, focusing on the outcomes related to mobile money usage. We adopt the identification proposed by Bassi and Rasul (2017), where the identification comes from the timing of the interview, before or after the tax. Controlling for individuals' characteristics, district and time FEs. To notice, as the authors propose, we cluster standard error at the week level. This clustering reflects that identification in our research design is based on time variation.

We provide further evidence of the drop of mobile money usage in districts with high

ATM density after the introduction of the tax, and exploit the following:

$$Y_{idt} = \alpha_d + \alpha_t + \beta \mathbf{I}[\text{High ATM density}]_d + \gamma \mathbf{X}_i + \epsilon_{idt} \tag{3}$$

where the outcome is referred to individual i in district d at time t. We control for the individual's characteristics, and include district and time FEs. Since during one wave individuals cannot be tracked (as they answer questions on mobile money just once), our source of variation comes from the timing of their interview, before or after the introduction of the tax. In Table 2 we report the results of the linear probability model described in Eq. 3, where outcome variables are dichotomous as they indicate whether the individual used a given mobile money service or not in the last week. For all measures, we find that individuals in high ATM density areas are up to 9% less likely to use mobile money.

Table 2: Mobile Money usage - Survey data

	Send	Transfer cash	Withdraw	Pay utilities	Pay school
	(1)	(2)	(3)	(4)	(5)
Tax dummy$_t$ × **I** [High ATM density] $_h$	-0.061*	-0.019*	-0.093***	-0.036**	-0.019*
	(0.034)	(0.010)	(0.030)	(0.015)	(0.010)
District FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Obs.	5044	5047	5060	5043	5044
Adj. R sq.	0.224	0.117	0.246	0.160	0.046
Mean Dep. Var.	0.336	0.021	0.320	0.030	0.010

Notes: This table reports the coefficients of Eq. 3. The outcome variables are dummy variables taking value 1 if the individual used a given mobile money service in the past week. We control for individual's characteristics such as gender, age and marital status. Time and district FEs are included. Standard errors are clustered at the week level, as suggested by Bassi and Rasul (2017). ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

4.2 Banking agents: Adoption of a new banking technology at district level

The introduction of the tax lowered the conveniency of Mobile Money with respect to other technologies that facilitate the exchange of money. Corroborating the findings of Crouzet et al. (2019), consistent with the predictions of a technology adoption model with complementarities, we show that the adoption of Banking Agents increased persistently as a response to the contraction registered by mobile money after the tax. As explained, banking agents are a technology that allows the execution of bank-related activities, such as deposits, in the fashion of branchless banking. The adoption of this technology is highly demand driven: indeed, it is not the bank who decides where to open a new banking agents. Like mobile money agents, it is merchants or individuals themselves who decide whether to start offering this service. While they bear the fixed costs needed to start such activity, they earn a fee on each transaction they perform.

In this subsection, we present evidence that the spread of banking agents spurred after the introduction of the mobile money tax. This is particularly true in districts with high ATM density. These results are justified by the complementary that arises between banking agents and ATMs. Indeed, banking agents have more incentive to start their activity where the users are already acquainted to the banking system or where there is a pervasive access to ATMs, that facilitate the withdrawal of deposited cash.

We first propose an event study to show the differential increase between high and low ATM-density districts in the number of new banking agents, and in the value and volume of deposits. In Figure 4 we show the results of the following:

$$Y_{dt} = \alpha_d + \alpha_t + \sum_{\tau=-3,\tau\neq-1}^{10} \beta_\tau \text{Month}_\tau \times \mathbf{I}[\text{High ATM density}]_d + \epsilon_{dt} \tag{4}$$

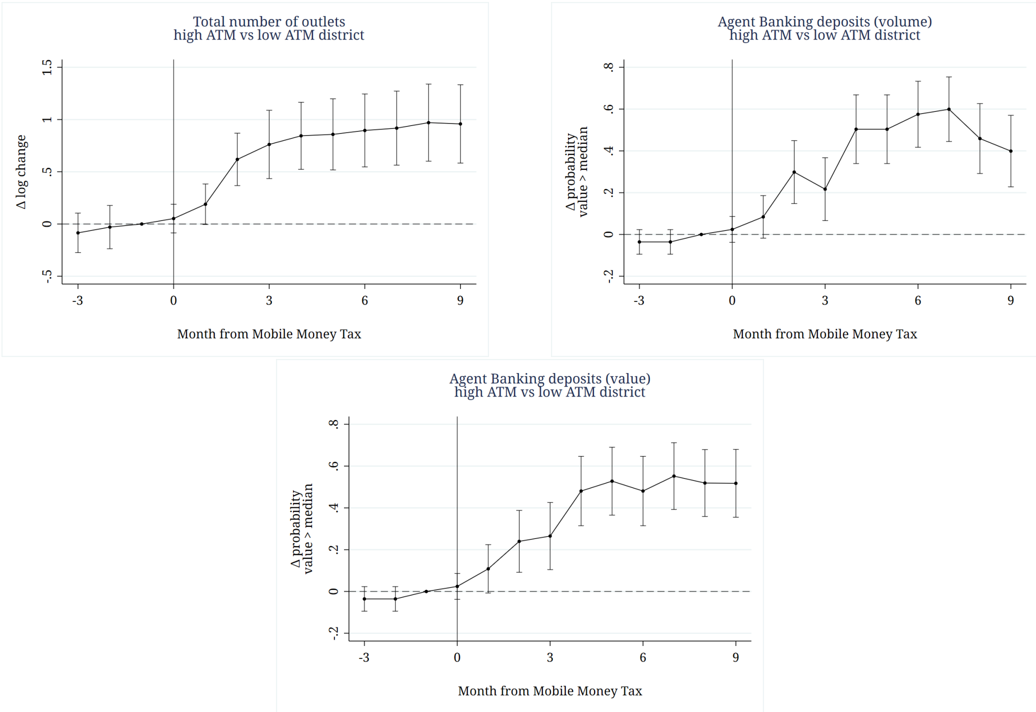
where $\mathbf{I}[\text{High ATM density}]_d$ indicates districts in the top quartile of the ATM density distribution. We include district, α_d, and time, α_t, FEs. Data start from three months before the introduction of the tax: before that date they were not collected by the Ugandan agent banking aggregator Agent Banking Company (ABC).

In Table 3 we present results from the following difference-in-differences:

$$Y_{dmy} = \alpha_d + \alpha_{my} + \beta \text{Post Tax}_{my} \times \mathbf{1}[\text{High ATM density}]_d + \epsilon_{dmy} \tag{5}$$

where the observations are at the district d, month m in year y level. The outcome Y is either the volume and value of deposits to banking agents. We use three different

Figure 4: Banking agents: high- vs low-ATM density



Notes: In this panel we plot the coefficients of Eq. 4, where we use as outcome variable the log number of banking agents (top left), a dummy for banking agents' deposits volume (top right) and value (bottom) above median. All outcome variables are at the district level. The plotted coefficient represents the differential between high- and low-ATM density district, with respect to the reference period. We use as reference the month before the introduction of the mobile money tax. Standard errors are clustered at the bank level and we report 90% confidence intervals.

specification outcome variable in order to overcome the issue related to the presence of zeros as described in Chen and Roth (2023): as suggested in the paper, we express the outcome variable in level, log, or as a dummy indicating values above and below the median.

We also show results by quartile of ATM density, exploiting the following specification:

$$Y_{dmy} = \alpha_d + \alpha_{my} + \sum_{i=1}^{4} \beta_i \mathbf{1}_i \left[\text{ATM density}_d\right] \times \text{Post}_{my} + \epsilon_{dmy} \tag{6}$$

where our unit of observation is the district and where we control for time and district FEs. The reference category is the group of district in the lowest quartile of ATM density distribution.

Table 3: Banking agents deposits

	Volume			Value		
	Δ Level ('000) (1)	Δ Log (2)	Δ Pr > median (3)	Δ Level ('000) (4)	Δ Log (5)	Δ Pr > median (6)
Tax dummy$_t$ × High ATM density$_c$	0.323**	2.164***	0.390***	0.098*	6.748***	0.395***
	(0.142)	(0.369)	(0.064)	(0.050)	(1.271)	(0.066)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1495	1495	1495	1495	1495	1495
Adj. R sq.	0.484	0.683	0.528	0.500	0.664	0.539
Mean Dep. Var.	0.076	1.098	0.146	0.023	4.863	0.157

Notes: This table reports the coefficients of Eq. 5. The outcome variables are the number and the value of deposits made by customers to Banking Agents. They are expressed in level, log, or as a dummy indicating whether the value is below or above the median as proposed in Chen and Roth (2023). Time and district FEs are included. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

4.3 Increased usage of banking

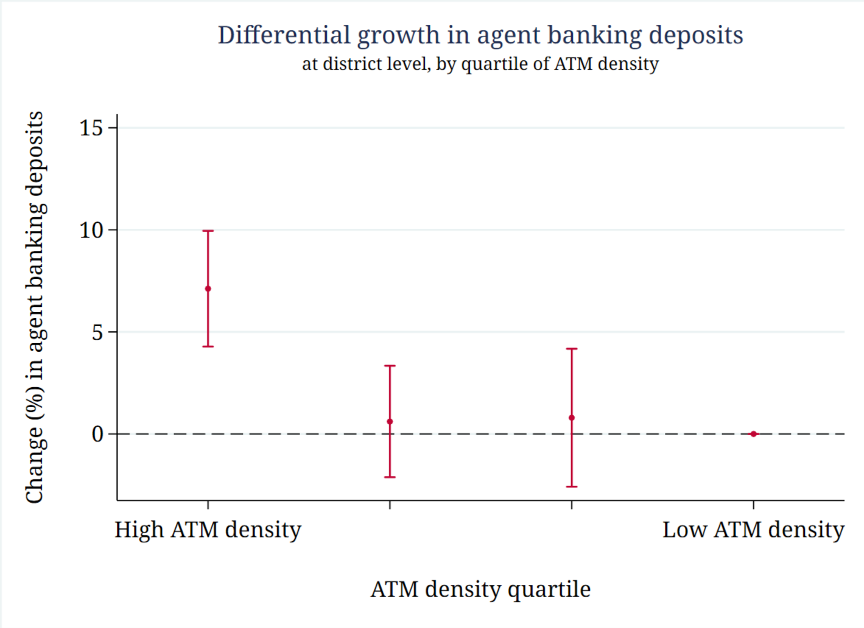
In this subsection, we present evidence at the bank level. We confirm the results in the previous subsection, by showing that the number of agents increases more for those banks with a higher share of ATMs. Again, this corroborate the hypothesis that banking agents benefit from the presence of other bank-related technologies. Being the individual merchant who decides with which bank to open the banking agent, we show that more pervasive banks are the ones registering the higher growth in banking agents. This reinforces the usage of ATMs themselves: we show that after the mobile money tax the value of ATM withdrawals for a given bank increases in the pervasiveness of its ATMs.

We estimate the following:

$$Y_{bqy} = \alpha_b + \alpha_{qy} + \beta \text{Post Tax}_{qy} \times \mathbf{I}[\text{ATM market share}]_b + \epsilon_{bqy} \tag{7}$$

where the unit of observation is bank b in quarter q in year y. The coefficient β express the differential change in the outcome after the tax for banks in the highest quartile of the ATM market share. The independent variable ATM market share$_b$ is defined at the bank level in the pre-policy period. It is interacted with a post-policy dummy. Bank and time FEs are included, hence all individual terms are absorbed. We report the results in Table 4, and also include the results when using as independent

Figure 5: Differential effect of the tax on cash issued in urban branches



Notes: This figure reports the coefficients of Eq. 6. The outcome variable is the monthly (log) value of deposits to banking agents in a given district. The unit of observation is the district. We include district and time FEs. The omitted category of reference is the group of districts in the lowest quartile of the ATM-density distribution. Standard errors are clustered at the district level. We include indicate significance at the 90% confidence interval.

variable the ATMs market share of the bank.

Eventually, we also provide event study evidence exploiting the following:

$$Y_{bt} = \alpha_b + \alpha_{qy} + \sum_{\tau=-6,\tau\neq-1}^{6} \beta_\tau \text{Quarter}_\tau \times \text{ATM Market share}_b + \epsilon_{bqy} \tag{8}$$

We show the results in Figure 6. We interpret the coefficient as the differential change in the log outcome for 1% higher ATM market share, with respect to the quarter before the introduction of the mobile money tax. In Figure B.6 we propose the same event study, where we use as independent variable the dummy $\mathbf{I}[\text{ATM market share}]_b$ as in Eq. 7.

4.4 Cash

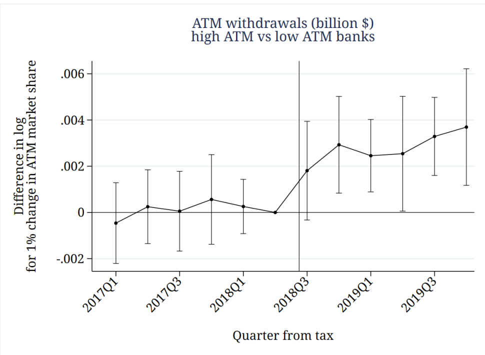
We present evidence that district with high ATM density present an increased demand for physical cash. These results further corroborates the hypothesis that mobile money is substituted by bank deposits and cash after the introduction of the tax: banks are used

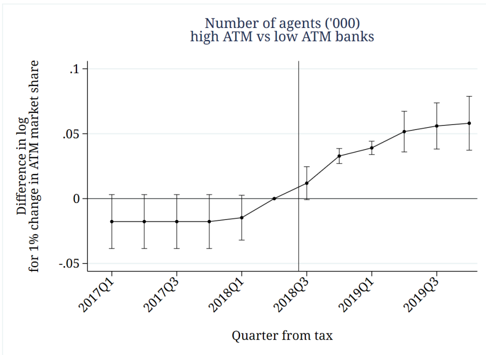
Table 4: ATM withdrawals and number of agents

	ATM withdrawals (billion)			Number agencies ('000)		
	Level (1)	Log (2)	Log (3)	Level (4)	Log (5)	Log (6)
Post Tax × **I**[ATM Market share]	0.034**	0.028**		1.309**	0.658***	
	(0.015)	(0.012)		(0.481)	(0.186)	
Post Tax × Market share of urban ATMs			0.003***			0.056***
			(0.000)			(0.007)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	263	263	263	264	264	264
Adj. R sq.	0.981	0.984	0.991	0.639	0.679	0.738
Mean Dep. Var.	0.025	0.025	0.025	0.007	0.007	0.007

Notes: This table reports the coefficients of Eq. 7. The outcome variables are the value of ATM withdrawals (in billion UGX) and the number of banking agents. The unit of observation is the private bank at quarterly level. We control for bank and time FEs. Standard errors are clustered at the bank level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Figure 6: Bank's ATM market share, ATM withdrawals and banking agents





Notes: In this panel we plot the coefficients of Eq. 8, where we use as outcome variable the log number of banking agents (right) and the value of ATM withdrawals. All outcome variables are at the bank level. The plotted coefficient represents the differential change in the outcome for 1% higher ATM market share, with respect to the reference period. We use as reference the quarter before the introduction of the mobile money tax. Standard errors are clustered at the bank level and we report 90% confidence intervals.

for money storage through banking agents, ATMs register an increase in withdrawals, and physical cash is now used for transaction.

We use data from total issuance of physical cash. While data on cash withdrawals at the individual branch do not exist, we exploit data at the bank-district level. We use data from 29 banks in 10 different districts. We define the bank-district pairs as branches. We use monthly data spanning from 2017 to 2022.

We exploit the following difference-in-differences specification, where we include the interactions between the post tax dummy and a dummy identifying those districts in the highest quartile of the ATM density distribution. This means that all branches within the same district will register the same ATM density. We exploit the following difference-in-differences:

$$\text{Y}_{bdmy} = \alpha_{bd} + \alpha_{my} + \beta \text{Post Tax}_{my} \times \mathbf{I}[\text{High ATM density}]_d + \epsilon_{bdmy} \tag{9}$$

where the outcome variable is the log value of notes issued by bank b in district d. Our preferred specification contains district-month FE that account for seasonality and bank-district FE that allow comparison of the same branch.

Table 5: Cash issuance

	Log cash withdrawn	
	(1)	(2)
Post Tax$_t$ × High ATM density $_d$	0.304***	0.231***
	(0.061)	(0.055)
Branch FE	Yes	Yes
Time FE	Yes	Yes
District × Month FE		Yes
Obs.	2622	2622
Adj. R sq.	0.543	0.542
Mean Dep. Var.	21.745	21.745

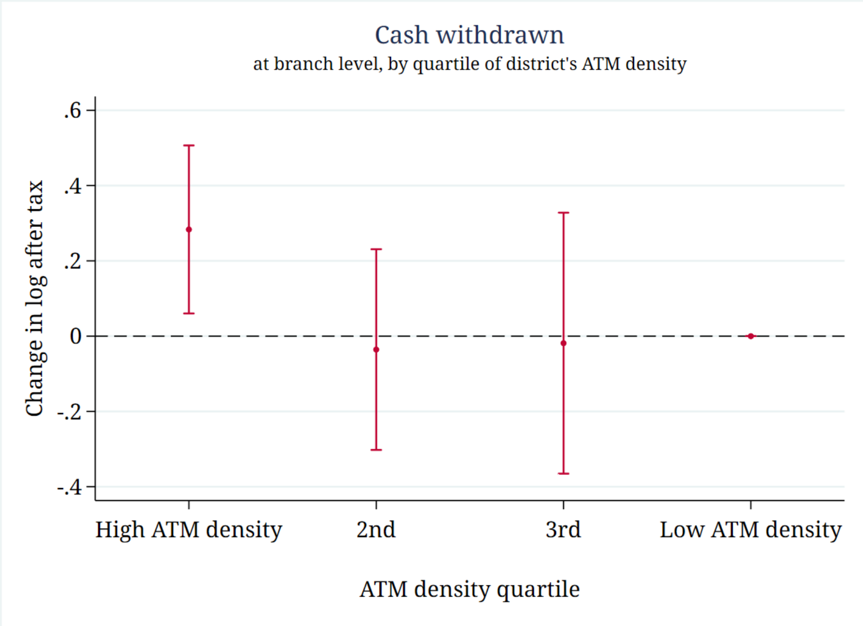
Notes: This table reports the coefficients of Eq. 9. The outcome variable is the log value of cash issued by the Central Bank to private banks. The unit of observation is the private bank-district pair, that we define as branch. We control for branch and time FEs in column (1), and add branch-month FEs in column (2) to account for seasonality. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Figure 7 shows the difference in the log of cash issued at the bank-district level. We plot the coefficients of an equation similar to Eq. 6:

$$Y_{bdqy} = \alpha_{bd} + \alpha_{qy} + \sum_{i=1}^{4} \beta_i \mathbf{I}_i \left[\text{ATM density quartile}\right]_d \times \text{Post TAx}_{qy} + \epsilon_{bdqy} \tag{10}$$

The coefficient represent the change in log cash withdrawn after the policy at the branch level after, with respect to the group of branches in the districts in the lowest quartile of ATM density distribution.

Figure 7: Differential effect of the tax on cash issued in urban branches



Notes: This figure reports the coefficients of Eq. 10. The outcome variable is the log value of cash issued by the Central Bank to private banks. The unit of observation is the private bank-district pair, that we define as branch. We include branch FE and quarter FE. Standard errors are clustered at the district level. We include 95% confidence interval.

5 Credit and transfer of rent

The imposition of the mobile money tax has engendered a multifaceted economic transformation. The discernible outcome of the tax has been a substantial reduction in the usage of mobile money services, precipitating a noteworthy exodus of funds from the mobile money system. Users, reacting strategically to the tax burden, have exhibited a pronounced reduction of the usage of mobile money, likely in favor of other means of payment, such as cash, and means of money storage, such as bank deposits.

The consequence of this shift has been twofold: a surge in traditional banking activities and heightened liquidity within the banking sector. As shown in Section 4.2, the surge in banking agents has emerged as a profitable alternative to mobile money services. This has led to a discernible increase in both the number of banking agents and volume/value of deposits to banking agents.

However, the newfound liquidity within the banking system is likely to be exceptionally volatile. Individuals, while utilizing banking agents for secure fund storage, overwhelmingly favor cash for transactions, a behavior validated by a concurrent rise in ATM withdrawals. This liquidity volatility has prompted banks to adopt risk management strategies in their lending practices.

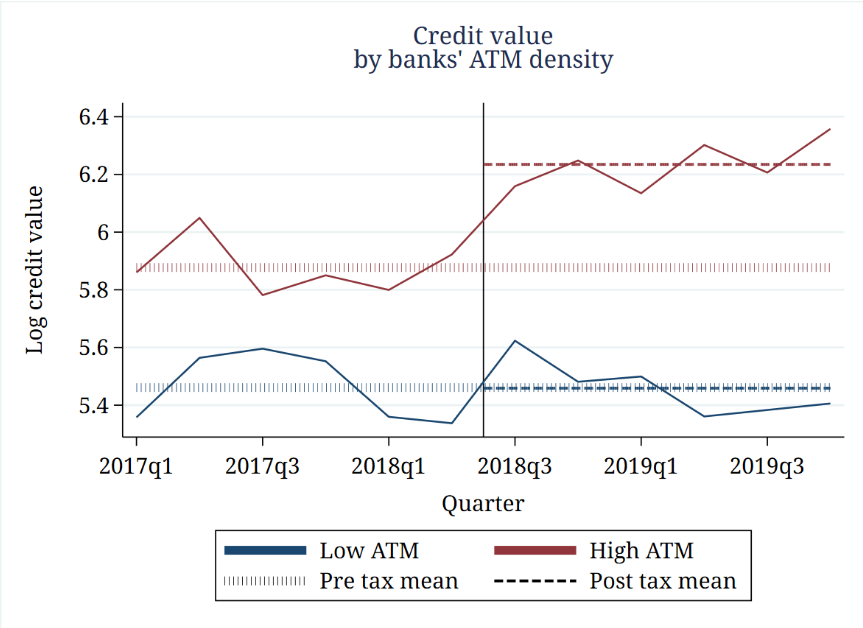
Our results show that banks have selectively increased lending to established customers with a demonstrated low risk of default. Conversely, lending to new customers, particularly those perceived as high risk, has contracted. To mitigate the potential risk of defaults, banks have raised interest rates for high-risk borrowers and shortened repayment terms. This cautious lending approach aligns with theoretical frameworks outlined in Berger and Bouwman (2015), illustrating how banks adapt their lending behavior in response to external shocks.

This intricate interplay between taxation, user behavior, and banking dynamics highlights the nuanced challenges within the financial ecosystem. Furthermore, the ongoing public discourse surrounding the mobile money tax introduces an element of uncertainty. The prevailing uncertainty in tax policy may influence user behavior (Gulen and Ion, 2016) and potentially lead to a reversion to mobile money. This complex landscape underscores the need for adaptive financial policies that can navigate the evolving dynamics of user preferences and regulatory frameworks.

In this section, we exploit data from the Uganda credit registry to study the behavior of banks in lending. We first show that in the first year and a half following the mobile money tax, lending from banks who were more exposed to liquidity shock increases by the equivalent of US $ 100 million. We identify these banks as the ones with the highest ATM market share. We identify as high-ATM those banks in the top quartile of the ATM market share distribution. As shown in previous results in Section 5, banks with the highest share of ATMs are also the ones experience the highest increase in banking agents, and hence in banking agents' deposits. Figure 8 plots the log of the credit granted by banks with high and low ATM market share, in the six quarters before and after the introduction of the mobile money tax. We see an increase in the total level of lending in the quarters following the tax for banks with high ATM share.

We propose an analysis adopting the methods proposed by Khwaja and Mian (2008)

Figure 8: Differential effect of the tax on cash issued in urban branches



Notes: This figure reports the coefficients of Eq. 10. The outcome variable is the log value of cash issued by the Central Bank to private banks. The unit of observation is the private bank-district pair, that we define as branch. We include branch FE and quarter FE. Standard errors are clustered at the district level. We include 95% confidence interval.

for estimating the bank-lending channel. Our data have the following structure: for each bank, district and quarter we manage to identify those loans provided to customers with or without credit history and who are defined are low or high risk.[11] The credit registry is comprehensive, and banks share customers' information. Hence, we manage to identify those customers who had previous credit relations with any bank. We hence study the distributional effect of the tax on credit by banks using the following regression:

$$Y_{bdt} = \alpha_b + \alpha_{dt} + \text{Post Tax}_t \times \mathbf{I}[\text{ATM market share}]_b + \epsilon_{bdt} \tag{11}$$

where Y_{bdt} is the outcome variable defined at bank b in district d at time t. The independent variable is the interaction between a post-policy dummy and an indicator variable taking value 1 for those banks in the upper quartile of the distribution of ATMs market share. We include bank and district-time FEs.

The regression is run for different groups of borrowers separately. In Table 6 we

[11]Banks define five levels of customer's risk: Substandard, Watch, Doubtful, Loss, Normal. We define as low risk those customers identified as "Normal".

report the results for the log amount of loans provided by banks

Table 6: Log amount lent

	w/ Credit history		w/o Credit History	
	Low risk (1)	High risk (2)	Low risk (3)	High risk (4)
Tax dummy$_{qy}$ × $\mathbf{I}$[ATM share]$_b$	0.152**	-0.027	-0.023	-0.043***
	(0.063)	(0.037)	(0.026)	(0.013)
Bank FE	Yes	Yes	Yes	Yes
District-Time FE	Yes	Yes	Yes	Yes
N. of banks	26	22	26	21
Adj. R sq.	0.372	0.329	0.357	0.141
Mean Dep. Var.	0.251	0.059	0.189	0.034

Notes: This table reports the coefficients of Eq. 11. The outcome variable is the log amount lent by private banks. Observations are defined at the bank, district, time level. We include bank and district-time FEs. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

We then provide evidence for the interest rate in Table 7 and the term of repayment in Table 8. In this case, the estimation weights for the number of loans of that given type provided by bank b.

Table 7: Interest rate on loans

	w/ Credit history		w/o Credit History	
	Low risk (1)	High risk (2)	Low risk (3)	High risk (4)
Tax dummy$_{qy}$ × $\mathbf{I}$[ATM share]$_b$	0.681	5.130**	-2.966	3.588***
	(4.063)	(1.905)	(2.004)	(0.699)
Bank FE	Yes	Yes	Yes	Yes
District-Time FE	Yes	Yes	Yes	Yes
N. of banks	26	22	26	21
Adj. R sq.	0.892	0.725	0.831	0.750
Mean Dep. Var. High ATM	22.690	26.240	23.460	26.964

Notes: This table reports the coefficients of Eq. 11. The outcome variable is the interest rate applied on loans provided by private banks. Observations are defined at the bank, district, time level. We include bank and district-time FEs. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

We interpret these results as a transfer of rent from high-risk customer with no credit history to low-risk ones with credit history. Indeed, we show that banks more affected by the positive liquidity shock increase their lending to low risk customers with credit history by 15%, while decreasing lending to high risk customer with no credit history by 4%. High risk customers register an increase in the interest rate by more than 3 percentage points. Eventually, repayment terms decrease for all customers, indicating the need

Table 8: Log term of repayment

	w/ Credit history		w/o Credit History	
	Low risk (1)	High risk (2)	Low risk (3)	High risk (4)
Tax dummy$_{qy}$ × $\mathbf{I}$[ATM share]$_b$	-2.240***	-0.875	-2.223***	-0.803**
	(0.654)	(0.543)	(0.638)	(0.327)
Bank FE	Yes	Yes	Yes	Yes
District-Time FE	Yes	Yes	Yes	Yes
N. of banks	26	22	26	21
Adj. R sq.	0.923	0.719	0.907	0.691
Mean Dep. Var.	5.966	5.874	6.138	6.179

Notes: This table reports the coefficients of Eq. 11. The outcome variable is the log term of repayment of loans provided by private banks. Observations are defined at the bank, district, time level. We include bank and district-time FEs. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

for the firm to deal with possible abrupt shortages of liquidity due to the possible shortages of liquidity that might derive by the nature of new deposits: as these are considered mainly a way to safely store money between transactions performed by individuals.

6 Conclusions

Our research delves into the dynamic landscape of digital payments, exploring the intricate interactions between digital and traditional payment systems and shedding light on their implications for bank lending and financial inclusion. The examination is contextualized within the ongoing debate on Central Bank Digital Currencies (CBDCs), emphasizing the necessity for empirical investigations into their potential repercussions on the banking sector.

Exploiting a quasi-experimental design and leveraging a comprehensive dataset encompassing the universe of Mobile Money transactions in Uganda, we study how competition between payment systems affects the credit market. In particular, our study investigates the consequences of an unexpected Mobile Money tax. We show that the increased cost of Mobile Money triggers the adoption of a new bank-related technology that facilitates deposits and that banks' deposits substitute Mobile Money for cash storage: we document that in those districts where the access to the banking system is made easier by the pervasiveness of ATMs, the flow of deposits and withdrawals increases after the introduction of the tax.

We leverage the transition from mobile money to bank deposits and its subsequent positive impact on bank liquidity to examine its effects on the credit market. Our study unveils novel insights into the lending behaviors of banks amidst increased deposit volatility. Despite observing heightened deposit flows and ATM withdrawals post the tax implementation, our evidence reveals no significant change in the overall deposit stock at the bank level. This suggests the precarious nature of the newfound liquidity, which banks cannot depend on for long-term and secure credit.

The data indicates a widespread reduction in the repayment term of new loans, reflecting the imperative for banks to cope with the continual cash withdrawals. Additionally, there is a discernible shift in rent from high-risk borrowers lacking credit history to low-risk borrowers with established credit records. These findings imply a shift in banks' strategies as they hedge against the risk of liquidity shortages. This mechanism is particularly relevant for financial inclusion, as reduced credit provision and higher interest rates to customers with no credit history might hinder local development of more fragile areas.

We contribute empirically to the debate on digital payments, banking competition, and financial inclusion. This research intersects with the literature on CBDCs, providing insights into how the introduction of digital payment systems may influence competition in the financial sector. Additionally, it aligns with literature exploring the impact of FinTech on traditional finance, emphasizing the expansion of financial services in response to evolving demands. Our empirical findings not only contribute to the ongoing dialogue surrounding the adoption of digital currencies but also unveil a novel mechanism that elucidates how volatile liquidity within banks can lead to discernible shifts in credit provision, impacting different customer segments.

Last but not least, we provide empirical evidence of a widely discussed topic developing countries, Mobile Money taxation, and contribute to the extremely scarce literature studying the effects of Mobile Money regulation. We highlight the possible negative implications of increased digital currency cost in developing countries, leading to both a drop in the usage of such system and to a drop in bank lending to more fragile households.

In conclusion, our empirical investigation offers nuanced insights into the complex interplay between digital and traditional payment systems, presenting implications for the credit market and financial inclusion. As the financial ecosystem continues to evolve, our research contributes valuable perspectives to the ongoing discussions surrounding the adoption of digital currencies and their impact on the broader financial services landscape.

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Back to bank:

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Online Appendix

Online Appendix A: Additional Tables

A.1 Mobile Money

A.1.1 Extensive margin: individual level

We present results from the difference-in-differences design of Eq. 1. To note is that we are estimating the regression on the sample of individuals that performed a transactions in the pre-tax period: hence, Y_{i0} is always equal to 1. Results are presented in Table A.1.

Table A.1: Extensive margin: performed transactions

	Extensive Margin				
	Active (1)	Sent (2)	Received (3)	Deposit (4)	Withdrawal (5)
Tax dummy$_t$	-0.374***	-0.730***	-0.708***	-0.491***	-0.399***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tax dummy$_t$ × High ATM density$_d$	0.129***	0.127***	0.103***	0.129***	0.120***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
User FE	Yes	Yes	Yes	Yes	Yes
N. of users	1230473	496897	727099	1095198	1108445
Obs.	2460946	993794	1454198	2190396	2216890
Adj. R sq.	0.214	0.528	0.513	0.301	0.231
Mean Dep. Var. High ATM	0.755	0.396	0.394	0.638	0.721
Mean Dep. Var. Low ATM	0.626	0.270	0.292	0.509	0.601

Notes: In this table, we use the specification presented in Eq. **??** and we show how mobile money users in areas with high ATM density respond less to the introduction of the mobile money tax at the extensive margin, relatively to users in districts with low ATM density. Users in high ATM density areas are between 10% and 12% more likely to perform transaction after the tax, with respect to other users. We estimate the effect on the sample of users that were active before the tax. We provide results for being active at all, i.e. performing any type of transaction (1), and we also differentiate between different types of transactions. Column (2) show the effects on the likelihood of sending money, column (3) on receiving money, column (4) on depositing money, column (5) on withdrawing money. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

In this case, the γ of Eq. 1 represents the percentage drop in the number of users in low ATM density districts, while β is the differential effect on the number of users in high ATM density districts. Users in low ATM density areas are between 40% and 75% less likely to perform a given type of transactions, and urban users are more than 10% more likely to keep performing it after the tax.

While these results may appear to be in contrast with our hypothesis, it is to be noted that high ATM density areas are especially urban center, which register higher economic activity. It is hence not surprising that, at the extensive margin, urban users are more likely than rural users to remain within the system. Indeed, this measure is not indicative of the intensity of usage, as in this case it is sufficient to perform one only transaction to be identified as active.

A.1.2 Intensive margin: individual level

Table A.2: Intensive margin: average daily number of transactions

	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$	-0.491***	-0.452***	-0.435***	-0.253***
	(0.003)	(0.002)	(0.002)	(0.001)
Tax dummy$_t$ × High ATM density$_d$	-0.086***	-0.092***	-0.015***	-0.048***
	(0.005)	(0.004)	(0.003)	(0.002)
User FE	Yes	Yes	Yes	Yes
N. of users	142522	225365	585690	691428
Obs.	285044	450730	1171380	1382856
Adj. R sq.	0.429	0.318	0.408	0.447
Mean Dep. Var. High ATM	0.070	0.049	0.131	0.108
Mean Dep. Var. Low ATM	0.059	0.044	0.131	0.096

Notes: In this table, we use the specification presented in Eq. **??** and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. Urban users perform between 2% and 6% less daily transactions with respect to rural users, after the tax. We estimate the effect on the sample of users that performed transactions of a given type before and after the tax. Column (1) show the effects on the number of transactions sent to another user, column (2) on the number of transactions received, column (3) on the number of deposits, column (4) on the number of withdrawals. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.3: Intensive margin: share of days for transaction

	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$	-0.031***	-0.019***	-0.033***	-0.022***
	(0.000)	(0.000)	(0.000)	(0.000)
Tax dummy$_t$ × High ATM density$_d$	-0.010***	-0.006***	-0.005***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
User FE	Yes	Yes	Yes	Yes
N. of users	156967	237653	601693	707320
Obs.	313934	475306	1203386	1414640
Adj. R sq.	0.552	0.402	0.476	0.538
Mean Dep. Var. High ATM	0.083	0.052	0.114	0.104
Mean Dep. Var. Low ATM	0.066	0.045	0.100	0.091

Notes: In this table, we use the specification presented in Eq. **??** and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. Urban users transact about 0.5% less days with respect to rural users, after the tax. We estimate the effect on the sample of users that performed transactions of a given type before and after the tax. Column (1) show the effects on the share of days in which the user sent mobile money, column (2) on the share of days in which the user received mobile money, column (3) on the share of days in which the user deposited mobile money, column (4) on the share of days in which the user withdrew mobile money. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.4: (Log) average daily value of transactions

	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$	-0.495***	-0.339***	-0.543***	-0.209***
	(0.003)	(0.003)	(0.002)	(0.001)
Tax dummy$_t$ × Urban$_c$	-0.034***	-0.037***	-0.034***	-0.037***
	(0.006)	(0.005)	(0.003)	(0.003)
User FE	Yes	Yes	Yes	Yes
Month FE	No	No	No	No
N. of users	434262	663043	1145494	1192352
Obs.	1667485	2398051	5797682	6327527
Adj. R sq.	0.494	0.408	0.452	0.446
Mean Dep. Var. Urban	1.1e+04	6630.113	1.1e+04	9155.623
Mean Dep. Var. Rural	8736.667	5446.040	8670.581	7235.526

Notes: In this table, we use the specification presented in Eq. **??** and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. In this case, we are using individual-month level data, and we are exclusively employing observed transactions, i.e. we are excluding zeros and hence estimating the intensive margin. Are outcome variable, we are using the log of the average daily value transacted in a month at the individual level. Urban users transact about 3.5% less with respect to rural users, after the tax. Column (1) show the effects on the value of transactions sent to another user, column (2) on the value of transactions received, column (3) on the value of deposits, column (4) on the value of withdrawals. Outcome variables are the log of the average daily amount. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.5: (Log) average daily number of transactions

	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$	-0.338***	-0.239***	-0.312***	-0.235***
	(0.002)	(0.001)	(0.001)	(0.001)
Tax dummy$_t$ × Urban$_c$	-0.039***	-0.027***	-0.024***	-0.028***
	(0.003)	(0.002)	(0.002)	(0.001)
User FE	Yes	Yes	Yes	Yes
Month FE	No	No	No	No
N. of users	434262	663043	1145494	1192352
Obs.	1667485	2398051	5797682	6327527
Adj. R sq.	0.449	0.308	0.491	0.397
Mean Dep. Var. Urban	0.132	0.079	0.180	0.134
Mean Dep. Var. Rural	0.111	0.073	0.179	0.122

Notes: In this table, we use the specification presented in Eq. **??** and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. In this case, we are using individual-month level data, and we are exclusively employing observed transactions, i.e. we are excluding zeros and hence estimating the intensive margin. Are outcome variable, we are using the log of the average daily number of transactions in a month at the individual level. Urban users transact about 3.5% less with respect to rural users, after the tax. Column (1) show the effects on the number of transactions sent to another user, column (2) on the number of transactions received, column (3) on the number of deposits, column (4) on the number of withdrawals. Outcome variables are the log of the average daily amount. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.6: Share of days in a month in which transaction type is made

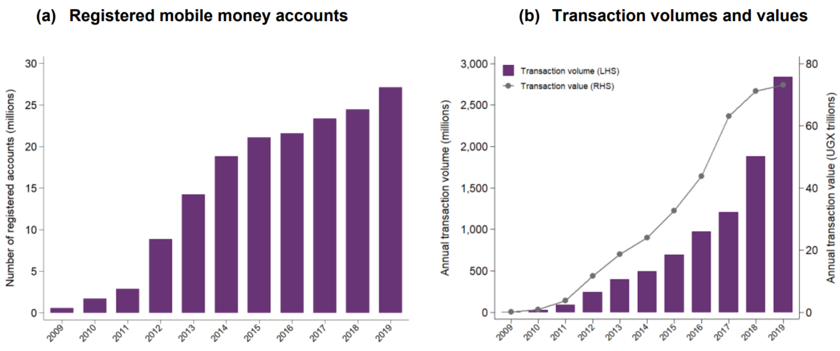
	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$	-0.034***	-0.018***	-0.033***	-0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
Tax dummy$_t$ × Urban$_c$	-0.007***	-0.003***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
User FE	Yes	Yes	Yes	Yes
Month FE	No	No	No	No
N. of users	434262	663043	1145494	1192352
Obs.	1667485	2398051	5797682	6327527
Adj. R sq.	0.498	0.377	0.520	0.474
Mean Dep. Var. Urban	0.102	0.071	0.131	0.120
Mean Dep. Var. Rural	0.089	0.066	0.121	0.110

Notes: In this table, we use the specification presented in Eq. **??** and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. In this case, we are using individual-month level data, and we are exclusively employing observed transactions, i.e. we are excluding zeros and hence estimating the intensive margin. Are outcome variable, we are using the share of days in a month in which the individual perfomed a given type of transaction. Urban users transact about 3.5% less with respect to rural users, after the tax. Column (1) show the effects on the share of days in which the user sent mobile money, column (2) on the share of days in which the user received mobile money, column (3) on the share of days in which the user deposited mobile money, column (4) on the share of days in which the user withdrew mobile money. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Online Appendix B: Additional Figures

B.1 Mobile Money and Tax

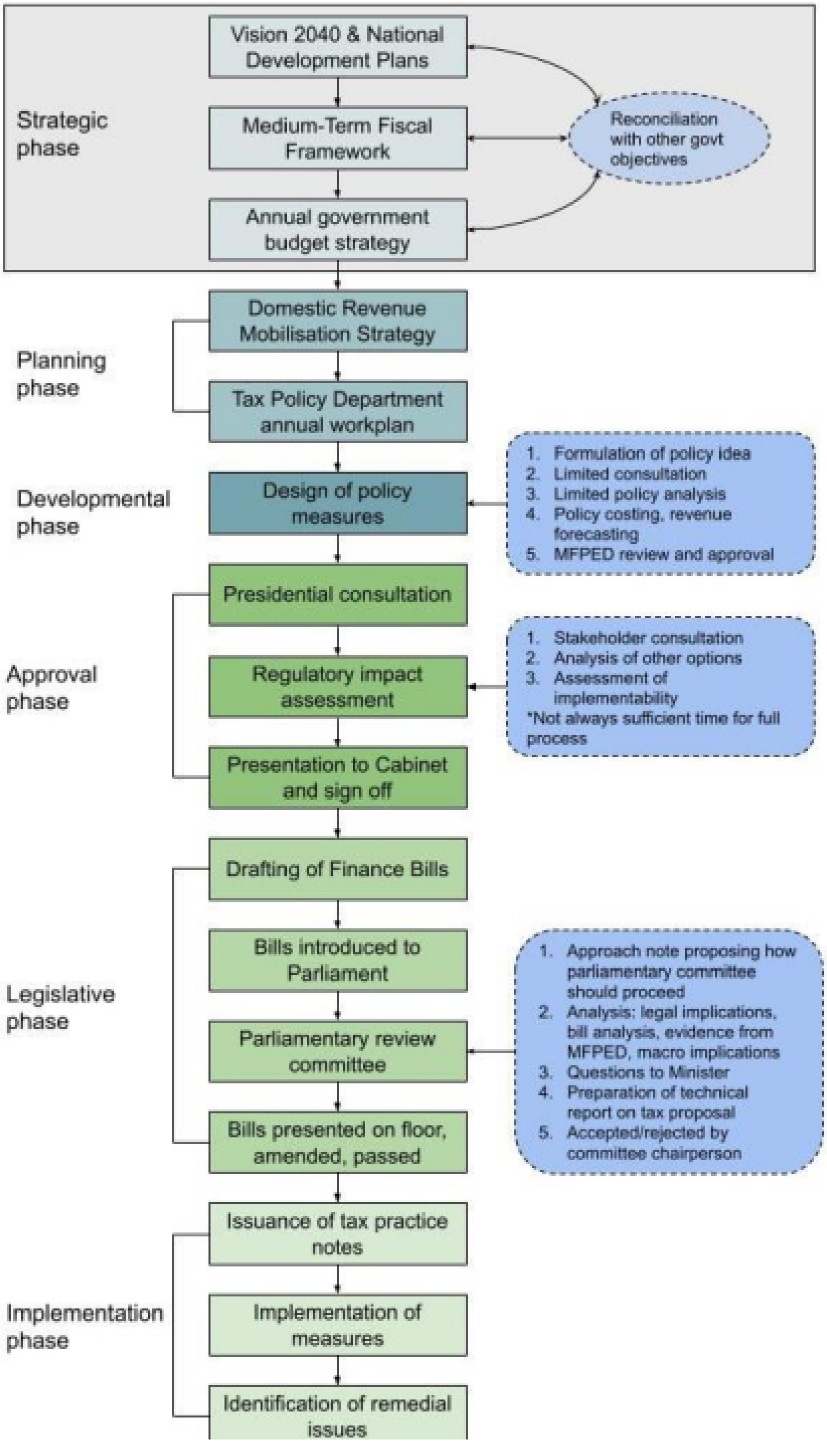
Figure B.1: Mobile volume in Uganda



Source: authors' calculations using data from the Bank of Uganda (2021).

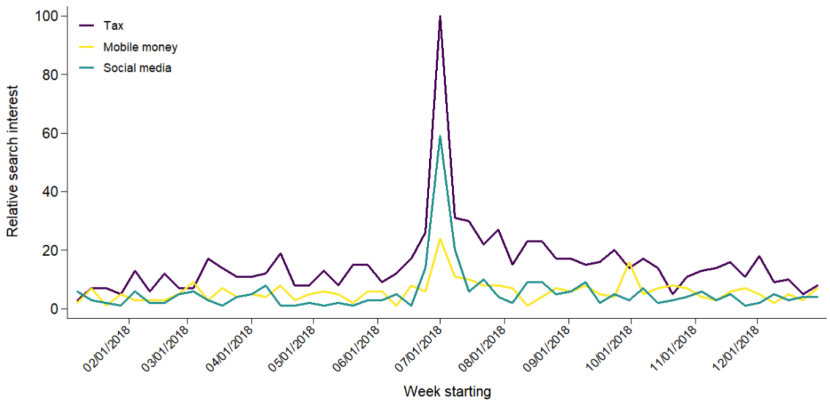
Notes: In Panel (a) we report the total number of registered users over time. In Panel (b) we show the volume (bars) and the value (line) of Mobile Money transactions in Uganda.

Figure B.2: General Tax process



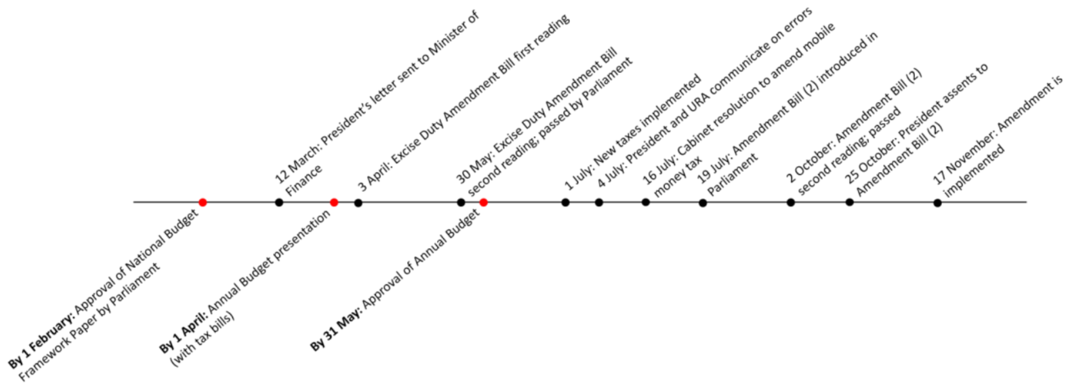
Notes: This figure presents the process for new tax approval in Uganda. As shown, there are multiple steps. These were not followed for the introduction of the mobile money tax.

Figure B.3: Google Trend for Mobile Money Tax



Notes: Google Trends gives the relative popularity of a search query for a defined location and time period. The data is indexed to 100, where 100 indicates the maximum search interest across the terms, time period, and geographical area. We assume that search indicators provide representative information about the behaviours of the literate and internet-enabled segment of the population (who may be more likely to be mobile money users). There is relatively limited interest in these terms before July, even in May when the Mobile Money tax proposals were discussed in Parliament.

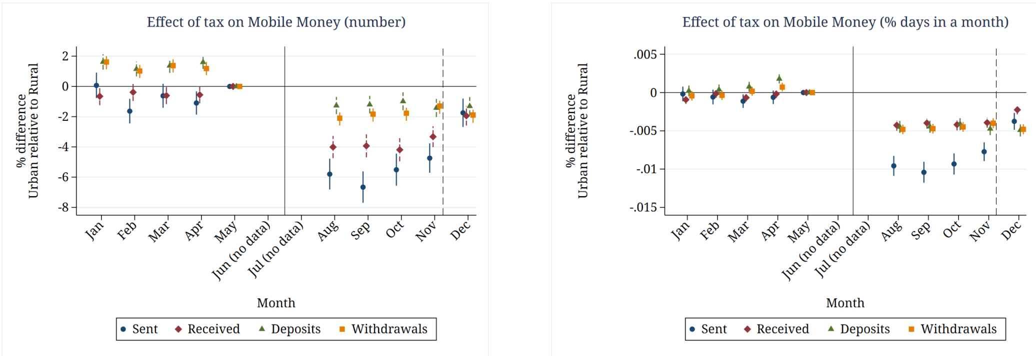
Figure B.4: Mobile Money Tax process



Notes: This figure reports the steps that led to the introduction of the Mobile Money tax in Uganda. Compared to Figure B.2, we see how the process for the introduction of this tax was extremely simplified.

B.2 Mobile Money

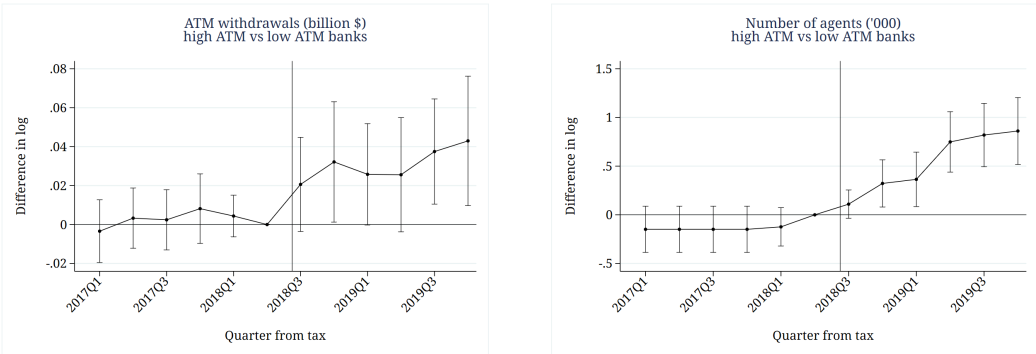
Figure B.5: Differential effect of the tax on urban areas



Notes: This figure plots the coefficients β of the event study described in Eq. **??**. We use as outcome variable the log of the average number of mobile money transactions in a month at the individual level (left panel) and the share of days in which a given type of transaction is performed by the individual (right panel). We differentiate between type of transactions. In the left panel, we already express the y axis in terms of % change. We use May as the baseline month. Data for June and July are excluded due to issues with data collection. Standard errors are clustered at the individual level, and the figure reports 95% confidence interval.

B.3 Banking agents

Figure B.6: Bank's ATM market share, ATM withdrawals and banking agents



Notes: In this panel we plot the coefficients of Eq. 8, where we use as outcome variable the log number of banking agents (right) and the value of ATM withdrawals. All outcome variables are at the bank level. In this case, we use as independent variable a dummy indicating whether the bank is in the highest quartile of the ATM market share distribution. The plotted coefficient represents the differential change in the outcome for banks with high relatively to banks with low ATM market share, with respect to the reference period. We use as reference the quarter before the introduction of the mobile money tax. Standard errors are clustered at the bank level and we report 90% confidence intervals.

Online Appendix C - Theoretical Framework for currency substitution

We propose a finite-horizon model where we include mobile money, cash and bank deposits as means of payment and money storage in order to rationalize the empirical analysis. We differentiate between two types of household: rural and urban ones. Urban household can use all three types of payments/money storage, while rural households have no access to bank deposits (lacking, in their case, access to the banking system). This setting mirrors our assumptions in the empirical model.

To keep the model simple, we assume that there are only two means of payment and money storage, cash B and mobile money M. Households can decide whether to pay for their consumption using cash or mobile money. Households can also decide how to store their money, in cash on mobile money. We assume that neither money storage system pays interest (as it actually happens in Ugandan economy). We assume that money stored in cash is subject to a known depreciation rate. This reflects the access to safe cash storage systems, such as banks and ATMs. The more pervasive ATMs are, the less cash is subject to theft (for example, a high density of ATMs allows you not to carry cash around). For simplicity, we assume it to be fixed.

We base our model on Sarkisyan (2023), however allowing households to buy any good with both type of currencies, cash and mobile money. We solve the partial equilibrium for the household only, providing a hint for guiding our empirical results.

C.1 The Model

Households defined on the continuum $[0,1]$ are denoted by i. Households decide on their consumtpion C_t, the quantity of mobile money M_t and of cash B_t to hold. They maximize their utility function

$$U_0^i = \sum_{t=0}^{T} \log C_t^i \tag{C.1}$$

and they are subject to two constraint. An intertemporal budget constraint:

$$C_t^i + M_{t+1}^i + B_{t+1}^i \leq Y_t^i + M_t^i + B_t^i \delta \tag{C.2}$$

where δ is a certain depreciation rate that household know to face when deciding to keep money as cash, and it is such $\delta \in [0,1)$. This reflects the fact that cash is easily subject to theft. A higher δ implies a safer cash storage: we can think of it as the easy access to ATMs or banks, that allow households not to carry cash around and withdraw it near the point where the make the purchase. The model is qualitatively the same if we introduce bank deposits as mean of storage of cash. The implicit assumption in this simplified model is that households always store cash in banks, but they are subject to theft is banks are not widespread. We do not include any interest rate paid on cash or mobile money, as this would not change the model implications.

The second constraint is written in the fashion of a liquidity-in-advance constraint in the fashion of Lucas Jr (1982), Lucas Jr and Stokey (1985) and Svensson (1985). We however allow households to be able to purchase any consumption good with both cash or mobile money. While households pay no additional cost in using cash for consumption, they might incur in an additional cost u_t^i when using mobile money. This reflects changing fees applied to mobile money, and we include it as an i.i.d. shock with mean $\bar{u}$ and support $[0, u^{upper})$.

$$C_t^i \leq B_t^i + u_t^i M_t^i \tag{C.3}$$

This model hence reflects the decision of households as follows: (i) the shock u_i^t is realized and household decide their consumption; (ii) households choose how to store their money for the next period, whether in cash B_{t+1}^i or in mobile money M_{t+1}^i.

If the support of of u_t^i is large enough, households will keep precautionary savings in cash, in order not to have to face extreme negative shocks to their consumption.

C.2 Solving the model

In order to solve the model, we first write down the Lagrangian as:

$$\begin{aligned} \mathscr{L}\left(C_t, M_{t+1}, B_{t+1}, \lambda_t, \mu_t\right) = \sum_{t=0}^{T} \beta^t \Bigg[& \log C_t^i + \\ & \lambda_t \left(Y_t^i + M_t^i + B_t^i \delta - C_t^i - M_{t+1}^i - B_{t+1}^i\right) + \\ & \mu_t \left(M_t^i u_t^i + B_t^i - C_t^i\right) \Bigg] \end{aligned} \tag{C.4}$$

and we obtain the following F.O.C.:

$$C_t: \qquad \frac{1}{C_t} - \lambda_t - \mu_t = 0 \tag{C.5}$$

$$M_{t+1}: \qquad -\beta\lambda_{t-1} + \beta\lambda_t + \beta\mu_t \mathbf{E}_{t-1} u_t^i = 0 \tag{C.6}$$

$$B_{t+1}: \qquad -\beta\lambda_{t-1} + \beta\lambda_t \delta + \beta\mu_t = 0 \tag{C.7}$$

We proceed by combining Eq. C.6 and Eq. C.7, obtaining:

$$\lambda_t(1-\delta) = \mu_t\left(1-\mathbf{E}_{t-1}u_t^i\right) \tag{C.8}$$

From this equation conclude that, since $\mathbf{E}_{t-1}u_t^i \neq 1$, then $\lambda_t \neq 0$. This implies that the constraint of Eq. C.2 binds. Similarly, also the constraint in Eq. C.3 binds: if it were not so, we would have that $\mu_t = 0$, implying that $\delta = 1$. This would reduce our model to have no conveniency in mobile money, as cash would be completely safe.

Since the constraints bind, we can equate consumption C_t from both Eq. C.2 and C.3, to obtain:

$$I_t^i = M_t^i(1+u_t^i) + B_t^i(1-\delta) \tag{C.9}$$

where $I_t^i = Y_t^i - M_{t+1}^i - B_{t+1}^i$. Starting from this equation, we can rewrite B_t and M_t as:

$$B_t^i = \frac{I_t^i - M_t^i(u_t^i - 1)}{1-\delta} \tag{C.10}$$

$$M_t^i = \frac{I_t^i - B_t^i(1-\delta)}{u_t^i - 1} \tag{C.11}$$

In order to obtain the consumtpion expressed as function of M_t or B_t we combine one of the two binding constraints (Eq. C.2 or Eq. C.3) respectively with the second F.O.C. in Eq. C.10 and with the third F.O.C. in Eq C.11, to obtain:

$$C_t^i = \frac{M_t^i(1-\delta u_t^i) + I_t^i}{1-\delta} \tag{C.12}$$

$$C_t^i = \frac{B_t^i(\delta u_t - 1) + u_t^i I_t^i}{u_t^i - 1} \tag{C.13}$$

C.3 Equilibrium

From now on we drop the superscript i to ease notation.

C.3.1 Obtaining μ_t as function of M_t and λ_{t-1}

What we need to do now is the following: we need to combine the consumption expressed in term of M_t in Eq. C.12 with the first F.O.C. in Eq. C.5 and then with the F.O.C. obtained deriving by B_{t+1} in Eq. C.7.

By combining Eq. C.12 with Eq. C.5 we first obtain:

$$\lambda_t = \frac{1-\delta}{M_t(1-\delta u_t) + I_t} - \mu_t \tag{C.14}$$

Then combining Eq. C.14 with Eq. C.7 we get:

$$\mu_t = \left[\beta\delta\frac{1-\delta}{M_t(1-\delta u_t)+I_t} - \lambda_{t-1}\right]\cdot\beta(\delta-1) \tag{C.15}$$

Similarly, we proceed for obtaining the same expressed in terms of B_t. We combine the consumption expressed in term of B_t in Eq. C.13 with the first F.O.C. in Eq. C.5 and then with the F.O.C. obtained deriving by M_{t+1} in Eq. C.6.

C.3.2 Obtaining μ_t as function of B_t and λ_{t-1}

By combining Eq. C.13 with Eq. C.5 we first obtain:

$$\lambda_t = \frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t} - \mu_t \tag{C.16}$$

Then combining Eq. C.16 with Eq. C.6 we get:

$$-\lambda_{t-1} + \beta\left[\frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t} - \mu_t\right] + \beta\mu_t\mathbf{E}_{t-1}u_t = 0 \tag{C.17}$$

Notice that we need to get rid of the expectation term $\mu_t\mathbf{E}_{t-1}u_t$. We can do this by combining Eq. C.17 with Eq. C.8, and substituting $\mu_t\mathbf{E}_{t-1}u_t$ with $\lambda_t(1-\delta)$, obtaining:

$$-\lambda_{t-1} + \beta\left[\frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t}\right] = \beta\lambda_t(1-\delta) \tag{C.18}$$

Now we need to subtitute λ_t again with Eq. C.16, finally obtaining:

$$\mu_t = \left[\beta\delta\frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t} - \lambda_{t-1}\right]\cdot\beta(\delta-1) \tag{C.19}$$

C.3.3 Equilibrium

Now that we obtained μ_t expressed in terms of λ_{t-1} and rispectively in terms of M_t in Eq. C.15 and in terms of B_t n Eq. C.19, we can equate these two equations to obtain:

$$\frac{1-\delta}{M_t(1-\delta u_t)+I_t} = \frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t} \tag{C.20}$$

and simplifying further this equation we obtain:

$$M_t(1-u_t) = B_t(1-\delta) + I_t \tag{C.21}$$

Let us suppose to be in the simplest case in which $Y_t == 0$ for $t! = 0$. At $T-1$ the households will choose to allocate no money neither to cash B_T or mobile money M_T. We can extremely simplify the model to a two-period model, at time 0 and 1. Indeed households will have to choose only C_0, M_1, B_1 and C_1, since $B_2 = 0$ and $M_2 = 0$. If we assume $Y_1 = 0$, we get:

$$\frac{B_t}{M_t} = \frac{1-u_t}{1-\delta} \tag{C.22}$$

Let us suppose a shock to u_t, the ratio between cash B_t and M_t would change by:

$$\partial_u \frac{B_t}{M_t} = -\frac{1}{1-\delta}$$

it is clear that a higher conveniency of storing cash δ leads to a higher elasticity of substitution between cash and mobile money.