Mobile Internet, Digital Collateral, and Banking*

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Abstract

Combining administrative credit data and a digitally-empowered reform on land in Rwanda, this paper investigates the impact of mobile Internet on the banking sector through the digital collateral channel. Leveraging quasi-experimental variation from two sources of 3G connectivity, lightning strike frequency and topographical incidental coverage, we show that mobile Internet plays a pivotal role in steering borrowers from microfinance to commercial banks, offering improved loan terms. Our quantification reveals that the digital collateral's availability mediates 35% of the effect of mobile Internet on credit and 80% of the effect for collateralized loans.

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1 Introduction

The Internet has brought lasting changes to contemporary societies, influencing political engagement (Gavazza et al., 2019; Enikolopov et al., 2020; Manacorda and Tesei, 2020; Guriev et al., 2021), employment opportunities (Hjort and Poulsen, 2019; Bircan and De Haas, 2020; Bandiera et al., 2022; Bahia et al., 2023), social media (Braghieri et al., 2022), trade patterns (Couture et al., 2021; Akerman et al., 2022; Dolfen et al., 2023), and more. Simultaneously, this technological innovation has led to a revolution in the financial system through the rise of financial technology companies, also known as fintech (Goldstein et al., 2019; Berg et al., 2020).

This paper offers an empirical contribution by investigating how Internet technologies affect individuals' financial decision-making, focusing on the role of private information (Stiglitz and Weiss, 1981), a central feature of local credit markets. Traditional financial institutions develop methods to screen and monitor their customers by leveraging local officers (Fisman et al., 2017), specializing in certain industries and networks (Giannetti and Saidi, 2019; Haselmann et al., 2018), and employing specific forms of contract design (Beck et al., 2018) to deal with private information. The Internet has the potential to change this context. By making individual behavior measurable, Internet technologies lower the intrinsic unobservability of private information. Furthermore, Internet technologies may help develop new forms of "digital collateral", allowing financial institutions that are external to the local economy and lack access to traditional screening methods to enter and compete.

Digital collateral takes on various definitions based on the specific application and context. Two influential papers have significantly contributed to shaping this concept. Berg et al. (2020) introduced the idea of a "digital footprint" in finance, referring to user-generated online information that complements traditional credit bureau data in assessing credit risk. Gertler et al. (2021) defined "digital collateral" as a lockout technology, which allows lenders to suspend services from a capital asset without physical repossession. Our definition of digital collateral combines both aspects and draws inspiration from the foundational work in digital economics by Goldfarb and Tucker (2019). In this paper, digital collateral refers to an asset that a borrower pledges to a lender as security for a loan, facilitated by Internet technologies.

This mechanism and definition lead us to study two specific questions: 1) Does the introduction of mobile Internet change the borrower's choice of financial institution? 2) What is the role of digitally-empowered collateral in this reallocation? To answer these questions, we focus on Rwanda, an emerging country that combines the ideal setting for our study: extensive administrative data on financial decisions with a reform introducing a source of digital collateral combined with granular data on 3G, which is the dominant source of Internet connectivity in the country.

An empirical investigation of these topics requires identifying sources of variation in mobile Internet independent of local confounding factors. We leverage two distinctive geographical features of Rwanda that we use to build instrumental variables. Firstly, the heterogeneous distribution of lightning strikes in Rwanda's municipalities affects the development of mobile Internet infrastructures, as outlined in Manacorda and Tesei (2020). Secondly, Rwanda's topography significantly impacts its telecommunications as demonstrated by Yanagizawa-Drott (2014), which also includes a highly uneven 3G availability across the country. In this regard, we use the quantification of "incidental coverage" by Björkegren (2019), which measures mobile signal availability based on idiosyncratic topographic features, such as a municipality's proximity to the electric grid and its location on different sides of hill slopes in a country known as the "Land of a Thousand Hills"[1]. Importantly, we show that these two exogenous sources of Internet availability exhibit no correlation with income and other predetermined characteristics.

To conduct our empirical analysis, we leverage extensive administrative data sources from Rwanda. Our primary dataset, obtained from the Credit Reference Bureau, spans from 2008 to 2015, encompassing detailed loan-level information from all regulated credit institutions operating within Rwanda. This comprehensive dataset includes details on the loan amount, lending rate, collateral status, and borrower attributes like location, age, gender, and marital status for each loan. In total, our dataset comprises information on 113,897 distinct individuals across 337 municipalities. Each borrower is uniquely identified by a numerical code, facilitating the tracking of

[1] In this paper, a *municipality* refers to the third level administrative subdivision in Rwanda, corresponding to the so-called *sector*. There are 5 provinces in Rwanda that are subdivided into 30 districts. Each district is in turn divided into sectors. Overall, there are 416 sectors.

their lending engagements over different time periods and with various lenders.

We augment our dataset by incorporating data on 3G mobile Internet coverage from the GSM Association, which reports annual 3G coverage across all Rwandan municipalities from 2008 to 2015. Notably, the introduction of 3G mobile Internet at the country level occurred in 2011, providing a key source of time-series variation in Internet connectivity. Additionally, we add to the dataset information on the instrumental variables. Data on lightning strike frequency is obtained from the Global Hydrology Resource Center, whereas data on incidental coverage are from Björkegren (2019).

Finally, our analysis incorporates information on a digitally-empowered reform that introduced a form of digital collateral. The Land Tenure Regularization (LTR) program marked the initiation of a land tenure system, accomplished through the "development and maintenance of the digital registry" and the creation of "digital records for over 10 million land parcels"(World Bank, 2020)[2]. The implementation of this reform benefited from the expanding role of mobile Internet, with digital advertising playing a pivotal role. Recognizing the ubiquity of mobile phones as one of the most widespread modes of communication in the country, the National Land Authority extensively used online advertising and social networking. To analyze this aspect, we collaborate with the Rwanda Land Management and Use Authority, examining the distribution of digital land certificates, the number of transactions, and the share of mortgaged lands at the municipal level.

Rwanda not only provides an ideal econometric setting but also offers a unique opportunity to investigate how internet technologies shape the financial system. The latter is usually characterized by the coexistence of "traditional" institutions, employing informal procedures for handling private soft information, and "innovative" financial institutions, relying more on hard information and operating through more formal methods (Liberti and Petersen, 2018). Technology induces a transition from traditional to innovative institutions, and many instances exhibit this division, such as relationship versus transactional lending (Fuster et al., 2019; Agarwal and Hauswald, 2021), small local banks versus large national ones (Berger et al., 2005; Liberti and Mian, 2009),

[2]As reported by United Nations Economic Commission for Africa (2021): "Rwanda is one of the few countries in Africa that has successfully delivered a digital land registry system to its citizens".

and commercial banks versus fintech (Goldstein et al., 2019; Berg et al., 2022). In our setting, as well as in many emerging markets, traditional lenders are microfinance institutions (MFIs) that extract private information from their customers through local agents and group information (Besley and Coate, 1995; Ghatak and Guinnane, 1999; De Quidt et al., 2016). The innovative institutions are the commercial banks, which, while not as ubiquitous as MFIs, offer products that are otherwise unavailable.

The first set of results in the paper concerns the effect of mobile Internet on banking. Our analysis reveals that increased mobile Internet availability leads individuals to shift from microfinance institutions to traditional banks, as evidenced by a 3.4% increase in the probability of having a loan from a commercial bank and a 3.6% decrease in the probability of having an MFI loan for a one standard deviation rise in 3G coverage. Additionally, a one standard deviation increase in 3G coverage corresponds to a 1.1% rise in the probability of a MFI customer transitioning to a commercial bank. Interestingly, this transition does not alter overall financial inclusion, defined as the likelihood of individuals receiving a loan from any financial institution. In exploring potential variations in the effects, we identify municipality-level socioeconomic characteristics as relevant, while individual-specific traits play no discernible role. This underscores the inclusive nature of Internet technologies, rejecting evidence of discrimination based on observable characteristics like gender, marital status, and age. Furthermore, our study presents aggregate and loan-specific evidence highlighting the positive impact of mobile Internet on borrowing opportunities and loan characteristics for individuals accessing formal bank loans. Borrowers with access to mobile Internet tend to have larger outstanding loan amounts without adverse effects on interest rates. For switchers from MFIs to formal banks, especially those in the upper tail of the interest rate distribution, we observe a significant reduction in the rate paid.

After verifying that mobile Internet induces an expansion in banking at the detriment of microfinance, we test whether part of this effect is mediated by mobile Internet promoting digital collateral. Our first piece of evidence is that the implementation of the land reform is larger, faster, and more effective in municipalities with higher mobile coverage. We find that a one standard deviation increase in 3G coverage led to 23 percentage points higher likelihood that land transactions in the municipality started in the first year of the reform, 13 percentage points more registrations, and 16 percentage points higher likelihood that the municipality quickly achieves the median of total transactions. Using additional data from the land registry, we verify that the share of mortgaged lands increases significantly with the presence of mobile Internet, as a one standard deviation higher 3G coverage led to a 1.7 percentage points higher share of mortgaged lands. After this, we analyze again the credit bureau data and exploit the specific information on loans, in particular, whether the loan is pledged by collateral and whether it is a mortgage. Our findings indicate that the probability of receiving a bank loan with collateral and loans classified as mortgages increases by 0.6 percentage points and 0.8 percentage points with a one standard deviation higher 3G coverage.

These results, together with the previous ones, establish that mobile Internet contributes both to the expansion of banking and to empowering the availability of land titles as a form of digital collateral. In the last tests, we quantify the role of collateral as a mediator of the effect of mobile Internet on banking. Following the work of Doerr et al. (2022), we employ a Sobel-Goodman (SG) test and assess the mediation effect, i.e. the impact of 3G coverage on the probability of receiving a bank loan, with the presence of a digital land certificate as the mediator. Our findings reveal that approximately 35% of the effect of mobile Internet on the probability of receiving a bank loan is indirect and facilitated by the acquisition of digital collateral, whereas 65% is directly attributed to mobile Internet[3]. The "direct effect" of mobile Internet is a residual effect and catches many potential channels through which the Internet may make individuals seek bank credit: better job opportunities (Hjort and Poulsen, 2019), higher income (Bahia et al., 2023; Calderone et al., 2018), and lower information frictions (Gupta et al., 2023). To provide additional evidence in line with our hypothesis, we repeat our estimation using as dependent variable the probability of receiving a collateralized loan and find that the direct effect of mobile Internet decreases to 20% and is borderline significant, while the indirect effect mediated by the land titles accounts for 80% of the total impact. This quantification points to the pivotal role of digital collateral in securing a

[3] These results are corroborated by the findings in Table A2 of the appendix, where we implement sequential g-estimation following Acharya et al. (2016).

mortgage and steering individuals from MFIs toward commercial banks.

Our findings are robust to a wide range of tests, changes in the sample, and model specification. We replicate our analysis with different definitions of the dependent variables, the main predictors, and the two instrumental variables and find that the results remain unaffected. The main findings are also robust to the inclusion of control variables, aiming to control for municipality time trends, and to the confounding effects of reforms other than the introduction of the 3G, as the introduction of the Umurenge Savings and Credit Cooperatives (U-SACCOs) and the rolling out of the fiber, which happened in the period of our analysis. Finally, our results on the mediation role of land collateral are robust to a falsification test focusing on the availability of the fiber-optic technology and the implementation of a sequential g-estimation procedure that produces comparable quantifications.

The paper contributes to several strands of the literature. First, our research brings a perspective to the emerging literature on digital collateral by demonstrating that mobile Internet facilitates the acquisition of digitally-empowered collateral, encouraging increased engagement with specialized financial institutions. Building on previous research by Berg et al. (2020) and Gertler et al. (2021), our work aligns with findings that highlight the complementarity of digital collateral with traditional financial screening methods, impacting access to credit. Additionally, insights from Gambacorta et al. (2023) suggest a potential shift in the importance of traditional collateral, as credit from innovative providers proves less correlated with local economic conditions and more responsive to firm characteristics. In this respect, our findings resonate with the importance of technology in mortgage lending (Fuster et al., 2019) and the expanding role of household finance in emerging markets, as reviewed by Badarinza et al. (2019). Second, our research offers insights into the literature emphasizing the role of new Internet technologies in information access and dissemination. Internet technologies, notably mobile Internet, impact various societal aspects, from political perceptions (Guriev et al., 2021) to social organizations, protests (Manacorda and Tesei, 2020), and financial outcomes (Gao and Huang, 2020; Hvide et al., 2022). Specifically, we highlight the indirect impact of mobile Internet on information spread in linked markets, aligning with cross-market spillover effects discussed by Bos et al. (2018). In this respect, our paper adds to a growing literature documenting the impact of new IT technologies on banking (Core and De Marco, 2021; Kwan et al., 2021; Mazet-Sonilhac, 2021; Lin et al., 2021; Jiang et al., 2022; Pierri and Timmer, 2022; D'Andrea et al., 2023; D'Andrea and Limodio, 2023). Thirdly, in explaining our findings on the indirect effects of mobile Internet, the paper connects with the literature on land titles and access to credit (Besley and Ghatak, 2010; Besley et al., 2012; Acampora et al., 2022; Manysheva, 2021). Our primary contribution to this literature is to unveil the link between new Internet technologies, land certificates, and access to formal banking. In doing so, our findings align with the broader literature on the relevance of collateral for accessing bank credit (Benmelech et al., 2005; Benmelech and Bergman, 2009; Ioannidou et al., 2022) by emphasizing the significance of mobile Internet in mitigating frictions in the collateral market. Our research highlights the crucial need for the development of formal and digital collateral recording systems, serving as a catalyst for the advancement of formal banking and innovative financial institutions.

The rest of the paper is organized as follows. Section 2 presents the institutional setting in Rwanda. Section 3 describes our data and the main empirical specifications. Section 4 presents the results, sheds light on the mechanism behind our findings, and provides robustness checks. Finally, Section 5 concludes.

2 Institutional Setting

2.1 Credit Market in Rwanda

Historically, Rwanda's credit market faced numerous challenges, including limited access to financing, lack of financial infrastructure, and inadequate regulatory frameworks. The formal banking sector, consisting of commercial banks and other financial institutions, was primarily concentrated in urban areas, leaving a significant portion of the population, particularly those engaged in agricultural and informal sectors, with limited access to formal credit channels.

To address the financial needs of underserved populations, microfinance institutions emerged as key players in the credit market. MFIs provided small loans, savings accounts, and other financial services to individuals, primarily in rural and peri-urban areas. These institutions played a role in promoting financial inclusion, especially for micro and small-scale entrepreneurs who lacked access to traditional banking services. By leveraging group lending methodologies and maintaining close relationships with borrowers, MFIs helped fill the gap left by formal banks and stimulated economic activity at the grassroots level.

In recent years, Rwanda has made significant strides in strengthening its credit market, fostering financial sector development, and enhancing access to credit for both individuals and businesses. These changes have been driven by a combination of factors, including economic development, policy reforms, and technological advancements.

Formal banks have sensibly expanded their reach. With improved regulatory frameworks and technological advancements, formal banks have been able to extend their services to previously underserved areas. Nowadays, they offer a wide range of financial products and services, including loans, savings accounts, and digital banking solutions, and play a central role in facilitating investments, supporting businesses, and promoting economic growth. The expansion of credit by formal banks in recent years is clearly visible in Figure 1.

Parallel to the expansion of formal banking, there has been a shift away from microfinance institutions as the primary source of credit for individuals and small businesses. While microfinance played an important role in providing financial services to the unbanked population, the growth of formal banking has gradually reduced the reliance on microcredit (see Figure 2). This shift can be attributed to several factors, such as increased awareness and confidence in formal banking systems, improved regulatory frameworks, and the availability of alternative credit options.

In this paper, we show that technological advancements have contributed to facilitating the expansion of formal banking and the transformation of the credit market in Rwanda. In particular, the widespread adoption of mobile Internet has made banking products more accessible, convenient, and cost-effective.

2.2 Mobile Internet

In the last two decades, Rwanda has made significant strides in improving its information and communication technology (ICT) connectivity. Following the devastating civil conflict from 1990 to 1994, the country recognized the potential of ICTs as catalysts for economic development and growth. In line with this vision, President Paul Kagame launched the "Vision 2020" program in 2000, aiming to transform Rwanda into a middle-income knowledge economy by 2020. ICT was identified as one of the key drivers for achieving this vision (GoR, 2012). President Kagame himself acknowledged the transformative power of broadband, stating, "The broadband cannot solve all world problems, but we know it can accelerate progress in overcoming the biggest obstacles to global prosperity and well-being"[4]. This belief in the potential of new technologies has driven strong activism and political commitment in Rwanda's journey towards ICT connectivity.

The government has taken various steps to establish a foundation for high-speed connections. Initially, the focus was on attracting private-sector investments through the introduction of enabling laws and the establishment of a regulatory authority for the ICT sector. Subsequently, the country privatized its incumbent telecommunications operator and fostered wireless competition, thereby encouraging additional private-sector investments. Concurrently, the government ensured that new technologies were accessible nationwide, not limited to commercially lucrative areas. Finally, the transparent and dedicated public administration played a crucial role in promoting ICT adoption and building trust between businesses and the government (UN-OHRLLS, 2017).

Mobile technology has become pervasive in Rwanda. In 2015, the country ranked third in Africa in terms of the percentage of the population covered by 3G, following South Africa and Lesotho (GSMA, 2015). The Rwanda Utilities Regulatory Authority (RURA) reported 3.8 million mobile Internet subscriptions among a population of almost 11.5 million, surpassing the average for the continent and least developed countries. The impressive diffusion of mobile technology can be attributed to several factors, with affordability being a key driver. Rwanda boasts the cheapest price per gigabyte of data in East Africa when considered as a percentage of per capita income. Consequently, it is often regarded as a positive example for developing countries transitioning to a modern economy. The country serves as a benchmark for broadband installation, penetration, and successful implementation of ICT investments.

[4] Mugabo, Peter. 2016. "Kagame says broadband can accelerate progress". News of Rwanda, September 19. http://www.newsofrwanda.com/abanyapolitiki/31583/kagame-says-broadband-can-accelerate-progress/

By leveraging these advancements in mobile technology and ICT infrastructure, Rwanda has laid the groundwork for exploring the impact of mobile Internet on access to credit. The widespread availability and affordability of mobile Internet have opened new avenues for financial inclusion and the development of the banking sector. In the following sections, we delve into the specific effects of mobile Internet on banking, highlighting its role in promoting traditional banking and facilitating the transition from microfinance.

2.3 The Land Tenure Regularization Program

In the aftermath of the civil conflict, the large-scale migration of returnees had a dramatic impact on land ownership, escalating tensions and land conflicts, making land reform a crucial condition to ensure social stability and improve land use management and investments. With this background, in 2009 the government of Rwanda launched the Land Tenure Regularization program, a reform aimed to regulate the ownership and control of the lands, enhance land utilization, and promote its efficient management (Abbott and Mugisha, 2015).

In order to successfully complete such a large-scale initiative, the National Land Authority of Rwanda experienced a significant expansion of its activity, collecting and centralizing a massive amount of data on parcels. After allowing for a period of corrections and addressing objections, with a large-scale mobilization of citizens involving approximately 110,000 people, the data was digitized to facilitate the issuance of land titles. By the year 2012, the database had accumulated information on an impressive 10.4 million land parcels.

The LTR program introduced a land tenure system based on the digital registry (World Bank, 2020). This registry played a pivotal role in favoring access to formal credit since land titles could be used as collateral for loans and thus facilitated access to credit for the landowner (Besley and Ghatak, 2010; Acampora et al., 2022; Manysheva, 2021). In line with this argument, in 2013 all financial institutions in Rwanda were connected to the digital registry, which made it easier the tracking and verification of land ownership.

The execution of the land reform highly benefited from the expansion of mobile Internet, with digital advertising playing a prominent role. Recognizing the ubiquity of mobile phones as one of the most diffused modes of communication in the country, the National Land Authority initiated an extensive online advertising campaign, further strengthened by the introduction of its Twitter account in March 2011 (Schreiber, 2017). Mobile Internet was used in two ways to promote the program and provide timely updates on its progress: directly, being a network where people could search for information and gain knowledge about the land certificates; and indirectly, as a channel through which people could learn about other sources of information such as radio broadcasts, TV programs and local public meetings.

In this paper, we leverage both the role played by mobile Internet in promoting land reform and the availability of the digital registry, and show that part of the effect of mobile Internet on banking is channeled through digitally-empowered land collateral. The latter reduces information frictions between borrowers and commercial banks and allows individuals to move away from microfinance institutions towards formal banking.

3 Data and Empirical Strategy

3.1 Data

Our study utilizes comprehensive loan-level data obtained from the Credit Reference Bureau (CRB), a private credit bureau regulated by the National Bank of Rwanda (NBR). The dataset encompasses loans provided by all supervised credit institutions in Rwanda, including commercial banks, microfinance institutions, and savings and credit co-operatives (SACCOs), which are government-backed financial institutions aimed at enhancing financial inclusion for Rwandan citizens. The loan-level information is reported on a monthly basis, from January 2008 to December 2015, with no minimum loan size requirement. The credit registry data, that we aggregate at the yearly level, offer a highly representative view of the total banking sector loans (Agarwal et al., 2023).

In our baseline analysis, we focus on loans granted to individuals. For each loan, we have access to information such as the loan amount and price, borrower's location (down to the municipality level), and borrower characteristics like age, gender, and marital status. After carefully cleaning the data, we compile a comprehensive dataset that captures the local currency lending activities of banks and MFIs for 113,897 unique individuals across 337 municipalities[5]. Borrowers are identified with a unique numerical code that allows us to track their lending activity over time and across lenders.

To examine the impact of mobile Internet on traditional banking, we incorporate data on mobile phone coverage from the GSM Association (GSMA), a global trade association representing the interests of the mobile phone industry. The data, obtained through a partnership with Collins Bartholomew[6], provide yearly geolocated information on mobile coverage in Rwanda from 2008 to 2015[7]. The dataset distinguishes between the availability of 2G, 3G, and 4G technologies, with 3G coverage accounting for most of the variation over the sample period. Our data allow us to measure the penetration of 3G at a very disaggregated geographical level, ranging between 1 km^2 on the ground (for high-quality submissions based on a geographic information system (GIS) vector format) to 15-23 km^2 (for submissions based on the location of antennas and their corresponding radius of coverage) (GSMA, 2012). For the purpose of our analysis, we map the adoption of mobile Internet at the municipality-year level. Figure 3 presents a visual representation of the coverage of 3G in Rwanda.

To address endogeneity concerns and establish a causal relationship, we construct instrumental variables (IV) using external datasets. Our first IV is based on the frequency of lightning strikes, which we obtain from the Global Hydrology Resource Center (GHRC) in Huntsville, Alabama. Data on lightning strikes are collected through the spaceborne Optical Transient Detector (OTD) on Orbview-1, and the Lighting Imaging Sensor (LIS) onboard the Tropical Rainfall Measuring Mission (TRMM) satellite, respectively. The LIS detection efficiency ranges from 88% during the

[5] It is worth noting that the total number of municipalities in Rwanda is 416, and the missing municipalities in our sample are a result of the inability to differentiate between municipalities with the same name but in different districts within the credit bureau data. Additionally, we exclude observations where borrowers have missing age information to ensure the accuracy of the analysis and avoid including borrowers who may be under the age of 16 in our balanced panel analysis.

[6] Collins Bartholomew is a digital mapping provider.

[7] The GSM network is the dominant standard in Africa and covers around 96% of the market share. These data come from submissions made directly by mobile operators for the purposes of constructing roaming coverage maps for end users.

night, to 69% at noon. The OTD has an efficiency of 52% during the night and 37% at noon. All the data are top-coded and released in the LIS/OTD Gridded Lightning Climatology Data Collection. For each grid cell, time and lightning are summed and scaled for the sensor precision's rate providing as outcome daily, monthly, seasonal, or yearly data. We follow the methodology in Manacorda and Tesei (2020) and improve in precision, using a grid resolution of 0.1 instead of 0.5. The left panel of Figure 4 illustrates the map of average lightning frequency by municipality, this time-invariant measure represents the first instrumental variable for mobile Internet coverage.

The second IV we employ is incidental coverage, and captures the variation in mobile Internet based on the combination of geographical attributes with the preexisting electric grid. Rwanda's topography, characterized by hilly terrain, influences the cost of providing mobile Internet to nearby villages. To account for this, we compute a measure of fictitious coverage that would have resulted if mobile operators had built towers along the entire network of power lines. This variable is constructed following the work by Björkegren (2019), and allows us to capture idiosyncratic variation based on the interaction between geography features and the electric grid[8]. Figure 4, right panel, plots the map of average incidental coverage by municipality, which represents the second instrumental variable for mobile Internet coverage.

To understand the underlying mechanisms behind our findings, we incorporate additional data from the Rwanda Land Management and Use Authority's land dashboard, which provides information on land certificates, transactions, and mortgaged lands, that we use to study the spillover effects of mobile Internet. While data on land titles are available at the district level, we obtain proprietary data at the municipality level from the authority to further analyze the relationship between digitally-empowered land collateral and bank credit access.

Lastly, we gather municipality-level data from the National Institute of Statistics (NISR) and the Integrated Household Living Conditions Survey (EICV). These data capture various indicators related to local economic and financial activities, focusing on the period prior to the introduction of the 3G mobile technology (before 2011). By incorporating these municipality-level controls, we

[8] Data on incidental coverage have been kindly provided by Daniel Bjorkegren.

aim to reinforce the robustness and comprehensiveness of our empirical analysis.

Table 1 presents summary statistics of the main variables used in our empirical analysis. Panel A examines access to credit, specifically the probability of having an outstanding loan, and separately having a loan with a commercial bank or a microfinance institution, and identifies the switching borrowers. Panel B provides yearly average characteristics of the bank credit relationship: outstanding amount; principal amount; interest rate; and the probability that the loan is secured. Finally, panels C and D present summary statistics for the main predictor, 3G mobile coverage, and its instrumental variables, including lightning frequency and incidental coverage.

3.2 Identification

A concern with the estimates of a model in which we regress credit features on mobile Internet is that new technologies are unlikely to be randomly allocated across areas, potentially generating a bias in the estimates of model parameters. In order to deal with this concern, we use an instrumental variable strategy that exploits exogenous differential rates of 3G adoption across Rwandan municipalities.

The first instrument is lightning frequency, which leverages the negative correlation between frequent lightning strikes and mobile connectivity. During storms, frequent electrostatic discharges can disrupt the signal transmitted by ground-based antennas, thereby reducing both the supply and demand for mobile phone services. This, in turn, hampers the profitability of technology investments and discourages the adoption of mobile services (ITU, 2003). Therefore, areas with a higher incidence of lightning strikes are expected to exhibit slower adoption of mobile technologies compared to areas with lower lightning frequency (Manacorda and Tesei, 2020). Figure 5, left panel, provides initial evidence supporting this hypothesis in the context of Rwanda. We observe that municipalities below and above the median of lightning strikes had zero 3G coverage before the introduction of the technology in 2011, after which their trends diverge in a monotonic manner.

The second instrument is incidental coverage, and builds on the heterogeneity in the cost of providing mobile Internet to different areas based on their proximity to the existing electric grid and the topography of their land. Operating mobile towers connected to the electric grid is more cost-effective than establishing standalone towers. Hence, a tower's transmitter has a higher probability of being constructed close to the existing grid. However, only places that are visible from a height of 35 meters above the tower are likely to receive mobile coverage, and that depends on the topography of the area. Exploiting this heterogeneity in the interaction between the presence of the electric grid and land characteristics, we create a measure of incidental coverage. We anticipate that areas with higher incidental coverage exhibit higher 3G rates. Figure 5, right panel, supports this expectation, as municipalities below and above the median of incidental coverage had zero 3G Internet before 2011, after which their trends diverge in a monotonic manner.

To further support our preliminary evidence, we provide additional analysis in Table A1 of the appendix. This balance table compares the mean values of geographical and socioeconomic indicators, before the introduction of 3G in 2011, for municipalities in different quartiles of the distribution of lightning strikes and incidental coverage. This analysis allows us to explore the potential correlation between our instruments and the predetermined characteristics of the municipalities. Regarding lightning strikes, the results are particularly reassuring. In each of the examined quartiles, the two groups of municipalities exhibit similar socioeconomic indicators, suggesting comparability in terms of pre-existing characteristics. While there are slight differences in some geographical characteristics, these variations are not substantial and are difficult to link with a change in the trend in access to credit unrelated to the introduction of the 3G. As for incidental coverage, the results are similar. Apart from some correlations with socioeconomic indicators around the median, there are no significant differences throughout the distribution. Although the absolute differences in mean values around the median are small, we further control for these correlations to ensure that our results are not biased, as discussed in the robustness section.

Overall, the analyses in Figure 5 and Table A1 support the validity of our instruments by demonstrating that the two groups of municipalities, divided based on lightning strikes frequency and incidental coverage, show different trends after the introduction of the 3G while they are largely comparable in terms of pre-existing geographical and socioeconomic characteristics.

Importantly, we define our instrumental variables as the interaction between lightning strikes and incidental coverage with a dummy post-2010. This definition further mitigates potential bias arising from the non-random allocation of mobile Internet across different municipalities, and helps us identify the causal effect of mobile Internet on banking.

3.3 Empirical Methodology

To examine the effects of mobile Internet on access to credit, the probability of switching to banking, and bank loan characteristics, we employ a balanced panel dataset at the borrower-year level[9]. Our baseline model is the following:

$$Y_{imt} = v + \beta_1 3G\ Coverage_{mt} + \alpha_i + \phi_t + \varepsilon_{imt} \tag{1}$$

where i denotes the borrower, m her municipality, and t the year. The dependent variable Y_{imt} differs depending on the specification. In the main one, which focuses on access to credit, Y_{imt} is a binary variable that takes the value of 1 if an individual i, in municipality m, has an outstanding loan with any financial institution, or separately with a commercial bank or a MFI, at time t, and 0 otherwise. When examining the transition to banks or MFIs, Y_{imt} is a binary variable that equals 1 when individual i, in municipality m, switches to the banking sector (or the MFI sector) at time t or before, and 0 otherwise. When focusing on loan characteristics, Y_{imt} is a continuous variable that represents the amount of the outstanding loan, or the associated interest rate. The key independent variable of interest is $3G\ Coverage_{mt}$, which is the standardized measure of the percentage of mobile Internet coverage in municipality m, at time t. We control for borrower fixed effects, (α_i), to account for unobserved time-invariant characteristics of borrowers that may be correlated with the dependent variable. Additionally, we include time-fixed effects, (ϕ_t), to capture common time-varying shocks affecting all borrowers simultaneously, such as changes in economic conditions. We estimate Equation 1 using a linear probability model (LPM) and compute robust standard errors clustered at the municipality level to address potential heteroscedasticity and correlated errors within the same municipality.

[9] When examing the effect on bank loan characteristics, the methodology is similar but we use an unbalanced panel dataset based on outstanding relationships.

By estimating this model, we examine the relationship between 3G Internet coverage and access to credit, switching behavior, and loan characteristics while controlling for individual and time-specific factors.

To address endogeneity concerns, we employ a two-stage least squares (2SLS) methodology. The first stage, outlined earlier, utilizes the relationships between mobile Internet coverage and the two instruments: lightning frequency and incidental coverage. The 2SLS equations are as follows:

$$3G\ Coverage_{mt} = q + \delta_1 Z_{mt}^{light} + \delta_2 Z_{mt}^{incid} + \theta_i + \xi_t + \epsilon_{imt} \tag{2}$$

$$Y_{imt} = v + \beta_1 3G\ \widehat{Coverage}_{mt} + \alpha_i + \phi_t + \varepsilon_{imt} \tag{3}$$

where $3G\ Coverage_{mt}$ is instrumented by Z_{mt}^{light} and Z_{mt}^{incid}. The first instrument, Z_{mt}^{light}, is the interaction between the time-invariant average of lightning strikes Z_m^{light} and a dummy variable post-2010, which takes a value of 1 after 2010. This accounts for the fact that before 2011, 3G Internet was not available in Rwanda[10]. The second instrument, Z_{mt}^{incid}, is the interaction between the time-invariant average of incidental coverage Z_m^{incid} and the dummy variable post-2010.[11] The other variables are defined as in Equation (1).

Equation 3 represents the second stage, where the dependent variable, Y_{imt}, is regressed on the predicted values of $3G\ Coverage_{mt}$ (denoted as $3G\ \widehat{Coverage}_{mt}$) obtained from the first stage, along with borrower fixed effects (α_i), time fixed effects (ϕ_t), and the error term (ε_{imt}).

The identification assumption underlying our model is that any correlation between lightning strikes and incidental coverage with municipality characteristics remained unchanged at the time of the 3G technology introduction. Indeed, we identify the effect of the change in the impact of lightning strikes and incidental coverage on the outcomes of interest, assuming that any changes in this impact occurred solely due to the update in mobile Internet technology.

Table 2 presents the first-stage estimates as specified in Equation 2. Columns 1 to 3 correspond to the sample of Rwandan municipalities, with one observation for each municipality-year. Column

[10] 3G was officially introduced in 2010. However, during the first year, less than 8% of the country was connected.

[11] We opted for an alternative version of the two instruments, Z_m^{light} and Z_m^{incid} interacted by a linear time trend t, as a robustness check.

1 utilizes lightning strikes as the sole instrument for 3G coverage. Column 2 employs incidental coverage as the instrument. Column 3 includes both instruments simultaneously. Columns 4 to 6 pertain to the sample of all borrowers in the credit registry. From the table, we observe that the coefficients for lightning strikes are negative and statistically significant, while the coefficients for incidental coverage are positive and statistically significant, aligning with our hypothesis. Furthermore, the F-statistics are generally high, surpassing typical threshold values, indicating instrument relevance.

4 Results

This section outlines the primary findings of our study, emphasizing the impact of mobile Internet on access to bank credit, the transition of borrowers from microfinance to formal banking, and bank loan characteristics. Additionally, we present evidence on the mechanisms elucidating our findings, showing the spillover effects of mobile Internet that empower a digital collateral channel. Finally, we perform robustness checks to validate the reliability of our results. To estimate these effects, we follow the empirical methodology outlined in Section 3.

4.1 Access to Bank Credit

We investigate the impact of mobile Internet on borrowers' access to the bank credit market by constructing a balanced panel dataset covering the period from 2008 to 2015[12]. For each borrower-year pair, we identify whether the borrower has an outstanding loan with any financial institution, and separately, whether the loan is obtained from a commercial bank or a microfinance institution. We define three dummy variables: $Probability\ (Any\ Loan)_{imt}$, indicating whether borrower i, in municipality m, has an outstanding loan in year t; $Probability\ (Bank\ Loan)_{imt}$, indicating whether the loan is from a bank; and $Probability\ (MFI\ Loan)_{imt}$, indicating whether the loan is from a MFI. We use these as the dependent variables in the baseline OLS regression of equation (1).

[12] The panel is actually "almost" balanced, since we remove observations for which borrowers are younger than 16 years old.

The results, shown in Table 3, suggest a mild positive relationship between mobile Internet and the probability of getting a loan, although the coefficient is statistically indistinguishable from zero. When we decompose the results between loans granted by commercial banks and microfinance institutions, we observe considerably different patterns. Column 2 of Table 3, which refers to $Probability\ (Bank\ Loan)_{imt}$, shows a positive and statistically significant coefficient, indicating that higher 3G coverage in the municipality increases the probability of obtaining a loan from a commercial bank. On the other hand, column 3, which refers to $Probability\ (MFI\ Loan)_{imt}$, shows a negative and statistically significant coefficient, thus suggesting that mobile Internet has a negative effect on accessing loans from MFIs.

To address endogeneity concerns and claim for causality, we replicate our analysis using the 2SLS methodology in equation (3). The results, reported in columns 4 to 6 of Table 3, confirm those from the OLS regressions. The effect of mobile Internet on the probability of getting a loan remains statistically indistinguishable from zero. However, when examining the decomposition, we find a significant positive effect on the probability of obtaining a loan from a commercial bank and a significant negative effect on the probability of obtaining a loan from a microfinance institution. The coefficients indicate that a one standard deviation increase in 3G coverage is associated with a 3.4 percentage point increase in the probability of having a loan from a bank (column 5) and a 3.6 percentage point decrease in the probability of having a loan from a MFI (column 6)[13]. These results imply that the impact of mobile Internet on access to credit is heterogeneous. It positively affects access to formal banking while negatively affecting access to microfinance.

Our findings corroborate the idea that mobile Internet contributes to financial graduation. On the extensive margin, potential borrowers endowed with the new Internet technology prefer commercial banks to MFIs. On the intensive margin, incumbent borrowers transition to formal banking. This reallocation story is further supported by direct evidence presented in Section 4.2.

In least-developed countries, including those in Africa, efforts to establish a developed financial

[13] The p-values of the Hansen J-statistic associated with the specifications in columns 5 and 6 are 0.39 and 0.94, respectively. This indicates that the overidentifying restrictions on the instruments are not rejected, providing further support for the instrument validity.

system that promotes long-term credit and economic growth have often fallen short. Numerous regional and national policies have been implemented over the past four decades to facilitate this development but with limited success (Beck and Cull, 2013). The fact that new technologies, such as mobile Internet, facilitate the transition from an informal microcredit system to a formal and well-structured banking system is a powerful result. Previous studies have shown the importance of microfinance as a first stage for borrowers, who then seek banking credit (Banerjee et al., 2015; Agarwal et al., 2023). Other studies have highlighted the transformative role of credit bureaus in underdeveloped countries, enabling borrowers to build credit history and become transparent to banks (Pagano and Jappelli, 1993; Padilla and Pagano, 1997). Some research has even demonstrated the complementary actions between microfinance and credit bureaus (De Janvry et al., 2010). What this paper adds to the literature is the identification of another potential factor, Internet technology, which smooths the transition from an informal microcredit sector to a formal and well-developed banking sector.

4.2 Direct Evidence on the Transition to Banks

We examine the transition of borrowers from microfinance institutions to commercial banks, by introducing in our setting a dependent variable called $Probability\ (of\ Switching)_{imt}$. This variable represents the probability of a borrower, with her initial credit account in a MFI (bank), switching to a bank (MFI) at a later time.

The analysis proceeds as follows. We identify four types of borrowers: those who only have relationships with banks throughout the period analyzed; those who only have relationships with MFIs; those who initially have a relationship with a MFI and later switch to the banking system; and those who initially have a relationship with a bank and later access a MFI. The sample is then divided into two groups: "First MFI" consisting of borrowers whose initial relationship was with a MFI; and "First bank" consisting of borrowers whose initial relationship was with a commercial bank. Separately for each group, we estimate OLS and 2SLS regressions with $Probability\ (of\ Switching)_{imt}$ as the dependent variable, using equations (1) and (3).

The results are presented in Table 4. Columns 1 and 2 focus on the probability of switching to banks for borrowers whose initial relationship was with a MFI, using OLS and 2SLS respectively. Estimates from column 2 indicate that a one standard deviation increase in 3G mobile coverage is associated with a 1.1 percentage point increase in the probability of switching to banks. Columns 3 and 4 focus on the probability of switching to MFIs for borrowers who started with a banking relationship. Contrary to the previous findings, estimates from column 4 show that a one standard deviation increase in 3G mobile coverage is associated with a 1.1 percentage point decrease in the probability of switching to MFIs.

These results are consistent with those in section 4.1 and provide direct evidence of the positive effect of mobile Internet on the intensive margin of the transition from microfinance to formal banking. When endowed with mobile Internet, incumbent MFI borrowers relatively increase their probability of moving to commercial banks.

Given the focus of the paper on the banking sector, all subsequent analyses are dedicated to examining the impact of mobile Internet on banks and bank loans.

4.3 Heterogeneity in Access to Bank Credit

We investigate whether the effect of mobile Internet on accessing a commercial bank loan is heterogeneous along different dimensions. We do that by modifying the baseline specification from Table 3, considering time, socio-economic, and borrower-specific factors that may influence the relationship between our main predictor and bank loan access. On the one hand, we rely on a dynamic specification to account for time heterogeneity. On the other hand, we use splitting samples techniques to highlight potential differences coming from socio-economic and borrower-specific attributes. Our results provide insights into which groups benefit the most from the availability of mobile Internet and how different factors shape this relationship.

We use an event study to investigate the dynamics of the effect. By focusing on the year of the introduction of 3G in each municipality, we observe the evolution over time of the effect of mobile Internet by estimating the following model:

$$Y_{imt} = \nu + \sum_{k=-6}^{4} \beta_K I\{K_{mt} = k\} + \alpha_i + \phi_t + \varepsilon_{imt} \tag{4}$$

where K indicates the relative year from the introduction of the 3G ($K_{mt} = t - year\ 3G_m$), β_k are the coefficients associated with each (relative) year, and the other variables are defined as in equation (1). We set the year before the arrival of the 3G as the omitted category.

Figure 6, left plot, shows the event study associated with OLS regressions, whereas the plot on the right is based on 2SLS estimates. Both graphs demonstrate the lagged nature of the effect, indicating that the impact of mobile Internet on bank loans takes time to materialize. The effect becomes significant after two years following the introduction of 3G and it is notable in magnitude. Importantly, the analysis allows us to highlight the absence of pre-trends, suggesting that there were no systematic differences in bank loan access trends between municipalities with and without 3G prior to its introduction, reinforcing the validity of our identification strategy. Overall, the event-study analysis provides compelling evidence of the lagged and significant effect of mobile Internet on accessing a commercial bank loan.

In order to examine other forms of heterogeneity, we conduct additional tests based on the socio-economic characteristics of the municipalities in our sample. First, we split the sample into rural and urban municipalities based on the share of the urban population. Second, we divide the municipalities into poorer and wealthier using data from Household Surveys (EICV). Finally, we distinguish municipalities with a physical bank branch from those without one. The results of these tests are presented in Table 5, panel A. We observe that the effect of 3G coverage appears to be larger in urban areas, as well as in wealthier areas and where a physical bank branch is present. Although none of these differences show statistical significance, our findings suggest that the effect of mobile Internet on accessing a commercial bank loan may be more pronounced in developed regions, being negligible in extremely rural and the poorest areas of the country. Overall, these results highlight the importance of considering local economic conditions when analyzing the effects of Internet technologies on banking.

To further investigate the potential heterogeneous effects of mobile Internet, we leverage the individual characteristics of the borrowers in our sample. We divide the sample based on the gender (female vs. male), marital status (single vs. married), and age (young vs. adult) of the borrower. The results of these tests are summarized in Table 5, panel B. We find that, overall, the effect of

3G coverage on the probability of obtaining a loan from a commercial bank is homogeneous across different borrower characteristics. Although there may be slight variations in the magnitudes, these differences are not statistically significant. Our results suggest that the impact of mobile Internet on accessing bank credit is consistent across different borrower groups. Whether they are female or male, single or married, young or adult, the effect on their likelihood of obtaining a loan from a commercial bank remains relatively similar. This uniform effect implies that the adoption of mobile Internet has broad positive implications, regardless of individual borrower characteristics.

The latter has important implications for policymakers, which may create an enabling environment for individuals to access and utilize formal banking services by promoting the development of mobile infrastructure and improving Internet connectivity.

4.4 Bank Loan Characteristics

We focus on bank loan characteristics and how they are affected by the availability of mobile Internet. As a first step, we aggregate data at the bank-municipality-year level and estimate the following model:

$$Y_{bmt} = \upsilon + \beta_1 3G\ \widehat{Coverage}_{mt} + \alpha_{bm} + \phi_{bt} + \varepsilon_{bmt} \tag{5}$$

where b denotes the commercial bank, m the municipality, and t the year. The dependent variable Y_{bmt} captures different loan characteristics, including the number of loan relationships, the number of switching borrowers from microfinance institutions, the total amount of outstanding loans, and the average interest rate. The key independent variable of interest is the standardized measure of 3G coverage in the municipality-year, instrumented using lightning frequency and incidental coverage. The model controls for bank-municipality fixed effects (α_{bm}) to account for unobserved time-invariant characteristics that may be specific to each bank-municipality pair and could potentially influence the loan features. Additionally, bank-year fixed effects (ϕ_{bt}) are included to capture common time-varying shocks that affect the bank in a particular year. The estimation of equation (5) is conducted using clustered standard errors at the municipality level, which helps account for potential correlations within municipalities.

By investigating the relationship between 3G coverage and loan characteristics, this analysis aims to shed light on how the availability of mobile Internet influences the nature and extent of bank lending activities. The results provide insights into the potential effects of mobile Internet on loan amounts and costs, contributing to a comprehensive understanding of its impact on banking. Estimates, reported in table 6, indicate that mobile Internet has substantial effects on various bank loan features. Specifically, a one standard deviation increase in 3G coverage is associated with the following changes: a 14% increase in the number of loans granted, which suggests that 3G Internet positively affects lending; a similar increase in the number of borrowers switching from the microfinance sector, which implies that 3G Internet plays a role in attracting borrowers from microfinance institutions; a 33% increase in total loan outstanding, which indicate that 3G Internet is associated with larger loan volumes; no significant effect on average interest rates. These results are in line with those presented in sections 4.1 and 4.2 and show the contribution of mobile Internet in expanding formal banking activities through more loans granted, larger loan volumes, and greater borrowing opportunities for individuals switching from microfinance institutions.

As a second step, we exploit the granularity of our data and present results on the effects of mobile Internet on bank loan characteristics at the individual borrower-year level[14]. For this purpose, we use a borrower-bank-level version of equation (5) and focus on borrowers who have accessed bank loans, thus examining the impact of mobile Internet along the intensive margin.

The findings, presented in table 7, columns 1 and 2, align with those in table 6. A one standard deviation increase in 3G coverage is associated with an increase in outstanding loan amount by 6.5%, which indicates that borrowers who have access to 3G tend to have larger outstanding loan balances, and no significant effect on interest rates[15]. Borrowers with mobile Internet tend to have larger outstanding loan amounts without experiencing adverse effects on interest rates, which highlights the beneficial role of mobile Internet in enhancing borrowing opportunities and loan features for individuals accessing formal bank loans.

As a final step, we focus on borrowers who initially have a loan with a MFI, exploring the

[14] This time, the panel dataset is unbalanced and based on outstanding relationships.

[15] We also have preliminary findings pointing to the no deterioration of credit quality, measured by loan amounts in past due. This suggests that the increase in bank lending is not associated with lower screening or monitoring, or with less creditworthy borrowers. Results are available upon request.

heterogeneous effect of mobile Internet on loan conditions for those who switched to a commercial bank.[16] The model estimated is the following:

$$Y_{imt} = v + \beta_1 3G\ \widehat{Coverage}_{mt} + \beta_2 3G\ \widehat{Coverage}_{mt} \times Switcher_i + \alpha_i + \phi_t + \varepsilon_{imt} \tag{6}$$

where Y_{imt} is the dependent variable and represents: the total amount of loan outstanding and the average interest rate, by borrower i, in municipality m, in year t. The main predictors are: $3G\ \widehat{Coverage}_{mt}$, the standardized 3G coverage, in municipality m, at time t, instrumented by lightning strikes and incidental coverage; and $3G\ \widehat{Coverage}_{mt}$ interacted with $Switcher_i$, a dummy variable equal to one if borrower i, whose first loan is with a MFI, then switches to a bank. The four instruments that we use are: Z^{light}_{mt}, the standardized yearly average frequency of lightning Z^{light}_{m}, in municipality m, interacted with a dummy post-2010; Z^{incid}_{mt}, the standardized average of incidental coverage Z^{incid}_{m}, in municipality m, interacted with a dummy post-2010; Z^{light}_{mt} interacted with $Switcher_i$; and Z^{incid}_{mt} interacted with $Switcher_i$.

The results, presented in table 7, columns 3 and 4, provide insights into how mobile Internet relatively affects the loan characteristics of borrowers who transition from MFIs to commercial banks. Despite the borrowers that keep their relationships with MFIs, for whom access to the 3G Internet has no effect, switching borrowers experience a relative increase in loan outstanding and a significant decrease in the average interest rate[17]. These findings highlight the role of mobile Internet in facilitating and enhancing the loan conditions for borrowers making the transition.

The results from tables 6 and 7 provide compelling evidence that mobile Internet has positive effects on accessing credit from commercial banks and influencing loan characteristics. The analysis in columns 3 and 4 of table 7, which specifically focuses on borrowers who switch to banks, indicates that mobile Internet particularly contributes to better credit terms and improved financial opportunities for borrowers making the transition. Taken together, these findings have

[16] Here we focus on the overall credit characteristics of the borrower, without conditioning on having a loan with a formal bank.

[17] In the appendix, figure A1, we refine the analysis by plotting the distribution of interest rates for switchers, distinguishing between pre and post-switching. The graph shows that borrowers in the upper tail of the distribution particularly benefit from becoming bank customers.

relevant implications for policymakers, financial institutions, and individuals seeking to leverage the benefits of new Internet technologies.

4.5 Mechanisms

Fast internet has been recognized as a catalyst for banking activities, driven by demand and supply effects such as increased productivity (Akerman et al., 2015; Hjort and Poulsen, 2019), reduced searching costs (Mazet-Sonilhac, 2021), enhanced efficiency (D'Andrea and Limodio, 2023), and decreased information asymmetry (D'Andrea et al., 2023). Mobile Internet has its own peculiarities. It fosters banking through income effects (Bahia et al., 2023), as individuals potentially earn more with improved connectivity. Furthermore, it enables the proliferation of digital banking services (Jiang et al., 2022) and enhances access to information (Manacorda and Tesei, 2020; Guriev et al., 2021), a critical factor in financial decision-making (Hvide et al., 2022).

The impact of mobile Internet on banking through increased access to more and better information can be particularly significant. On the one hand, mobile Internet empowers borrowers by providing direct access to relevant information about banking services, thereby promoting financial graduation.[18] On the other hand, it facilitates indirect information spillovers from related markets, thereby amplifying its impact on the bank credit market. In this section, we specifically delve into the spillover effects of mobile Internet and examine its role in empowering a digital collateral channel.

4.5.1 The Digital Collateral Channel

One of the milestones of the Rwandan economy is the land, which is the main source of income for most of the population. In the aftermath of the civil conflict, the large-scale migration of returnees had a dramatic impact on land ownership, escalating tensions and land conflicts, making

[18] Using data from the Finscope Surveys 2008-2012-2016 and Findex 2011-2014-2017, in Figure A2 of the appendix, we provide preliminary evidence on how mobile Internet shapes information acquisition about banks. The histograms show a sensible reduction in the proportion of individuals indicating limited knowledge about banks or expressing distrust in their operations after mobile Internet becomes available. This evidence, which is aggregated and only suggestive, is in line with the dissemination of information through mobile Internet improving financial literacy and generating a more positive perception of commercial banks.

land reform a crucial condition to avoid social tensions, ensure social stability, and improve land use management and investments. With this background, in 2009 the government of Rwanda launched the Land Tenure Regularization program. This reform aimed to regulate the ownership and control of the lands, enhance land utilization, and promote its efficient management and administration (Abbott and Mugisha, 2015).

Within the LTR initiative, data on land parcels were digitized to facilitate the issuance of ownership certificates. By the year 2012, the main database had accumulated information on an impressive 10.4 million land parcels. In this way, the LTR program introduced a land tenure system based on the digital registry (World Bank, 2020), which played a pivotal role in favoring access to formal credit by facilitating the use of land titles as collateral (Besley and Ghatak, 2010; Acampora et al., 2022; Manysheva, 2021). In line with this argument, in 2013 all financial institutions in Rwanda were connected to the digital registry, which made it easier the tracking and verification of land ownership.

Mobile Internet played a crucial role in the initial phase of the LTR program by serving as a communication channel to raise awareness among landowners and disseminate information about the program's procedures, purposes, and technical aspects. Government agencies, officials, and institutions extensively utilized social media platforms, online newspapers, and micro-blogging sites to connect with the public and provide timely updates on the program's progress.[19] Furthermore, the widespread use of mobile phones in Rwanda made disseminating information through the mobile Internet particularly effective. In this way, the LTR program reached a larger audience and engaged with individuals directly, such as through social networking forums. This utilization of mobile Internet significantly contributed to the success of the LTR program and, combined with the digital nature of the land registry, created a form of digitally-empowered collateral in the sense of Goldfarb and Tucker (2019).

To support the argument that the digital collateral channel can partly explain the effects of mobile internet on banking presented in the previous sections, we provide four pieces of evidence.

[19] In March 2011, the RNRA launched its Twitter account @Lands_Rwanda and created a Facebook page (https://www.facebook.com/LandsRwanda/).

First, we test the relationship between 3G Internet coverage and the number of land title transactions. The availability of mobile Internet likely facilitates access to information and processes related to land title registrations, which can lead to an increased number of transactions. Second, we examine the association between 3G Internet coverage and the amount of mortgaged land parcels. This measure proxies the share of land being used as collateral for loans. We expect that areas with higher mobile Internet coverage exhibit a greater proportion of digitally-collateralized land, as mobile Internet enhances access to information on mortgage procedures and requirements. Third, we analyze the relationship between 3G Internet connectivity and bank credit collateral. Specifically, we investigate the probability of obtaining a loan pledged by collateral and having a mortgage with a bank for borrowers connected to mobile Internet. We anticipate that borrowers with access to mobile Internet have a higher likelihood of obtaining collateralized loans. Finally, we quantify the extent to which the effect of mobile Internet on banking outcomes is mediated through the digital collateral channel.

Table 8 presents the first set of results. It focuses on the relationship between 3G coverage and land transactions, using data at the municipality level. The empirical methodology is the same as in equation (3), with data aggregated at the level of the municipality. The only difference is that the period of analysis ends in 2013, which includes the hot phase of the LTR program[20]. Our dependent variables are: $First\ Mover$, a dummy variable indicating whether a municipality is a first mover, i.e. there has been at least one land transaction in the first year of the program; $Asinh\ (Number\ of\ Transactions)$, the inverse hyperbolic sine transformation of the cumulative of the total number of transactions, in municipality m and year t, scaled by the population in the municipality; and $Median\ Transactions$, a dummy variable indicating whether at least 50% of the total number of transactions, in municipality m, has been implemented in year t. Estimates in Table 8 show a positive relationship between 3G Internet coverage and various proxies of land transactions, suggesting a role for mobile Internet in promoting the LTR program and facilitating the marketing of land titles. Specifically, the results show that a one standard deviation increase

[20] In 2012, around 80% of all transactions, were completed.

in 3G coverage is associated with a 26 percentage point higher probability of being a first mover municipality, a 14% increase in the number of transactions, and a 17 percentage point increase in the probability of completing at least half of the transactions in a given year[21].

Table 9, columns 1 to 3, studies the relationship between 3G Internet coverage and the amount of mortgaged land parcels. Our dependent variable is the share of mortgaged parcels over the total amount of parcels. Since these data are only available in cross-section, our results are suggestive of the relationship between mobile Internet and mortgaged lands. In column 1, we report the cross-sectional results, where the share of mortgaged lands is regressed on the level of 3G coverage in 2011. In columns 2 and 3 we report OLS and 2SLS estimates using a panel 2010-2011, where we assign value zero to the share of mortgaged land in 2010, and its current value to 2011, so as to resemble a regression pre-post 3G adoption. The results presented in Table 9 show a positive relationship between mobile Internet and mortgaged parcels. Specifically, a one standard deviation increase in 3G coverage is associated with a 1.7 percentage point increase in the share of land parcels used as collateral.

Table 9, columns 4 to 7, provides further insights into the relationship between mobile Internet and access to collateralized loans and bank mortgages. The analysis is based on a balanced panel dataset from the credit registry, and the methodology follows equation (3) as mentioned earlier. Our dependent variables are *Probability* $(Bank\ Collateral)$, a dummy variable that indicates whether the bank loan is backed by collateral, and *Probability* $(Bank\ Mortgage)$, a dummy variable indicating whether the loan is a mortgage issued by a commercial bank. The results confirm those in the previous columns. A one standard deviation increase in 3G Internet coverage is associated with a 0.6 percentage point increase in the probability of a bank loan being backed by collateral and a 0.8 percentage point increase in the probability of the loan being a mortgage issued by a commercial bank. This suggests that individuals in areas with better access to mobile Internet have a higher probability of benefiting from collateralized loans.

Our findings, taken together, provide robust evidence on the role of mobile Internet in promot-

[21] Results are confirmed using a simple dummy variable *transaction*, which indicates whether at least one land transaction has been implemented in municipality m, in year t.

ing land reform and its impact on accessing formal credit through the digital collateral channel.

To conclude and refine our analysis, we offer a Sobel-Goodman mediation test to quantify how much of the effect of mobile Internet on banking is mediated through the effect of the former on the LTR (Doerr et al., 2022). We report estimates from the Sobel-Goodman test in Table 10. Consistently with our story, we find that approximately 35% of the probability of receiving a bank loan is due to an indirect effect facilitated by the acquisition of digital collateral[22], whereas 65% is directly attributed to mobile Internet. The "direct effect" of mobile Internet is a residual effect and catches many potential channels through which the Internet may make individuals seek bank credit: better job opportunities (Hjort and Poulsen, 2019), higher income (Bahia et al., 2023; Calderone et al., 2018), and lower information frictions (Gupta et al., 2023). Then, when repeating our estimation using as dependent variable the probability of receiving a collateralized loan, we find that the direct effect of mobile Internet decreases to 20% and is borderline significant, while the indirect effect mediated by the land titles accounts for 80% of the total impact. This quantification points to the pivotal role of digital collateral in securing a mortgage and steering individuals from MFIs, which lack this product, towards commercial banks.

Overall, our results highlight the interplay between mobile Internet, digitally-empowered collateral, and access to formal credit, and underscore the importance of considering the links coming from different markets when evaluating the effects of a general-purpose technology such as mobile Internet.

4.6 Robustness

We conduct a series of robustness checks to gauge the sensitivity of our main results to different specifications. In particular, we make modifications of Table 3, 2SLS-specification.

Our original dataset is made of 190,138 individual borrowers. Since we lack information on the age of some of them, we decide to drop these borrowers from the main analysis.[23] As a first

[22] These results are corroborated by the findings in Table A2 of the appendix. Here, we implement sequential g-estimation following Acharya et al. (2016) and show that two-thirds of the total effect of mobile Internet on the probability of accessing a bank loan is not mediated through land titles.

[23] This is relevant when we create the balanced panel dataset.

robustness check, we test the sensitivity of our results to this choice. Estimates from the model considering the full sample are reported in Table B1 of the appendix. As we can see from the table, all the coefficients are unaffected. They keep their sign and magnitudes, as well as their statistical significance.

When studying the effect of mobile Internet on access to bank credit, our main dependent variable is a dummy indicating whether the borrower has an outstanding loan with a bank (MFI). An alternative definition might refer to the first year since the borrower becomes a bank (MFI) client. We create a staggered measure of bank (MFI) loan that takes value 1 from the first year in which the borrower has an outstanding loan with the lender. Our analysis is reported in Table B2 of the appendix. As we can see from the table, all the results are coherent with those in Table 3. The magnitude of the coefficient associated with bank loans is higher, whereas that associated with MFI loans is lower.

Our main predictor is the share of 3G coverage in the municipality. As a first robustness check, we substitute this variable with a dummy that takes value 1 from the first year in which the municipality is reached by mobile Internet. Our analysis, which resembles a two-way fixed effects regression, is reported in Table B3 of the appendix. As we can see from the table, 3G coverage is associated with an increase in the probability of having a loan with a bank of about 10 percentage points, and a similar decrease in the probability of having a loan with a MFI. As a second robustness check, we create a predictor which weights 3G coverage for population density and total population. Results from these revised specifications are reported in Table B4 of the appendix and are in line with those in Table 3, with larger magnitudes.

In the main analysis, we adopt a version of the instruments where the latter are the interactions of the time-invariant component of Z and a dummy post-2010. As a robustness check, we replicate our analysis by using two alternative definitions of the instruments. First, we interact the time-invariant component of Z with a linear time trend. Second, we interact the baseline instruments with the linear time trend. Results are reported in Table B5 of the appendix and are qualitatively in line with those in Table 3, even larger in magnitudes.

Our 2SLS estimates use two instruments for one endogenous variable. The textbook motivation for this choice is statistical efficiency. However, there is a deeper reason based on the fact that this allows for heterogeneous treatment effects. In an influential paper, Imbens and Angrist (1994) showed that estimand from a 2SLS with multiple IVs can be interpreted as a positively weighted average of LATEs for subpopulations whose treatment status is affected by the instruments (thus allowing for heterogeneous treatment effects). This result holds for any number of instruments, as long as the monotonicity condition is satisfied.[24] Recently, Mogstad et al. (2021) extended the framework of Imbens and Angrist (1994) and showed that these results can be generalized if a partial monotonicity condition is satisfied.[25] Throughout the paper, we first show that our estimates do not suffer from overidentification problems. Then, we provide direct evidence of the validity of using multiple instruments. First, we follow Mogstad et al. (2021) and find that, in our case, the null hypothesis of negative weights is rejected at conventional levels (p = 0.000), while a test of the null of positive weights does not reject and generates a high p-value of 1.0. Second, we replicate our analysis by instrumenting 3G coverage with a single instrument, i.e. lightning strikes and incidental coverage, separately. Results are reported in Table B6 of the appendix and are coherent with our main findings.

Our basic identification assumption can be violated if underlying trends affect the outcomes of interest and correlate with the 3G coverage. To control for these confounding factors, we augment our specifications with several economic and socio-demographic municipality characteristics. The group of control variables is selected taking into account table A1 and includes: 2G coverage, which controls for alternative mobile technologies; total population, urban population, and employed population, which control for demographic and economic features; the number of total bank branches, which control for bank physical infrastructures; and a dummy for the presence of a

[24] In our case, the monotonicity condition requires all individuals to respond more to lightning strikes than to incidental coverage, or vice versa

[25] The partial monotonicity condition is that the IA monotonicity condition is satisfied for each instrument separately, holding all of the other instruments fixed. In our case, a sufficient condition for partial monotonicity is that all individuals are at least as likely to have 3G coverage if they live in municipalities with a low frequency of lightning strikes or in municipalities with higher incidental coverage. However, unlike the IA monotonicity condition, partial monotonicity does not restrict heterogeneity in the relative impacts of different instruments; it allows for some individuals to respond more to lightning than to incidental coverage, and for others to respond more to incidental coverage than to lightning

primary road, which controls for the level of connection of the municipality. For variables obtained from the 2012 Census, we use an interaction with the dummy post-2010. Table B7 reports the estimates related to this augmented specification. As we can see from the table, the coefficients keep the same sign as in the baseline regressions and remain statistically significant at standard levels. Interestingly, the magnitudes in columns 1 and 2 are slightly affected by the inclusion of control variables.

In 2009, the government of Rwanda launched the Umurenge SACCOs program, with the aim to boost up rural savings and increase financial inclusion. The program helped people to have access to credit and eventually to access formal banking (Agarwal et al., 2023). Since the program became effective in 2011, we test whether the coefficients associated with mobile Internet may capture part of the (confounding) effects generated by the U-SACCOs expansion. We test this alternative hypothesis by augmenting our main specification with the inclusion of a dummy variable for the presence of a U-SACCO in the municipality. Estimates from these regressions are reported in Table B8 of the appendix. As we can see from the table, our coefficients remain entirely unaffected. The effect of mobile Internet on the probability of having a bank loan is orthogonal to the nationwide U-SACCO program.

In 2008, the government of Rwanda began rolling out a national fiber optic backbone that was completed at the end of 2010, with over 3,000 kilometers of fiber, distributed to all 30 districts. This capillary terrestrial fiber optic backbone, which facilitates the transfer of high-speed data across the country, can be a confounder if associated with our main predictor. To test this hypothesis, we combined information on the national fiber-optic backbone from AfTerFibre Maps, with those of the Liquid Telecom private network. We generate a dummy variable for the presence of fixed broadband at the municipality level and augment our main specifications with this variable. Results are reported in Table B9 and are in line with those in Table 3.

As a last robustness, we check the sensitivity of our results in Table 8, which is related to the mechanism, to the presence of fixed broadband. When examining the impact of mobile Internet on land transactions, the expectation is that the effect is specifically driven by the ability of mobile Internet to facilitate the dissemination of information about the land reform program through channels such as social media. If this is the case, a horse race test with fixed broadband, which represents a different mode of internet access, should not affect the main results. This is because fixed broadband is less likely to be directly linked to the promotion of the LTR through the web and social media platforms. To overcome the endogeneity of the presence of fixed broadband, we instrument this variable using the presence of post-colonial surfaced roads, in line with the works by Dalgaard et al. (2018) and Barjamovic et al. (2019). In particular, we exploit the fact that underground fiber-optic cables are mainly laid along highways and by city roads (Nyarko-Boateng et al., 2019; Redifer et al., 2020) together with the availability of post-colonial road maps from the Perry-Castañeda Library Map Collection of the University of Texas.[26] Results from this falsification test are reported in Table B10 and provide robust evidence in favor of the digital collateral channel as advocated in section 4.

5 Conclusion

This paper examines the role of mobile Internet in promoting banking in developing countries. By focusing on Rwanda and utilizing a rich dataset from the credit registry, we provide compelling evidence of the positive effect of mobile Internet on various aspects of formal banking.

Our findings demonstrate that increased 3G coverage, a proxy for mobile Internet access, is associated with higher levels of bank credit. We observe an increase in the number of loans granted and overall loan outstanding. Importantly, we observe that mobile Internet helps borrowers switch from micro-finance institutions to banks.

In order to identify a specific mechanism explaining our results, we uncover a significant link between mobile Internet and the market of land titles. This spillover effect, channeled through the spread of information, highlights the role of mobile Internet in facilitating access to bank credit through a digitally-empowered land collateral.

Overall, our study provides strong evidence of the transformative power of mobile Internet

[26] We digitize the map of all surfaced roads in Rwanda in 1975 (the oldest map available in the archive) and use them as a source of exogenous variation for fiber deployment. The map of post-colonial roads in Rwanda is presented in Figure B1 of the appendix.

in promoting formal banking. The findings highlight the important role of mobile technology in bridging information gaps, thus facilitating access to bank credit. These insights can inform policymakers and stakeholders in designing strategies to enhance financial inclusion, not only in Rwanda but also in other developing economies facing similar challenges.

As technology continues to advance and mobile Internet access becomes more widespread, it is crucial to recognize its potential to drive inclusive development and empower individuals and communities. By harnessing the power of mobile Internet, countries can unlock new opportunities for economic growth, poverty reduction, and sustainable development.

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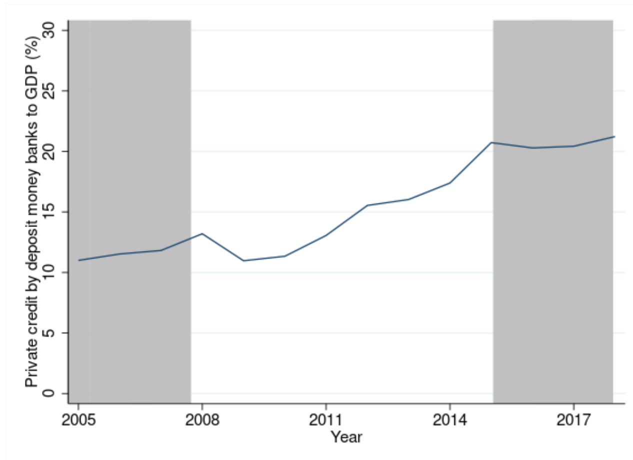
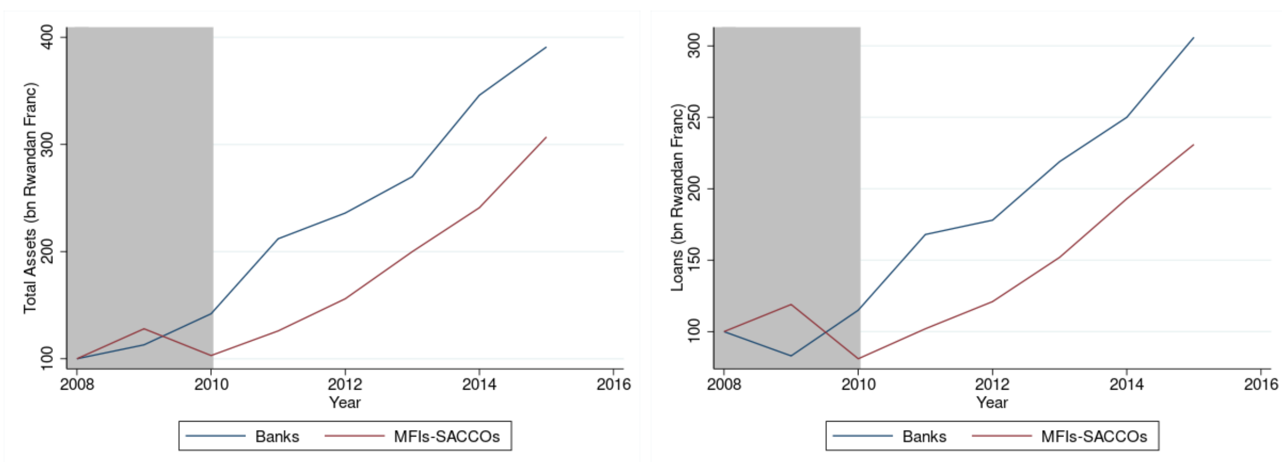
Figures

Figure (1) Private credit to GDP in Rwanda



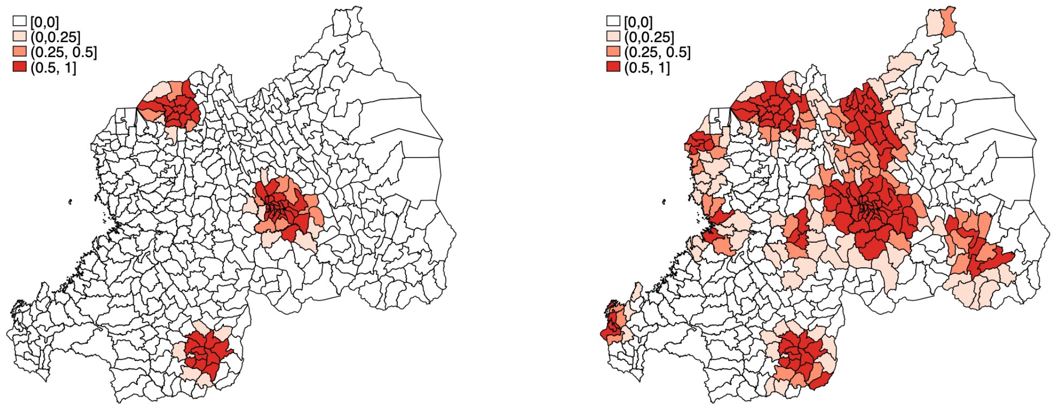
Notes: This figure plots Private credit by deposit money banks to GDP (%) in Rwanda. The shaded area is out of our sample of analysis.

Figure (2) Assets and Loans in Rwanda



Notes: This figure plots Total Assets and Loans by banks (MFIs) in Rwanda. The first year, 2008, is normalized at 100 and serves as a benchmark. The shaded area refers to the period before the introduction of 3G mobile internet.

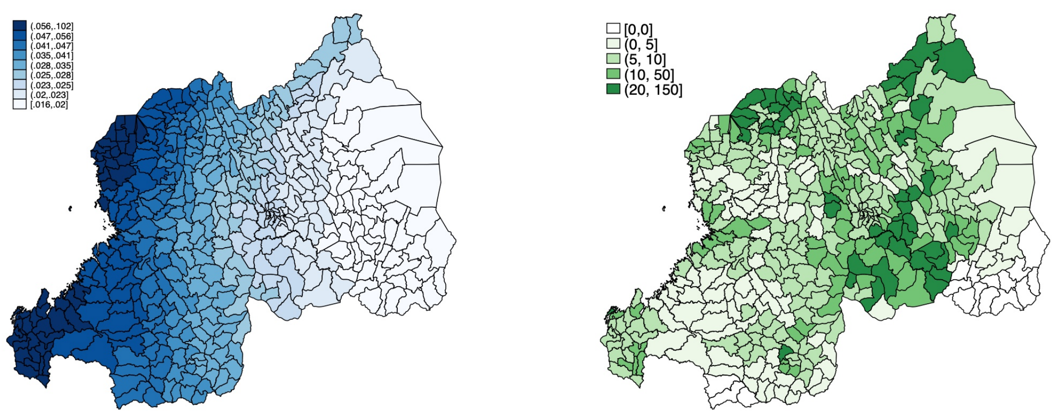
Figure (3) 3G coverage in Rwanda



2008 2015

Notes: This figure plots the diffusion of the 3G mobile Internet by municipality in Rwanda. The panel on the left refers to 2011, the first year of the introduction of 3G. The panel on the right refers to 2015, the last year for which we have data on 3G coverage.

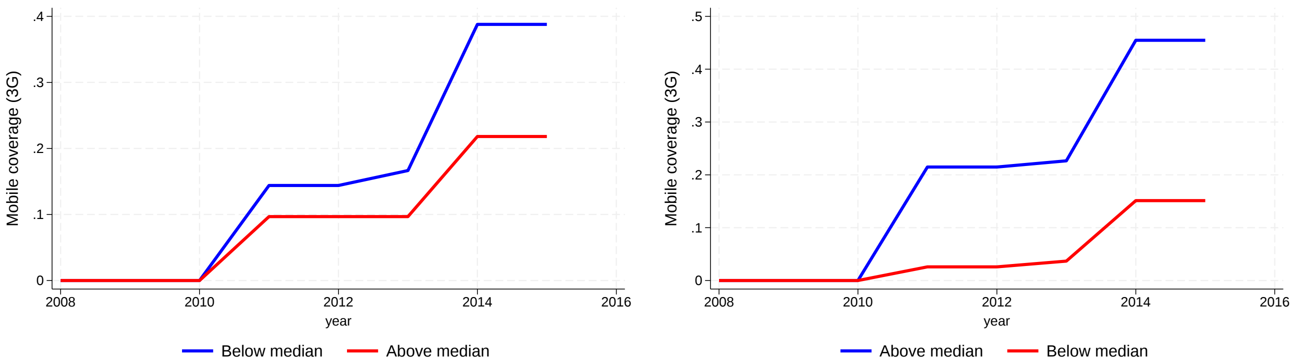
Figure (4) Cross-sectional variation mobile Internet: Lightning frequency and Incidental coverage



Lightning frequency Incidental coverage

Notes: This figure shows the average frequency of lightning strikes and incidental coverage, by municipality in Rwanda. On the left panel, there is lightning frequency, a time-invariant indicator computed as the yearly average of strikes in the municipality, during the period 1998-2013. On the right panel, is incidental coverage (Björkegren, 2019), a time-invariant measure of the fictitious coverage that would have resulted had the operator built towers for mobile internet along the full network of power lines.

Figure (5) 3G coverage, Lightning frequency, and Incidental coverage

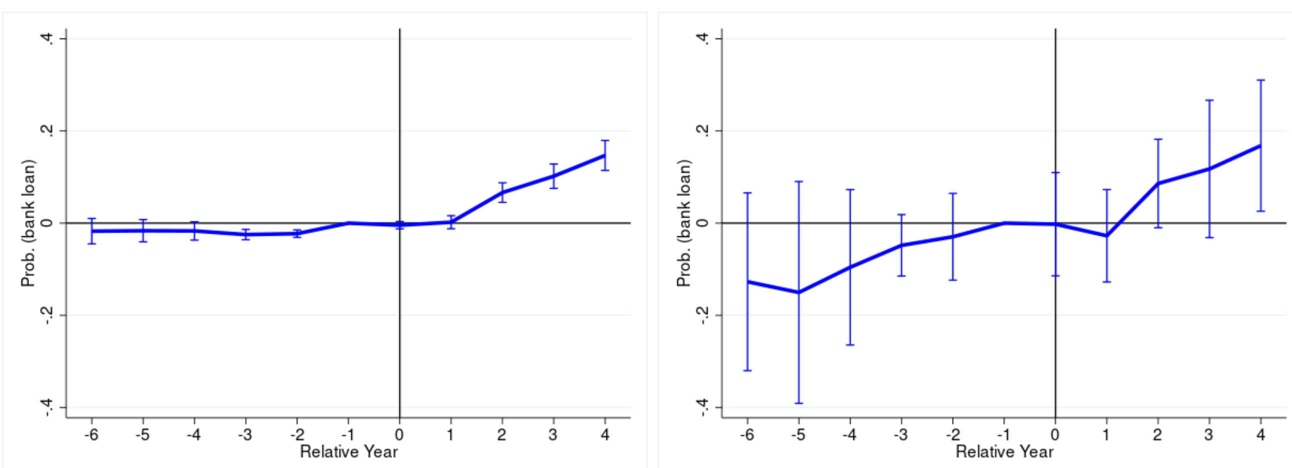


Lightning frequency

Incidental coverage

Notes: This figure provides visual evidence in support of the relevance of our instruments. On the left, we focus on lightning strikes. On the y-axis is a measure of 3G mobile coverage. On the x-axis are years. The solid blue line refers to municipalities with lower than median lightning frequency. The solid red line refers to municipalities with above median lightning frequency. On the right, we focus on incidental coverage. On the y-axis is a measure of 3G mobile coverage. On the x-axis are years. The solid blue line refers to municipalities with higher than median incidental coverage. The solid red line refers to municipalities with lower than median incidental coverage.

Figure (6) The dynamic effect of mobile Internet on Access to bank credit



Notes: This figure shows a staggered DiD event study. The treatment group is made up of borrowers in municipalities covered by the 3G technology. The control group is made up of borrowers in municipalities not reached by the 3G technology. Year 0 corresponds to the first year in which the municipality is reached by mobile internet. On the y-axis is *Prob.*(*bank loan*), the probability that the borrower has an outstanding loan with a commercial bank. The blue solid line refers to coefficients. 90% confidence intervals are also reported. In the left panel, we report OLS regressions. In the right panel, we report 2SLS estimates.

Tables

Table (1) Summary statistics

	n	mean	sd	p50	min	max
	PANEL A: Access to bank credit					
Probability of Any Loan	909168	0.28	0.45	0.00	0.00	1.00
Probability of Bank Loan	909168	0.14	0.34	0.00	0.00	1.00
Probability of MFI Loan	909168	0.16	0.37	0.00	0.00	1.00
Switching borrowers	909168	0.09	0.29	0.00	0.00	1.00
	PANEL B: Bank loan characteristics					
Outstanding loan	124,806	2011.88	3665.80	693.11	16.67	27859.83
Principal loan	125,507	2820.34	4706.01	1062.00	30.00	34000
Interest rate	124,388	19.20	5.73	19.00	6.14	70.10
Collateral	128,639	0.12	0.32	0.00	0.00	1.00
	PANEL C: 3G coverage					
3G coverage	2696	0.12	0.28	0.00	0.00	1.00
Std 3G coverage	2696	0.03	1.02	-0.40	-0.40	3.24
	PANEL D: Instrumental variables					
Lightning frequency	2696	0.04	0.02	0.03	0.02	0.10
Std Lightning	2696	0.03	0.83	0.00	-1.24	4.10
Incidental coverage	2696	10.66	12.20	9.54	0.00	135.43
Std Incidental	2696	0.01	0.83	0.00	-0.91	10.81

Notes: This table reports summary statistics for the main variables in the empirical analysis. Panel A refers to access to credit: the probability of having an outstanding loan (and separately with a bank or a MFI-SACCO). Panel B focuses on borrowers' bank credit accounts: outstanding loans (in thousands of Rwandan francs), principal loans (in thousands of Rwandan francs), interest rates (in percentage terms), and collateral (a dummy variable indicating that the loan is secured). Panel C shows the summary statistics for the main predictor: 3G Mobile coverage (and its related standardized measure). Finally, Panel D focuses on the two instruments: average lightning frequency and Std Lightning, the interaction between the standardized lightning frequency and a dummy post-2010; average incidental coverage and Std Incidental, the interaction between the standardized coverage and a dummy post-2010. The standardizations have been implemented on the sample of all Rwandan municipalities.

Table (2) First stage regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	All municipalities			Credit Registry sample		
	Standardized 3G coverage					
Std Lightning	-0.156***		-0.141***	-0.341***		-0.330***
	(0.048)		(0.046)	(0.079)		(0.079)
Std Incidental		0.250***	0.240***		0.231***	0.207***
		(0.052)	(0.050)		(0.067)	(0.064)
Municipality FE	Yes	Yes	Yes	No	No	No
Borrower FE	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	10.64	23.17	17.74	18.49	11.81	16.22
Obs.	2696	2696	2696	909165	909165	909165
Adj. R sq.	0.540	0.551	0.557	0.607	0.593	0.613
Mean Dep. Var.	0.032	0.032	0.032	0.276	0.276	0.276
S.D. Dep. Var.	1.024	1.024	1.024	1.302	1.302	1.302

Notes: This table reports estimates of the first stage presented in equation (2). The dependent variable is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. The main predictors are: $Std\ Lightning_{mt}$, the standardized yearly average frequency of lightning $Std\ Lightning_{m}$, in municipality m, interacted with a dummy post-2010; $Std\ Incidental_{mt}$, the standardized average of incidental coverage $Std\ Incidental_{m}$, in municipality m, interacted with a dummy post-2010. Columns 1 and 3 refer to the sample of all municipalities in Rwanda between 2008 and 2015. Columns 2 to 4 refer to a balanced sample at the borrower level. Obs. refers to the number of observations; Adj.R sq. is the adjusted R2; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the municipality (borrower) and year level. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (3) Mobile Internet and the Probability of having a loan

	(1)	(2)	(3)	(4)	(5)	(6)
	Probability of					
	Any Loan	Bank Loan	MFI Loan	Any Loan	Bank Loan	MFI Loan
Std 3G coverage	0.002	0.018***	-0.017***	-0.002	0.034***	-0.036***
	(0.002)	(0.003)	(0.003)	(0.006)	(0.012)	(0.012)
Estimation	OLS	OLS	OLS	IV	IV	IV
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SW F-statistic				16.22	16.22	16.22
Obs.	909165	909165	909165	909165	909165	909165
Adj. R sq.	0.480	0.374	0.370			
Mean Dep. Var.	0.284	0.136	0.164	0.284	0.136	0.164
S.D. Dep. Var.	0.451	0.343	0.370	0.451	0.343	0.370

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Any Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan in year t, and zero otherwise; *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (MFI *loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. In the IV specifications, we instrument our main predictor with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. Columns 1 to 3 refer to OLS estimates. Columns 3 to 6 refer to 2SLS estimates. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Adj.R sq. is the adjusted R2; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (4) Mobile Internet and Transition to banks

	(1)	(2)	(3)	(4)
	Probability of Switching from			
	MFI to Bank		Bank to MFI	
Std 3G coverage	0.007***	0.011***	-0.006***	-0.011**
	(0.002)	(0.003)	(0.001)	(0.005)
Estimation	OLS	IV	OLS	IV
First MFI	Yes	Yes	No	No
First BANK	No	No	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SW F-statistic		16.47		13.89
Obs.	514372	514372	380974	380974
Adj. R sq.	0.255		0.296	
Mean Dep. Var.	0.010	0.010	0.034	0.034
S.D. Dep. Var.	0.100	0.100	0.181	0.181

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability (of Switching to Bank)*, a dummy variable equal to one if borrower i, in municipality m, whose first financial relationship was with a MFI, has an outstanding loan with a bank in year t, and zero otherwise; *Probability (of Switching to MFI)*, a dummy variable equal to one if borrower i, in municipality m, whose first financial relationship was with a bank, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. In the IV specifications, we instrument our main predictor with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_m^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_m^{incid}, in municipality m, interacted with a dummy post-2010. Columns 1 and 3 refer to OLS estimates. Columns 2 and 4 refer to 2SLS estimates. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Adj.R sq. is the adjusted R2; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (5) Heterogeneity - Socioeconomic and Borrowers' characteristics

	(1) Rural	(2) Urban	(3) Poorer	(4) Wealthier	(5) No branches	(6) Branches
	Probability of Bank Loan					
Std 3G coverage	0.009	0.032*	0.003	0.044***	0.024	0.034**
	(0.021)	(0.017)	(0.032)	(0.011)	(0.017)	(0.016)
Estimation	IV	IV	IV	IV	IV	IV
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SW F-statistic	10.51	8.47	9.88	9.31	12.32	6.64
Obs.	482259	426906	338929	570236	397445	511720
Mean Dep. Var.	0.099	0.179	0.106	0.154	0.107	0.159
S.D. Dep. Var.	0.298	0.383	0.308	0.361	0.309	0.366
	(1) Female	(2) Male	(3) Single	(4) Married	(5) Young	(6) Adult
Std 3G coverage	0.029**	0.037***	0.050***	0.030**	0.037***	0.030**
	(0.012)	(0.013)	(0.017)	(0.012)	(0.012)	(0.014)
Estimation	IV	IV	IV	IV	IV	IV
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SW F-statistic	14.17	16.89	12.84	16.46	16.64	15.62
Obs.	324226	584939	106749	802416	466877	442288
Mean Dep. Var.	0.137	0.136	0.178	0.131	0.136	0.136
S.D. Dep. Var.	0.343	0.343	0.382	0.337	0.343	0.343

Notes: This table reports estimates from 2SLS as presented in equation (3). The dependent variable is *Probability (of Bank Loan)*, a dummy equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t, instrumented by: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. Panel A. Columns 1 and 2 distinguish between rural and urban municipalities. Columns 3 and 4, between poorer and wealthier municipalities. Columns 5 and 6, between municipalities with a bank branch and those without. Panel B. Columns 1 and 2 distinguish between females and males. Columns 3 and 4, between singles and married. Columns 5 and 6, between young and old. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (6) Mobile Internet and Aggregate bank characteristics

	(1) Number of Loans	(2) Number of Switchers	(3) Volume of Loans	(4) Lending Rate
Std 3G coverage	0.130**	0.118***	0.285***	0.279
	(0.065)	(0.034)	(0.091)	(0.287)
Estimation	IV	IV	IV	IV
Bank-municipality FE	Yes	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes	Yes
SW F-statistic	15.97	15.97	15.62	15.70
Obs.	12695	12695	12459	12467
Mean Dep. Var.	1.307	0.171	8.650	18.75
S.D. Dep. Var.	1.301	0.420	1.696	5.375

Notes: This table reports estimates from 2SLS as presented in equation (3). The dependent variables are as follows: $Number\ of\ Loans$, the natural logarithm of the total number of loans by bank b, in municipality m, in year t; $Number\ of\ Switchers$, the natural logarithm of the total number of switchers to banks; $Volume\ of\ Loans$, the natural logarithm of the total amount of outstanding loans; *Lending Rate*, the average interest rate on the loan. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t, instrumented by: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the bank-municipality and bank-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (7) Mobile Internet and Bank loan characteristics

	(1) Volume of Loans	(2) Lending Rate	(3) Volume of Loans	(4) Lending Rate
Std 3G coverage	0.063**	0.154	0.032	-0.077
	(0.025)	(0.154)	(0.032)	(0.207)
Std 3G coverage × Switcher			0.159***	-2.235***
			(0.054)	(0.660)
F-test (p-value)			0.001	0.001
Estimation	IV	IV	IV	IV
First MFI	No	No	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Bank-year FE	Yes	Yes	No	No
SW F-statistic	22.44	21.64	18.96	19.00
Obs.	104766	104423	110391	79081
Mean Dep. Var.	6.750	18.51	6.609	20.71
S.D. Dep. Var.	1.421	5.472	1.287	8.603

Notes: This table reports estimates from 2SLS as presented in equation (3). The dependent variables are as follows: $Volume\ of\ Loans$, the natural logarithm of the total amount of outstanding loans by borrower i, in municipality m, in year t; *Lending Rate*, the average interest rate on the loan. The main predictors are: *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t; and *Std 3G coverage* $\times$ $Switcher_i$, where the latter is a dummy variable equal to one if borrower i switches to a bank, and zero otherwise. The four instruments are: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_m^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_m^{incid}, in municipality m, interacted with a dummy post-2010; and the two above interacted with $Switcher_i$. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and bank-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (8) Mobile Internet and Land transactions

	(1) First Mover	(2) Number of Transactions	(3) Median Transactions	(4) First Mover	(5) Number of Transactions	(6) Median Transactions
Std 3G coverage	0.169***	0.047***	0.071***	0.231**	0.128***	0.160***
	(0.020)	(0.007)	(0.007)	(0.094)	(0.036)	(0.046)
Estimation	OLS	OLS	OLS	IV	IV	IV
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SW F-statistic				19.19	19.19	19.19
Obs.	2022	2022	2022	2022	2022	2022
Adj. R sq.	0.578	0.804	0.811			
Mean Dep. Var.	0.141	0.229	0.356	0.141	0.229	0.356
S.D. Dep. Var.	0.348	0.316	0.479	0.348	0.316	0.479

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3), by using data at the municipality level. The dependent variables are as follows: $First\ Mover$, a dummy variable equal to one if transactions in municipality m have started in 2011; $Number\ of\ Transactions$, the inverse hyperbolic sine of the cumulative function of transactions in municipality m, scaled by the total number of parcels in the municipality; *Median Transactions*, a dummy variable equal to one if the number of land transactions in municipality m has reached at least 50% of the total, in year t. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t, instrumented by: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_m^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_m^{incid}, in municipality m, interacted with a dummy post-2010. Columns 1 to 3 refer to OLS estimates. Columns 3 to 6 refer to 2SLS estimates. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Adj.R sq. is the adjusted R2; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the municipality and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (9) Mobile Internet, Land mortgaged and Bank collateral

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Share of Land Mortgaged			Probability of		
				Bank Collateral	Bank Mortgage	Bank Collateral	Bank Mortgage
Std 3G coverage	0.016***	0.024***	0.017***	0.009***	0.003***	0.006**	0.008***
	(0.004)	(0.003)	(0.005)	(0.001)	(0.001)	(0.003)	(0.002)
Estimation	OLS	OLS	IV	OLS	OLS	IV	IV
District FE	Yes	No	No	No	No	No	No
Municipality FE	No	Yes	Yes	No	No	No	No
Borrower FE	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
SW F-statistic			18.58			16.22	16.22
Obs.	337	674	674	909165	909165	909165	909165
Adj. R sq.	0.685	0.567		0.499	0.512		
Mean Dep. Var.	0.014	0.007	0.007	0.015	0.016	0.015	0.016
S.D. Dep. Var.	0.034	0.025	0.025	0.120	0.125	0.120	0.125

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3), by using data at the municipality level. The dependent variables are: *Share* (*Land Mortgaged*), the share of land mortgaged in municipality m; *Probability* (*Bank Collateral*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan in year t backed by collateral, and zero otherwise; *Probability* (*Bank Mortgage*), a dummy variable equal to one if borrower i, in municipality m, has mortgage with a bank in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t, instrumented by: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Adj.R sq. is the adjusted R2; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the district (column 1), municipality (columns 2 and 3), borrower (columns 4 to 7), and year level. Standard errors, in parentheses, are clustered at the district or municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

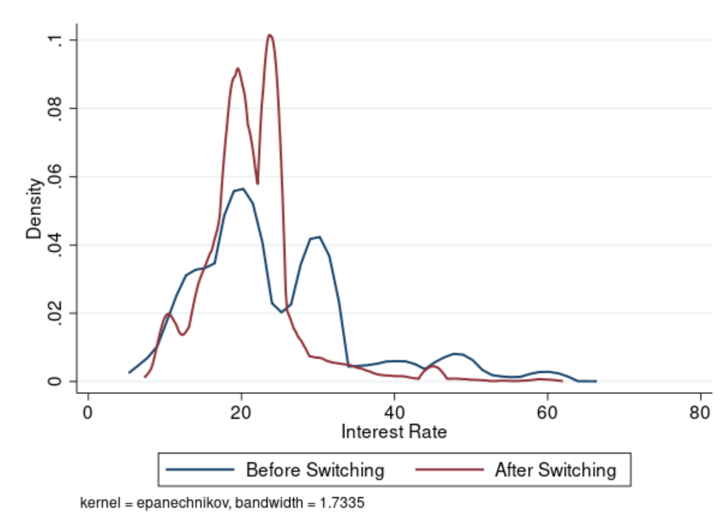
Table (10) Sobel-Goodman mediation test

	(1)	(2)
	Probability of	
	Bank Loan	Bank Collateral
Sobel	0.013**	0.005**
Aroian	0.013**	0.005**
Goodman	0.013**	0.005**
Indirect Effect (Digital Collateral)	0.013**	0.005**
Direct Effect (Mobile Internet)	0.021**	0.001
Total Effect	0.034**	0.006^{+}
Proportion Indirect	**37%**	**80%**

Notes: This table reports Sobel-Goodman mediation test. The outcome variables are: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; and *Probability* (*Bank Collateral*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan in year t backed by collateral, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. The mediation variable is a dummy variable indicating whether the municipality of the borrower, m, has reached at least 50% of the total number of land transactions in the first year of the LTR program. The first three columns report the Sobel, Aroian, and Goodman tests. The last column indicates the proportion of the total effect of mobile Internet on the dependent variable that is mediated through land titles. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

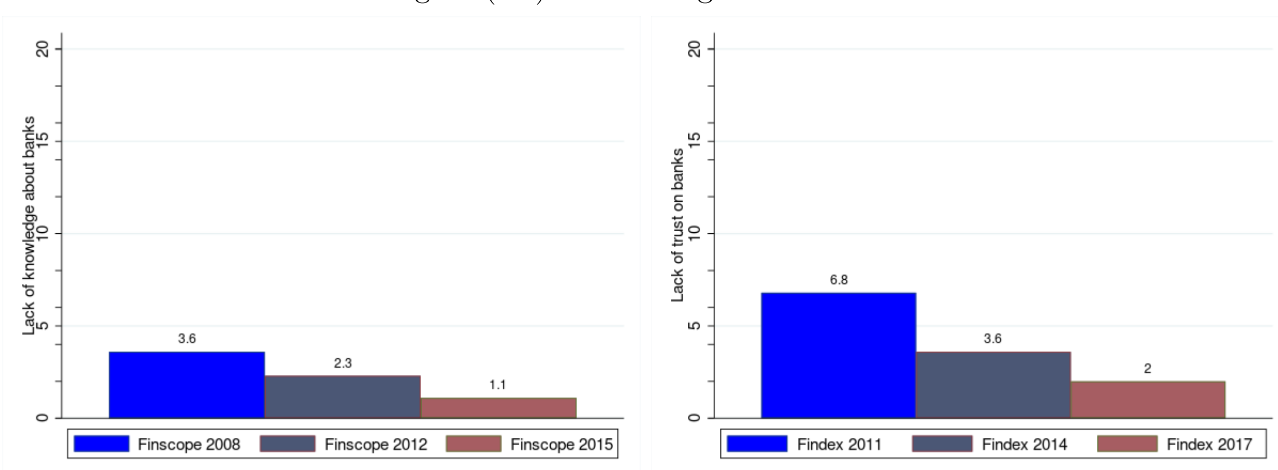
Additional figures and tables

Figure (A1) Distribution of Interest rates for Switchers to banks



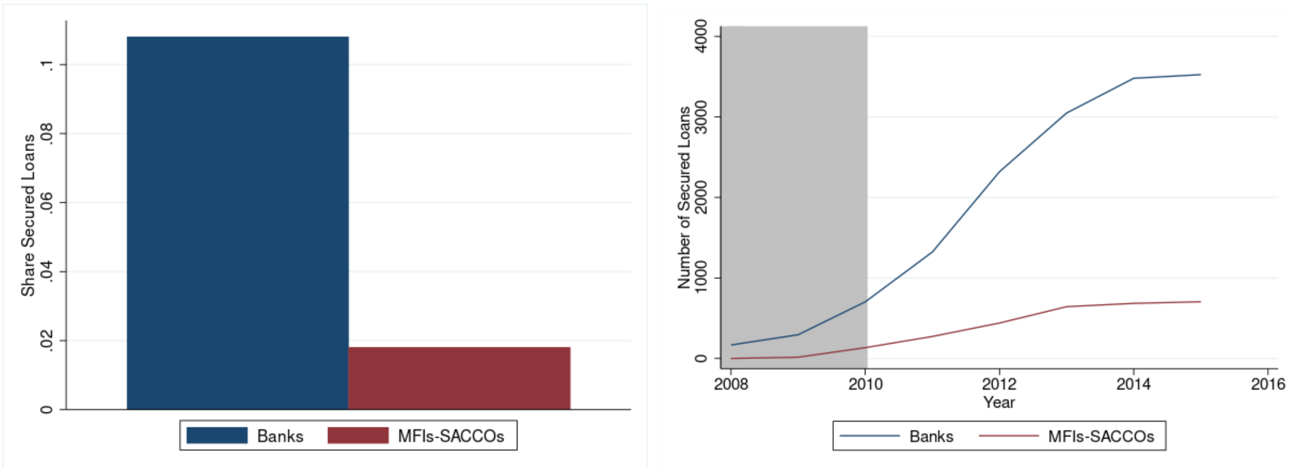
Notes: This figure plots the density function of interest rates for the sample of switchers to banks. The blue solid line refers to the density of interest rates before the switching, i.e., when the borrower is still a client of the MFI. The red solid line refers to the density after the switch.

Figure (A2) Knowledge about banks



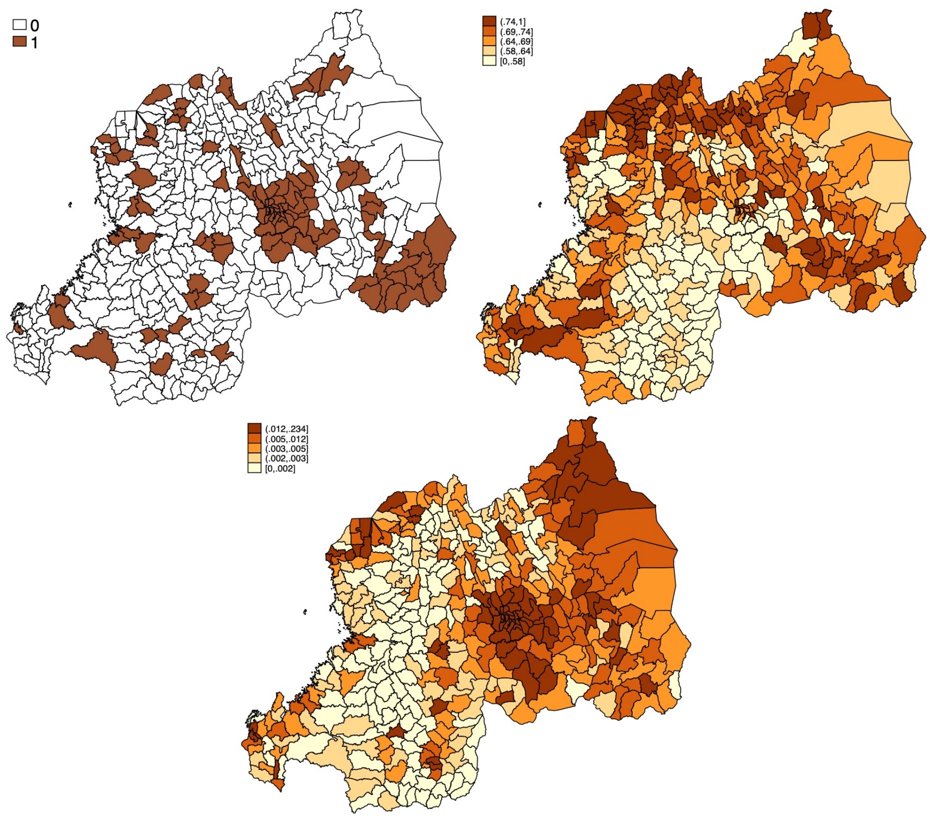
Notes: This figure plots the measures of bank knowledge in the Finscope Surveys 2008-2012-2016 and Findex 2011-2014-2017. On the left is the share of individuals who do not know what is a bank (or which products it serves). On the right is a proxy of bank trust.

Figure (A3) Loans backed by collateral



Notes: This figure plots the share and number of loans backed by collateral, for banks and MFIs-SACCOs respectively. On the left is the share of secured loans in our sample. On the right is the number of secured loans, where the shaded area refers to the period before the introduction of 3G mobile technology.

Figure (A4) Land title transactions



Notes: This figure plots information about land title transactions. The first panel highlights the first set of municipalities making land title transactions. The second panel reports the cumulative number of transactions as of 2013, scaled by the total number of parcels. Finally, the last panel shows the share of mortgaged land parcels.

Table (A1) Balance table. Municipalities by quartiles of Lightning and Incidental coverage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	25th Percentile			50th Percentile			75th Percentile			
	PANEL A: Lightning Strikes (Z^{light})									
	Below	Above	Diff.	Below	Above	Diff.	Below	Above	Diff.	N. mun.
2G coverage	.93	.928	(.01)	.937	.92	(.08)	.924	.942	(-.09)	337
Mean altitude	1.499	1.839	**(-1.06)**	1.582	1.922	**(-.91)**	1.673	1.988	**(-.69)**	336
Wood	.04	3.453	**(-.26)**	.024	5.175	**(-.32)**	.683	8.349	**(-.37)**	336
Water	3.008	1.042	**(.26)**	1.629	1.437	(.03)	1.866	.535	(.22)	336
Sand	0	.001	(-.04)	.001	0	(.08)	.001	0	(.07)	336
Main Power line	.226	.246	(-.03)	.232	.25	(-.03)	.222	.298	(-.12)	336
Hospital	.143	.115	(.06)	.131	.113	(.04)	.119	.131	(-.03)	336
ln Population	10.175	10.03	**(.31)**	10.117	10.016	(.22)	10.057	10.095	(-.09)	337
ln Urban	3.583	2.644	(.15)	3.622	2.138	(.24)	2.736	3.298	(-.09)	337
Unemployment	.036	.031	(.13)	.037	.028	(.21)	.033	.031	(.06)	337
Night lights	.404	.700	(-.12)	.763	.49	(.09)	.674	.484	(.07)	337
Poverty Index	1.049	.984	(.16)	.996	1.004	(-.02)	.997	1.008	(-.03)	337
ln Conflicts	.145	.435	**(-.31)**	.242	.482	(-.23)	.318	.494	(-.16)	337
Bank branches	.762	.743	(.01)	.863	.633	(.10)	.75	.741	(0.00)	337
	PANEL B: Incidental Coverage (Z^{incid})									
	Above	Below	Diff.	Above	Below	Diff.	Above	Below	Diff.	N. mun.
2G coverage	.956	.845	**(.49)**	.969	.888	**(.41)**	.974	.913	**(.36)**	337
Mean altitude	1.734	1.806	(-.16)	1.693	1.810	**(-.27)**	1.669	1.779	(-.23)	336
Wood	.604	8.586	**(-.38)**	.447	4.726	**(-.27)**	.083	3.425	-(.25)	336
Water	1.756	.866	(.14)	2.197	.878	(.18)	3.079	1.026	(.24)	336
Sand	.001	0	(.03)	.001	0	(.07)	0	.001	(-.07)	336
Main Power line	.274	.143	(.23)	.287	.195	(.15)	.229	.245	(-.03)	336
Hospital	.139	.071	(.16)	.15	.095	(.12)	.084	.134	(-.11)	336
ln Population	10.091	9.993	(.23)	10.111	10.022	(.19)	10.102	10.054	(.10)	337
ln Urban	3.481	1.063	**(.44)**	4.237	1.527	**(.45)**	3.191	2.774	(.07)	337
Unemployment	.034	.027	(.19)	.038	.026	**(.3)**	.028	.034	(-.14)	337
Night lights	.77	.193	(.23)	1.006	.249	**(.27)**	.774	.577	(.06)	337
Poverty Index	.988	1.037	(-.16)	.968	1.032	(-.18)	1.03	.990	(.11)	337
ln Conflicts	.411	.217	(.20)	.454	.272	(.17)	.289	.387	(-.10)	337
Bank branches	.866	.393	(.25)	1.054	.444	**(.28)**	.583	.802	(.11)	337

Notes: This table reports a balance table on average municipalities' characteristics, in 2010, by quartiles of the instruments. Panel A refers to the lightning strike frequency. Panel B refers to incidental coverage. Columns 1 to 3 use the 25th percentile of the distributions as a threshold. Columns 4 to 6 use the 50th percentile. Finally, Columns 7 to 9 use the 75th percentile. Column 10 reports the number of municipalities. For each tern of columns is reported whether municipalities are below or above the threshold and the normalized difference as proposed in Imbens and Wooldridge (2009). This is the difference in averages by treatment status, scaled by the square root of the sum of the variances, and represents a scale-free measure of the difference in distributions. Values exceeding 0.25 are considered sensitive for linear regressions. The list of covariates under evaluation is the following: the coverage of 2G; mean altitude; the percentage of wood, water, and sand; an indicator of the presence of a main line power/hospital; the log of the population and the urban population; the unemployment rate; an indicator of night lights and poverty (computed with respect to the average value in the district); a measure of conflict; and the number of bank branches.

Table (A2) Sequential g-estimation

	(1)	(2)	
	Probability of		
	Bank Loan	Bank Loan	Total Effect
Std 3G coverage	0.008***	0.020*	0.034***
	(0.003)	(0.011)	(0.012)
Estimation	OLS	IV	IV
Borrower FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
SW F-statistic		16.22	16.22
Obs.	909165	909165	909165
Adj. R sq.	0.001		
Mean Dep. Var.	0.136	0.136	0.136
S.D. Dep. Var.	0.343	0.343	0.343

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variable is *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise. This variable has been de-mediated by regressing it on the mediator, a dummy variable indicating whether the municipality of the borrower, m, has reached at least 50% of the total number of land transactions in the first year of the LTR program. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. We instrument it with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. Column 3 reports the total effect as in Table 3, which we use as a benchmark. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Adj.R sq. is the adjusted R2; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Robustness

Table (B1) Mobile internet and Access to credit - all borrowers

	(1)	(2)
	Probability of	
	Bank Loan	MFI Loan
Std 3G coverage	0.033***	-0.035***
	(0.012)	(0.013)
Estimation	IV	IV
Borrower FE	Yes	Yes
Year FE	Yes	Yes
SW F-statistic	15.76	15.76
Obs.	1.268e+06	1.268e+06
Mean Dep. Var.	0.157	0.190
S.D. Dep. Var.	0.363	0.392

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (MFI *loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. We instrument it with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (B2) Mobile internet and Access to credit - first relationship

	(1)	(2)
	Probability of	
	Bank Loan	MFI Loan
Std 3G coverage	0.048***	-0.025*
	(0.015)	(0.014)
Estimation	IV	IV
Borrower FE	Yes	Yes
Year FE	Yes	Yes
SW F-statistic	16.22	16.22
Obs.	909165	909165
Mean Dep. Var.	0.163	0.189
S.D. Dep. Var.	0.369	0.392

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (MFI *loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. We instrument it with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (B3) Mobile internet and Access to credit - Two-way fixed effects

	(1)	(2)
	Probability of	
	Bank Loan	MFI Loan
Dummy 3G	0.094***	-0.110***
	(0.036)	(0.035)
Estimation	IV	IV
Borrower FE	Yes	Yes
Year FE	Yes	Yes
SW F-statistic	19.17	19.17
Obs.	909165	909165
Mean Dep. Var.	0.136	0.164
S.D. Dep. Var.	0.343	0.370

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (MFI *loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Dummy 3G*, a dummy variable for the presence of 3G, in municipality m, at time t. We instrument it with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (B4) Mobile internet and Access to credit - weighted 3G coverage

	(1)	(2)	(3)	(4)
	Probability of			
	Bank Loan	MFI Loan	Bank Loan	MFI Loan
Std 3G coverage	0.051**	-0.047**	0.049***	-0.048***
(weighted)	(0.022)	(0.020)	(0.017)	(0.017)
Estimation	IV	IV	IV	IV
Borrower FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SW F-statistic	9.669	9.669	11.63	11.63
Obs.	905574	905574	905574	905574
Mean Dep. Var.	0.137	0.163	0.137	0.163
S.D. Dep. Var.	0.343	0.370	0.343	0.370

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (MFI *loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage* (*weighted*), the standardized measure of 3G mobile coverage, in municipality m, at time t, weighted by population density (columns 1 and 2) and total population (columns 3 and 4). We instrument it with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_m^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_m^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (B5) Mobile internet and Access to credit - different versions of the instruments

	(1)	(2)	(3)	(4)
	Probability of			
	Bank Loan	MFI Loan	Bank Loan	MFI Loan
Std 3G coverage	0.056***	-0.086***	0.047***	-0.070***
	(0.017)	(0.022)	(0.015)	(0.018)
Estimation	IV	IV	IV	IV
Borrower FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SW F-statistic	11.55	11.55	13.06	13.06
Obs.	909165	909165	909165	909165
Mean Dep. Var.	0.136	0.164	0.136	0.164
S.D. Dep. Var.	0.343	0.370	0.343	0.370

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (MFI *loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. In columns 1 and 2 we instrument our predictor with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a linear time trend; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a linear time trend. In columns 3 and 4 we instrument our predictor with two other instruments: the standardized yearly average frequency of lightning interacted with a post-2010 dummy $\times$ a linear time trend; the standardized average of incidental coverage interacted with a post-2010 dummy $\times$ a linear time trend. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (B6) Mobile internet and Access to credit - single instruments

	(1)	(2)	(3)	(4)
	Probability of			
	Bank Loan	MFI Loan	Bank Loan	MFI Loan
Std 3G coverage	0.036**	-0.035**	0.018	-0.037**
	(0.015)	(0.015)	(0.017)	(0.018)
Estimation	IV	IV	IV	IV
Borrower FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SW F-statistic	18.49	18.49	11.81	11.81
Obs.	909165	909165	909165	909165
Mean Dep. Var.	0.136	0.164	0.136	0.164
S.D. Dep. Var.	0.343	0.370	0.343	0.370

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (MFI *loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. We instrument it with two instruments, but separately: in columns 1 and 2, Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; in columns 3 and 4, Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (B7) Mobile internet and Access to credit - controls

	(1)	(2)
	Probability of	
	Bank Loan	MFI Loan
Std 3G coverage	0.037***	-0.028*
	(0.013)	(0.014)
Estimation	IV	IV
Borrower FE	Yes	Yes
Year FE	Yes	Yes
SW F-statistic	17.34	17.34
Obs.	931774	931774
Mean Dep. Var.	0.155	0.183
S.D. Dep. Var.	0.361	0.386

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (MFI *loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. We instrument it with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_m^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_m^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (B8) Mobile internet and Access to credit - active U-SACCO

	(1)	(2)
	Probability of	
	Bank Loan	MFI Loan
Std 3G coverage	0.035***	-0.037***
	(0.012)	(0.011)
Estimation	IV	IV
Borrower FE	Yes	Yes
Year FE	Yes	Yes
SW F-statistic	16.26	16.26
Obs.	909165	909165
Mean Dep. Var.	0.136	0.164
S.D. Dep. Var.	0.343	0.370

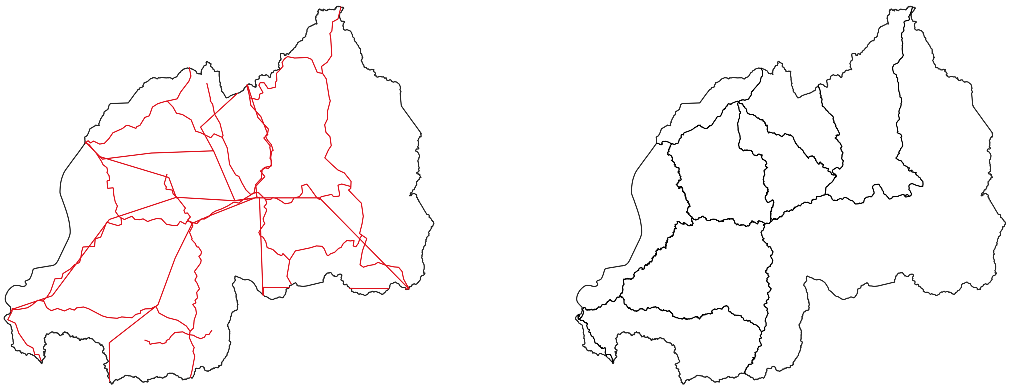
Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (*MFI loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. We instrument it with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_m^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_m^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (B9) Mobile internet and Access to credit - fiber

	(1)	(2)
	Probability of	
	Bank Loan	MFI Loan
Std 3G coverage	0.033***	-0.035***
	(0.012)	(0.011)
Estimation	IV	IV
Borrower FE	Yes	Yes
Year FE	Yes	Yes
SW F-statistic	16.31	16.31
Obs.	909165	909165
Mean Dep. Var.	0.136	0.164
S.D. Dep. Var.	0.343	0.370

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3). The dependent variables are as follows: *Probability* (*Bank Loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Probability* (MFI *loan*), a dummy variable equal to one if borrower i, in municipality m, has an outstanding loan with a MFI in year t, and zero otherwise. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. We instrument it with two instruments: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_{m}^{light}, in municipality m, interacted with a dummy post-2010; Z_{mt}^{incid}, the standardized average of incidental coverage Z_{m}^{incid}, in municipality m, interacted with a dummy post-2010. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the borrower and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Figure (B1) Distribution of Fiber-optic cables and Post-colonial roads



Notes: This figure, on the left panel, plots fiber-optic lines as in 2015. The public fiber was deployed in 2010, while private fiber complemented the main lines from 2014. On the right panel, are surfaced roads as in 1975, from the Perry-Castañeda Library Map Collection.

Table (B10) Table B10. Broadband Internet and Land transactions

	(1) First mover	(2) Number of Transactions	(3) Median Transactions
Fiber	0.010 (0.064)	0.014 (0.022)	0.028 (0.027)
Estimation	IV	IV	IV
Municipality FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
SW F-statistic	188.5	188.5	188.5
Obs.	2022	2022	2022
Mean Dep. Var.	0.141	0.229	0.356
S.D. Dep. Var.	0.348	0.316	0.479

Notes: This table reports estimates from OLS and 2SLS as presented in equations (1) and (3), by using data at the municipality level. The dependent variables are as follows: $First\ Mover$, a dummy variable equal to one if transactions in municipality m have started in 2011; $Number\ of\ Transactions$, the inverse hyperbolic sine of the cumulative function of transactions in municipality m, scaled by the total number of parcels in the municipality; $Median\ Transactions$, a dummy variable equal to one if the number of land transactions in municipality m has reached at least 50% of the total, in year t. The main predictor is $Fiber$, a dummy variable indicating the presence of a fiber-optic cable, in municipality m, at time t, instrumented by: $Z_{mt}^{old\ road}$, the dummy for the presence of an old surfaced road, interacted with a dummy post-2009 (since 2010 is the year of introduction of broadband). Columns 1 to 3 refer to OLS estimates. Columns 3 to 6 refer to 2SLS estimates. SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; Obs. refers to the number of observations; Mean Dep. Var. refers to the mean of the dependent variable; and S.D. Dep. Var. refers to the standard deviation of the dependent variable. Fixed effects are at the municipality and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.