Developing the Mortgage Market: Technology, Property Rights, and Banking*

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Abstract

Combining administrative data on credit, mortgages, and construction in Rwanda, this paper shows that technology helps overcome imperfections in property rights and foster the development of the mortgage market. Exploiting quasi-experimental variation in 3G internet coverage and a land title reform, we find that mobile connectivity shifts borrowers from microfinance to banks. 3G internet facilitates the distribution of land titles, which borrowers use as collateral for bank loans and mortgages, thus promoting household investment in real estate. A mediation analysis and structural estimation reveal that the property rights channel accounts for 30–37% of the effect of mobile internet on bank lending and 75–80% of the effect on collateralized loans.

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1 Introduction

Mortgage markets in emerging economies remain significantly underdeveloped, posing a persistent puzzle in the literature on household finance and development economics. Despite the fact that land and housing constitute the primary assets for households in low- and middle-income countries, mortgage penetration remains exceptionally low—typically below 10 percent of households and often close to negligible levels in semi-urban and rural localities (Badev et al., 2014; Badarinza et al., 2017, 2019).

Formal financial institutions typically rely on collateralized lending to mitigate information asymmetries. However, in developing countries commercial banks face severe frictions in verifying property rights and impose collateral requirements (De Soto, 2000; Djankov et al., 2007; Besley et al., 2012). As a result, mortgage markets are underdeveloped and households disproportionately borrow from microfinance institutions (MFIs) and informal lenders, drawn by easier access and the use of alternative screening mechanisms—such as social collateral—despite facing higher interest rates, smaller loan sizes, and shorter repayment terms (Agarwal et al., 2023; Fu et al., 2025).

Modern technologies offer significant potential to alleviate frictions related to property rights and collateral documentation in financial intermediation by lowering transaction costs and enabling real-time verification. Recent studies highlights that financial technology applications, particularly digital land registries and collateral management systems, substantially increase mortgage penetration and accessibility (Fuster et al., 2019). By mitigating problems of asymmetric information and collateral screening, these innovations foster deeper mortgage markets, allowing previously underserved households to transition from microfinance institutions and informal lending toward formal banking (Badarinza et al., 2017; Karlan and Zinman, 2009).

This paper provides empirical evidence on how internet technologies can reduce frictions in property rights and collateral transactions, thereby shaping access to bank credit and fostering the development of mortgage markets. We study whether the expansion of mobile internet connectivity affects borrowers' choice between MFIs and commercial banks. To understand the mechanisms driving the shift from MFIs to banks, we proceed in two steps. First, we analyze the role of digitally verifiable property rights in facilitating mortgage lending, which allows banks to expend their reach. Second, as the mortgage market develops, we examine its impact on investment in housing construction.

Studying how technology facilitates households' transition from microfinance to banks and promotes mortgage markets poses significant empirical challenges. First, administrative datasets that simultaneously track lending from both banks and MFIs are exceptionally rare. Second, credible identification requires exogenous variation in the diffusion of internet technologies and of mortgage market penetration, independent of other economic conditions. To overcome these challenges, we focus on Rwanda, where a digitally enabled Land Tenure Regularization (LTR) reform created digital records for over 10 million land parcels and established a comprehensive property rights and collateral system. Crucially, this digital registry was directly linked to commercial banks through a dedicated digital mortgage platform (World Bank, 2018, 2020).

This LTR reform was amplified by the expansion of mobile internet connectivity, allowing us to leverage distinct geographic and temporal variation in technology diffusion to study how it affected local mortgage markets through the reform channel. Our empirical strategy exploits two primary sources of variation in mobile internet coverage. First, we study the staggered introduction of 3G internet technology across Rwandan municipalities. Second, to address potential concerns regarding omitted variable bias stemming from non-random allocation of mobile internet infrastructures, we adopt two instrumental variables that isolate variation in mobile internet independently of local economic and social characteristics. Following Manacorda and Tesei (2020), we employ the heterogeneous distribution of lightning strikes across municipalities, which affects the local development and durability of mobile telecommunication infrastructure. Additionally, we exploit Rwanda's uneven topography, which substantially influences the rollout and quality of mobile networks. In particular, we use the measure of "incidental coverage" proposed by Björkegren (2019), capturing idiosyncratic variation in mobile internet availability driven by topographic features, such as municipal proximity to the electric grid and positioning relative to slopes.[1] Crucially, we verify empirically that both instrumental variables provide variation in mobile internet connectivity exogenous to and uncorrelated with income levels and other predetermined local attributes.

We conduct our empirical analysis using comprehensive administrative datasets from Rwanda. Our primary data, obtained from the Credit Reference Bureau, comprise detailed loan-level records from all regulated credit institutions—both commercial banks and microfinance institutions (MFIs)—between 2008 and 2015, capturing also the universe of mortgage and collateralized loans. The dataset provides extensive borrower and loan characteristics for 113,897 individuals across 337 municipalities, enabling borrower-level tracking over time. We complement these records with municipal-level information from the Rwanda Land Management and Use Authority on land certificate distribution, transaction activity, and mortgaged parcels, and leverage high-resolution satellite data on building volumes from Pesaresi and Politis (2023) to quantify real estate investment outcomes. Finally, we incorporate data on annual 3G mobile internet coverage (2008–2015) from the GSM Association, alongside instrumental variables measuring cross-sectional variation—specifically, lightning-strike frequency from the Global Hydrology Resource Center and incidental coverage metrics from Björkegren (2019).

Our findings indicate that the introduction of mobile internet significantly reshaped household financial decision-making in Rwanda, promoting the growth of local mortgage markets and stimulating investment in construction. The rollout of 3G internet triggered a shift from MFIs

[1] A *municipality* refers to Rwanda's third-level administrative division, termed a *sector*. Rwanda comprises five provinces, subdivided into 30 districts, which further divide into a total of 416 sectors.

to commercial banks, increasing the likelihood of obtaining bank loans by 3.4 percentage points and reducing reliance on MFI loans by 3.6 percentage points per standard deviation increase in 3G coverage. Despite this reallocation, overall financial inclusion—measured as access to credit from any financial institution—remained unchanged, echoing similar findings by Breza and Kinnan (2021) in India and Fu et al. (2025) in Bolivia.[2]

Next, we verify that mobile internet promotes property rights by amplifying the land title reform, which leads to the expansion of the mortgage market and boosts residential investments. First, the land reform is more effective in municipalities with greater mobile coverage: a one standard deviation increase in 3G coverage raises by 16 percentage points the likelihood that a large share of land titles is disbursed in the first year after the reform, and boosts the total number of transactions by 14%. This shift promotes the local mortgage market: inspecting the credit bureau data, we verify that a one standard deviation increase in 3G coverage raises the probability of a collateralized bank loan and mortgage by 0.6 and 0.8 percentage points, respectively. At the same time, land is more frequently used to access the financial system: a one standard deviation increase in 3G coverage results in a 1.7 percentage point rise in the share of mortgaged lands. Moreover, the observed variation in mortgage market expansion predominantly reflects municipality-level differences in property rights and their valuation, rather than individual borrower characteristics, underscoring the critical role of local property rights in shaping financial outcomes. Finally, using satellite data on local building volumes, we find that a one standard deviation increase in 3G coverage leads to an 8.3 percentage point increase in local real estate growth.

What is the role of mobile internet in shaping mortgage market development? Specifically, how critical are property rights — expanded through land tenure reform and facilitated by mobile internet — in driving this effect? To address these questions, we quantify the contribution of secure property rights in mediating the impact of mobile internet on mortgages and banking through two distinct empirical approaches. First, following Doerr et al. (2022), we employ a Sobel-Goodman (SG) mediation test to measure the extent to which land titles mediate the relationship between 3G coverage and access to mortgages and banking. Second, drawing from Christensen et al. (2024), we develop a structural model based on individual credit choices, identifying parameters through revealed preferences within a probit framework to isolate the specific roles of mobile internet connectivity and collateral availability. Although methodologically distinct, both approaches yield consistent results, emphasizing a central role for property rights in mortgage market expansion. Specifically, the mediation analysis attributes approximately 80% of the overall effect of mobile internet on mortgage uptake to improved land title availability, while the structural model reports

[2] Additional evidence highlights that mobile internet significantly improves borrowing conditions, primarily by facilitating access to cheaper and larger bank loans relative to MFIs. Individuals switching from MFIs to banks experience larger loan sizes and notably lower interest rates, without an accompanying increase in default rates, suggesting prior inefficiencies in credit allocation due to inadequate collateral verification.

a corresponding share of approximately 75%. Similarly, we find that part of the total effect of mobile internet on local building volumes is attributable to the indirect effect mediated by land titles. The robustness of these findings underscores the fundamental importance of clearly defined property rights in mortgage market development. The estimated contributions of property rights to the transition toward commercial banking are comparatively smaller, at roughly 37% (SG test) and 30% (structural model), suggesting that while land titles are crucial to mortgage growth, other channels related to internet expansion also significantly influence general banking behavior.[3]

Our main findings are robust to a wide range of tests, changes in the sample, and model specification. We replicate our analysis at a more aggregated bank-municipality-year level and find that the results remain unaffected. Then, we test different definitions of the dependent variables, the main predictors, and the instrumental variables. Results are very close when we replace the main instrumental variables (lightning strikes and incidental coverage) with pre-determined physical characteristics that are inputs into the instruments: the altitude of a municipality and the coverage of wood, water and sand. Reduced-form estimates for both IV strategies also show results in line with our main specifications. Our findings are robust to the inclusion of control variables, aiming to control for municipality time trends, and to the confounding effects of reforms other than the expansion of the 3G, such as the introduction of the Umurenge Savings and Credit Cooperatives (U-SACCOs) and the rolling out of the fiber, which happened in the period covered in 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 (Acharya et al., 2016).

This paper contributes to the literature on mortgage markets in low- and middle-income countries (LMICs), highlighting that these markets remain severely underdeveloped, driven by multiple frictions such as weak property rights, insufficient legal infrastructure, funding constraints, and behavioral factors (Djankov et al., 2007; Galiani and Schargrodsky, 2010; Andersen et al., 2020). An expanding set of papers suggest that robust institutions, effective regulation, and technological innovations can mitigate these frictions, potentially expanding mortgage access and promoting economic growth (Campbell, 2012; Fuster et al., 2022; Buchak et al., 2018). Empirical evidence from various countries underscores both the promise and limitations of interventions, such as property titling reforms, improved regulatory environments, fintech solutions, and property taxes in enhancing mortgage market penetration (Campbell et al., 2015; Anagol et al., 2023). Behavioral research also highlights that even when mortgage products are available, household inattention and limited financial literacy can hinder optimal use (Andersen et al., 2020; Gurun et al., 2016).

[3] The residual direct effect captures various other mechanisms by which mobile internet influences credit access, including improved employment opportunities (Hjort and Poulsen, 2019; Caldarola et al., 2023), increased household incomes (Bahia et al., 2023; Calderone et al., 2018), and reduced informational frictions (Gupta et al., 2023).

This paper contributes to the literature on the impact of new information technologies in banking and finance (Core and De Marco, 2021; Kwan et al., 2024; Mazet-Sonilhac, 2021; Lin et al., 2021; Pierri and Timmer, 2022; Brunnermeier et al., 2023). D'Andrea et al. (2023) highlight the role of broadband in reducing banks' information asymmetries, while D'Andrea and Limodio (2024) examine how high-speed internet facilitates the development of interbank infrastructures. Jiang et al. (2022) show that mobile internet enhances bank competition and access to credit. Through the development of mobile banking, internet technologies promote individual financial activity (Saka et al., 2021) and lead to more efficient investment strategies (Hvide et al., 2022). Our paper shows that the internet influences individuals' financial decision-making by increasing access to credit from banks while reducing reliance on microfinance institutions. Furthermore, the paper adds to the broader literature emphasizing the role of IT 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 productivity (Agarwal et al., 2024). We highlight the impact of mobile internet on information spread in the market of land titles, aligning with cross-market spillover effects discussed by Bos et al. (2018).

Finally, our research contributes to the literature examining how technology facilitates the acquisition and utilization of property rights in financial markets. Prior research highlights that strengthened property rights promote financial market participation by reducing enforcement and collateral costs (La Porta et al., 1998; Djankov et al., 2007; Besley et al., 2012; Djankov et al., 2022). Our analysis particularly relates to studies on land reform and technology, which demonstrate the effects of secure land titles on productivity, investment, and credit access (Besley and Ghatak, 2010; Ali et al., 2017; Deininger and Goyal, 2012; Manysheva, 2021; Montero, 2022). We extend this literature by explicitly quantifying how mobile internet enhances the effectiveness of property rights reforms in expanding mortgage markets and credit allocation.

2 Theoretical Framework

This theoretical framework analyzes the choice of financial institutions by households when accessing credit and the role of technology and property rights in shaping these decisions. We specifically study how households select between borrowing from a formal bank, which charges lower interest rates but requires paying a fixed entry cost, and borrowing from a microfinance institution (MFI), which charges higher interest rates but requires no initial fee. Additionally, we examine how technology influences these choices and helps the development of a mortgage market by favoring a land-title reform, which enables households to pledge land as collateral with banks.

2.1 Economic Environment

We consider an economy populated by a continuum of risk-neutral individuals, normalized to unit mass. Each individual has access to an investment project characterized by productivity parameter g, uniformly distributed over the interval $[0, 1]$. This parameter captures the return on each unit borrowed, so that more productive borrowers demand larger loans.

Each borrower faces a choice between two credit providers: a formal bank and a microfinance institution. The bank charges a relatively lower interest rate, denoted by r_B, but requires payment of a fixed, upfront cost $F > 0$ for joining (e.g., documentation fees, account opening costs, collateral registration cost, travel cost to a branch). In contrast, the microfinance institution charges a higher interest rate $r_M > r_B$ but imposes no initial fee (e.g., microfinance agents reaching customers directly, lack of collateral).

2.2 Borrowers' Decisions and Payoffs

Given the linear relationship between productivity and loan size, we assume an individual of type g borrows an amount equal to g. This simplification captures the intuition that more productive projects seek greater financing. Hence, the gross return from the project is g^2.

Borrowers' net payoffs under each credit alternative are thus $U_B(g) = g^2 - r_B g - F$ and $U_M(g) = g^2 - r_M g$. Households also have the option not to borrow at all, in which case their payoff is normalized to zero. Thus, individuals will participate in the credit market only if doing so provides a nonnegative net surplus, i.e., if $\max[U_B(g), U_M(g), 0] \geq 0$.

2.3 Borrowing vs. Non-Borrowing Decision

We first determine the minimal productivity threshold at which borrowers enter the credit market. For microfinance borrowers, the minimum productivity required is simply $g_M^0 = r_M$, since below this threshold the borrower's net payoff is negative. For bank borrowers, participation requires productivity to exceed a higher threshold, given by:

$$g_B^0 = \frac{r_B + \sqrt{r_B^2 + 4F}}{2}.$$

2.4 Bank vs. Microfinance Institution Choice

When borrowers decide to participate, they select the institution offering the highest net payoff. The surplus differential between the bank and the microfinance option is:

$$\Delta U(g) = U_B(g) - U_M(g) = (r_M - r_B)g - F.$$

This difference is strictly increasing in g, implying a unique productivity threshold, g^*, at which borrowers are indifferent between the two lenders:

$$g^* = \frac{F}{r_M - r_B}.$$

Therefore, borrowers with productivity below g^* prefer the microfinance institution to avoid the bank's fixed cost despite its higher interest rate. In contrast, borrowers with productivity above g^* prefer the bank to benefit from the lower interest rate, as their larger borrowing volumes justify paying the fixed fee.

2.5 Technology, Land-Title Reform and the Mortgage Market

We now extend the model to incorporate technology and its role in promoting a land-title reform which fosters the development of a mortgage market. Specifically, we assume a technology parameter $\tau \in [0, 1]$. Technology affects borrowers through two main channels. The first is a direct productivity boost: $g(\tau) = g \cdot (1 + \lambda_j \tau), \quad j \in \{B, M\}$. While in reality banks may benefit more than MFIs from technological progress[4], we assume for simplicity that $\lambda_B = \lambda_M = \lambda$. The second channel operates through a reform parameter $\theta(\tau) \in [0, 1]$, which captures the role of technology in enabling land reform and securing property rights.[5] We assume that technology enables land-title acquisition such that θ is an increasing function of τ. For simplicity, we define $\theta(\tau) = \delta \cdot \tau$ where $\delta \in [0, 1]$ captures the institutional responsiveness of land reform to technology access. Importantly, this property rights-channel — which further improves productivity — applies only to banks, since MFIs do not employ physical collateral.[6] Productivity becomes as follows:

$$g_B(\tau) = g \cdot (1 + \lambda\tau)(1 + \alpha\delta\tau)$$

$$g_M(\tau) = g \cdot (1 + \lambda\tau)$$

This latter productivity enhancement could reflect improved land-use efficiency, lower transaction costs, or increased access to complementary productive inputs facilitated by secure property rights.

Formally, we assume that individuals who are initially productive enough to borrow ($g \geq r_M$) experience an increase in their effective productivity proportionally related to their initial

[4] An income effect, for example, allows borrowers to access larger amounts, which are generally offered by banks.

[5] Technology plays a crucial role in current land title reforms. On the one hand, land titles are digital contracts directly connected to banks via the land registry. On the other hand, new mobile technologies help inform the population and disseminate information about the reform—particularly its procedures, objectives, and technical aspects.

[6] Indeed, only banks have access to the digital land registry.

productivity level. The economic justification for this assumption is straightforward: properties with productivity below r_M generate insufficient returns and thus have negligible collateral value. Consequently, such properties cannot realistically serve as collateral for mortgage lending.

After the arrival of the technology and the consequent introduction of the land reform, borrowers' payoffs become:

$$
\begin{aligned}
U_B(g;\tau) &= [g(1+\lambda\tau)(1+\alpha\delta\tau)]^2 - r_B[g(1+\lambda\tau)(1+\alpha\delta\tau)] - F \\
U_M(g,\tau) &= [g(1+\lambda\tau)]^2 - r_M[g(1+\lambda\tau)]
\end{aligned}
$$

The threshold at which borrowers become indifferent between borrowing from banks and microfinance institutions changes accordingly:

$$
g^*(\tau) = \frac{F}{(r_M - r_B)(1+\lambda\tau)(\alpha\delta\tau)}.
$$

As τ increases, the productivity threshold $g^*(\tau)$ decreases, causing borrowers previously relying on microfinance to shift toward bank financing without an overall increase in the level of individuals borrowing from banks and microfinance institutions. As a result, the likelihood of receiving a bank loan increases, the likelihood of receiving a microfinance loan decreases and there is an increase in switching away from microfinance to banks.

An important implication of this model is that technology not only reallocates borrowers from microfinance institutions to formal banks. Through the property rights-channel, it also significantly increases individual investment among those obtaining mortgages, from g to $g(1+\alpha\delta\tau)$. Specifically, borrowers pledging their land titles as collateral experience a productivity enhancement that proportionally raises the scale of their investments. Thus, individuals transitioning to bank financing following the reform increase their project sizes, reflecting improved economic opportunities stemming directly from enhanced property rights and the availability of mortgage markets.

The following Proposition guides the empirical analysis.

Proposition *In the presence of an improvement in technology (higher τ), the model predicts that:*

1. *The probability of an individual receiving a bank loan increases, the probability of receiving a microfinance loan decreases, and the probability of receiving a loan from either the bank or the microfinance institution remains unchanged;*

2. *There is a higher likelihood that individuals switch from microfinance to bank lending and a lower likelihood that individuals switch from banks to microfinance;*

3. *Individuals respond by transacting more intensively land titles and the mortgage market*

expands, since borrowers can pledge collateral to banks;

4. *Individual investment rises among borrowers obtaining mortgages, driven by reform-induced productivity enhancements.*

3 Institutional Setting

3.1 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 (about three quarters of the population is rural based), particularly those engaged in agricultural and informal sectors, with limited access to formal credit channels.

To address the financial needs of underserved populations, MFIs emerged as key players in the credit market and played a role in promoting financial inclusion, especially for micro and small-scale entrepreneurs who lacked access to traditional banking services. 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. Financial inclusion increased from 48% to 96% between 2008 and 2024, and the share of adult population using services and products from commercial banks increased from 14 to 31% over the same period (Access to Finance Rwanda, 2024). These changes have been driven by a combination of factors, including economic development, policy reforms, and technological advancements.

In this period, formal banks have expanded their reach. With improved regulatory frameworks and technological advancements, formal banks have been able to extend their services to previously underserved areas, offering a wide range of financial products and playing a central role in facilitating investments, supporting businesses, and promoting economic growth.

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, in favor of formal banking (Agarwal et al., 2023). 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 the expansion of formal banking and the transformation of the credit market in Rwanda. In particular, the widespread adoption of mobile internet has promoted a system of property rights which has been key for the development of the mortgage market.

3.2 The LTR and the Mortgage market

In the aftermath of the civil conflict, the large-scale return migration had a dramatic impact on land ownership, escalating tensions and making land reform a crucial condition to ensure social stability and improve land use management and investments. 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).

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 digitized parcels. By the year 2012, the database had accumulated information on an impressive 10.4 million land parcels.

The LTR program introduced a very efficient land tenure system based on the digital registry (World Bank, 2020). Figure 1 illustrates the average number of days required to register a land transaction between 2007 and 2015. Prior to the reform, Rwanda ranked among the poorest performers in Africa, with an average registration time exceeding 350 days, compared to the Sub-Saharan average of approximately 100 days. Following the introduction of the reform, the registration time dropped to less than 40 days. The 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 banks 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 across online newspapers and social media platforms, 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 a significant part of the effect of mobile internet on banking is channeled through a property rights-channel. The latter reduces information frictions between borrowers and commercial banks and allows individuals to move away from microfinance institutions towards formal banking, thus promoting a mortgage market.

The mortgage market in Rwanda has been in an infant stage during the period of our analysis. Financial products designed for home purchase have been limited, and the market infrastructure weak, thus constraining affordability and reach. However, the situation has changed markedly after 2012, in correspondence with the rollout of mobile internet and the Rwanda's LTR program, which massively accelerated land registration and enabled land titles to become viable collateral. Following these development, there has been a visible upward jump in mortgage activity, as reflected in Figure 1.

3.3 Mobile Internet

In the last two decades, Rwanda has made significant strides in improving its information and communication technology (ICT) connectivity. Following the civil conflict, the country recognized the potential of ICTs as catalysts for economic development and growth. In line with this vision, the "Vision 2020" program was launched in 2000, aiming to transform Rwanda into a middle-income knowledge economy by 2020. In the government development program Vision 2020, ICT was identified as one of the key drivers for achieving growth and development (Republic of Rwanda, 2012).

The government has taken various steps to establish a foundation for high-speed connections. As a result, 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 low- and middle-income countries transitioning to a modern economy. The country serves as a benchmark for broadband installation, penetration, and successful implementation of ICT investments.

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 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, especially through the property rights-channel.

4 Data and Empirical Strategy

4.1 Data

Our study uses 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, offers a highly representative view of total bank lending.

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 (at the municipality level), and borrower characteristics like age, gender, and marital status. After 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.[7] 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 commercial 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 (a digital mapping provider), provide yearly geolocated information on mobile coverage in Rwanda from 2008 to 2015.[8] 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 to 23 km^2 (GSMA, 2015). For the purpose of our analysis, we map the adoption of mobile internet at the municipality-year level. Figure 2 presents a visual representation of the coverage of 3G in Rwanda.

To address endogeneity concerns and establish a causal relationship between the 3G technology and access to credit, we construct two instrumental variables (IVs) using external datasets. The first IV is based on the frequency of lightning strikes, which we obtain from the Global Hydrology

[7] 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.

[8] 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.

Resource Center (GHRC). 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 3 illustrates the map of average lightning frequency by municipality.

The second IV 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 feature, 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.[9] The right panel of Figure 3 plots the map of average incidental coverage by municipality.

To understand the underlying mechanisms behind our findings, we incorporate additional data from the Rwanda Land Management and Use Authority's land dashboard on land certificates, transactions, and mortgaged lands, that we use to study the property rights-channel 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 analyze the relationship between land collateral and bank credit access. We integrate this dataset with data on building volumes constructed by Pesaresi and Politis (2023) using data from the Global Human Settlement Layer project (GHSL).

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.

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, interest rate, the probability that the loan is secured and the share of loans that are past due, hence in a state of default. Panel C reports data on land titles and building volumes. Finally, panels D and E present summary statistics for the main predictor, 3G mobile coverage, and its instrumental variables.

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

4.2 Identification

A concern when regressing credit features on mobile internet is that new technologies are unlikely to be randomly allocated across areas, potentially generating biased estimates. We deal with this concern by using an IV 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 4 (left panel) supports this hypothesis , as we observe that Rwandan 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 monotonically.

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 4, 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 explore the potential correlation between our instruments and the predetermined characteristics of the municipalities. Table B1 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. Results are reassuring and suggest comparability in terms of pre-existing characteristics. In each quartile of the lightning strikes distribution, the two groups of municipalities exhibit similar socioeconomic indicators. 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 technology. Results for incidental coverage 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 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 IVs 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.

4.3 Empirical Methodology

To examine the effects of mobile internet on households' financial decisions, we estimate the following model on a balanced panel dataset at the borrower-year level:

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

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 mortgages, Y_{imt} equals 1 if the individual i in municipality m has a mortgage with the bank at time t. 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 heteroskedasticity and correlated errors within the same municipality.[10]

[10] The choice of the LPM allows to interpret the estimates consistently with the Local Average Treatment Effect (LATE) interpretation (Imbens and Angrist, 1994) and removes the incidental parameters problem, that would be particularly relevant for maximum likelihood estimators in our setting. The analysis of bank loan characteristics, which focuses on the intensive margin of the credit relationship, uses a specification at the borrower-bank-year level. This allows to include bank-time fixed effects, which further controls for time-varying demand side factors.

To address endogeneity concerns, we employ a two-stage least squares (2SLS) methodology. The first stage, outlined earlier, exploits 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.[11] 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.[12] 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 (α_i) and time fixed effects (ϕ_t).

Our identification assumption is that any correlation between lightning strikes and incidental coverage with municipality characteristics remained unchanged at the time of the introduction of the 3G 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, while columns 4 to 6 consider the sample of all borrowers included in the credit registry. For each group, the first two columns use alternatively lightning strikes and incidental coverage as the only instrument for 3G coverage, while the third column includes both instruments simultaneously. In all cases, 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.

5 Credit and Transition to Banks

This section relates to points 1 and 2 of the *Proposition*: We test the impact of mobile internet on access to bank credit and the transition of borrowers from microfinance to formal banking.

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

[12] In the robustness section we also adopt for an alternative version of the two instruments, in which Z_m^{light} and Z_m^{incid} are interacted with a linear time trend t.

5.1 Access to Bank Credit

We investigate the impact of mobile internet on borrowers' access to the bank credit by constructing a balanced panel dataset covering the period from 2008 to 2015. For each borrower-year pair, we define three dependent variables that 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 MFI.

The results are shown in Table 3, columns 1-3. The OLS estimates, reported in panel A, suggest a mild positive relationship between mobile internet and the probability of getting a loan, although the coefficient is statistically indistinguishable from zero (column 1). Decomposing the results between loans granted by commercial banks and MFIs shows that higher 3G coverage is associated with a higher probability of obtaining a loan from a commercial bank (column 2). On the other hand, we find that mobile internet is negatively associated with the likelihood of accessing loans from MFIs (column 3). The 2SLS results (Panel B) confirm the OLS ones. The point estimates 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 2) and a 3.6 percentage point decrease in the probability of having a loan from a MFI (column 3).[13]

Our findings corroborate the idea that mobile internet plays an important role for financial graduation and the move towards commercial banks. 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.

5.2 Transition to Banks

To provide direct evidence on the transition of borrowers from microfinance institutions to commercial banks, we identify four types of borrowers: 1) those who only have relationships with banks throughout the period analyzed, 2) those who only have relationships with MFIs, 3) those who initially have a relationship with a MFI and later switch to the banking sector, and 4) those who initially have a relationship with a bank and later access a MFI. We divide the sample in 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 where the dependent variable is the probability that a borrower, with her initial credit account in a MFI (bank), switches to a bank (MFI).

[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.

The results are presented in Table 3, columns 4-6. The 2SLS estimates reported in panel B 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 (column 4) and with a 1.1 percentage point decrease in the probability of switching to MFIs. These results 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.

Evidence that new technologies, such as mobile internet, foster the transition from informal microcredit to a formal, well-structured banking system is particularly compelling, given that past efforts to build financial systems capable of supporting long-term credit and economic growth in developing countries have often fallen short. Previous studies have shown the importance of microfinance as stepping stone for borrowers, who then seek bank 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). Research has demonstrated the complementary actions between microfinance and credit bureaus (De Janvry et al., 2010). Our evidence identifies internet technologies an another factor which enable the transition from an microfinance to the formal banking sector.

5.3 Additional Results

In a set of additional tests, we ask whether the effect of mobile internet on accessing commercial bank loans could differ along several dimensions, considering time, socio-economic, and borrower-specific factors that may influence the relationship between mobile internet and access to bank loans. Our results are discussed in detail in Online Appendix A. First, we find that the impact of mobile internet on bank loans takes time to materialize and does not show pre-trends, reinforcing the validity of our identification strategy (Figure A1). Next, we find suggestive evidence that the effect of mobile internet on accessing a commercial bank loan could be stronger in richer and urban regions, while there are no significant differences across borrower characteristics. Turning to bank loan characteristics, we find that borrowers with access to mobile internet show larger outstanding loan amounts without experiencing adverse effects on loan prices and on the probability that the loan is past due, suggesting that mobile internet reduces financial frictions. Focusing on switchers, the evidence points to a relative increase in loan outstanding and a significant decrease in the average interest rate, without any deterioration in loan performance.

6 Access to Property Rights and the Mortgage Market

Technology has the potential to reduce the costs associated with accessing and utilizing property rights, enabling individuals to obtain land titles and leverage them as collateral for loans. This synergy between technology and the land reform allows individuals to overcome traditional financial barriers that hinder their access to banks, thereby making microfinance institutions and informal loans the primary options for most individuals. This section aims to test this hypothesis, that we refer to as the *property rights-channel*, explicated in points 3 and 4 of the theoretical *Proposition*.

6.1 The Property Rights Channel and Mortgages

The Land Tenure Regularization program regulated the ownership and control of the lands, enhanced land utilization, and promoted its efficient management and administration. In particular, a land tenure system based on the digital registry which connected all banks in the country played a pivotal role in favoring access to formal credit. For banks, it became easier to track and verify land ownership—a crucial step in allowing the third-party validation of titles as collateral.

To provide evidence that the property rights-channel explains a significant part of the estimated effect of mobile internet on banking, we provide both visual and empirical steps. First, we note the consequential overlap between the timing of the LTR reform and the rollout of mobile internet, the latter being a key enabler for the widespread implementation of the former. Similarly, by comparing the two panels of Figure 1, it is evident that the LTR acted as a necessary precondition for the development of the mortgage market. Second, we show the concurrent positive relationship between 3G coverage and the timing and number of land title transactions. Third, we document that greater 3G coverage is related to more bank credit collateral and mortgages, as recorded in the credit registry. Fourth, we examine the association between 3G coverage and the amount of mortgaged land parcels. Fifth, we show the existence of a positive relationship between the availability of 3G internet and the growth rate of building volumes. Finally, in the next section, we quantify the extent to which the effect of mobile internet on banking is mediated through the property-rights channel.

We analyze 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 municipality level. The only difference is that the period of analysis ends in 2013, which includes the hot phase of the LTR program (around 80% of all transactions were completed by 2012). Our dependent variables are: 1) a dummy variable indicating that at least 50% of the transactions have been made in the first year of the program ($Fast\ Completion$); and 2) the cumulative of the total number of transactions in municipality m and year t, scaled by the number of parcels in the municipality ($Number\ of\ Transactions$). The results reported in Table 4 show a positive relationship between 3G coverage and our proxies of the availability of land certificates, suggesting a role for mobile internet in promoting the LTR program and facilitating the marketing of land titles. The 2SLS estimates (columns 3-4) show that a one standard deviation increase in 3G coverage is associated with a 15 percentage point higher probability of disbursing at least 50% of the titles in the first year of the reform, and a 13% increase in the total number of transactions.[14]

We further investigate the role of mobile phones in facilitating the dissemination of information on land titles in Table 5, where we observe that districts with a high share of mobile phones account for the vast majority of the effects of mobile internet on land titles distribution. In response to a one standard deviation increase in 3G coverage, a municipality with a larger share of mobile phones experiences a 45 percentage point higher likelihood of exceeding the 50% benchmark and a further 6.5% increase in the volume of transactions.[15]

Next, we provide a direct test of the relationship between mobile internet and access to collateralized loans and bank mortgages using a balanced panel dataset from the credit registry, The dependent variables is either i) a dummy variable that indicates whether the bank loan is backed by collateral, or ii) a dummy variable indicating whether the loan is a mortgage issued by a commercial bank. The results indicate that individuals in areas with better access to mobile internet are more likely to benefit from collateralized loans and obtain a mortgage (Table 6). A one standard deviation increase in 3G coverage is associated with a 0.6 percentage point higher probability of a bank loan being backed by collateral (column 3) and a 0.8 percentage point higher probability of the loan being a mortgage issued by a commercial bank (column 4).

Turning to the relationship between mobile internet and the amount of mortgaged land, we regress the share between mortgaged parcels and the total amount of parcels on the level of 3G coverage in 2011. Since these data are only available in cross-section, our results are suggestive of the relationship between mobile internet and mortgaged lands.[16] The results 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 7, column 3).

Finally, we investigate the relationship between mobile internet and the growth of building volumes at the municipality level. The hypothesis is that increased access to credit, particularly mortgages, facilitated by mobile internet, should correlate with higher growth rates in local construction. The results support this hypothesis. As shown in in Table 7 (column 4), a one standard deviation increase in 3G coverage is associated with an 8.3 percentage point increase in the growth

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

[15] Data on the shares of mobile phones are taken from the EICV 4 survey implemented in 2013-2014. We define a district to have a high share of mobile phones if it belongs to the top 25th percentile of the distribution.

[16] Figure B1 provides a visual representation of the share of mortgaged lands.

rate of building volumes during the period 2010-2015.

Overall, our findings provide evidence of the role mobile internet plays in promoting land reform and its impact on accessing formal credit through the property rights-channel, potentially stimulating local real estate markets.

6.2 Quantification

To enrich our analysis, we quantify how much of the effect of mobile internet on banking is due to the land title reform. We employ two different methodological tools: a mediation analysis and a structural estimation.

6.2.1 Mediation Analysis

Our first quantification exercise is built using a reduced form methodology that implements a Sobel-Goodman mediation test (Doerr et al., 2022).[17] Estimates from the Sobel-Goodman test are reported in Figure 5 and Table 8, panel A. Consistently with our evidence, we find that approximately 37% of the probability of receiving a bank loan is due to an indirect effect facilitated by the acquisition of the collateral, whereas 63% is directly attributed to mobile internet.[18] 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). Taking the probability of receiving a collateralized loan as dependent variable shows 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 collateral in securing a mortgage and steering individuals from MFIs, which lack this product, towards commercial banks. We also conduct a mediation analysis for local building volumes and find that approximately 4% of the total effect is attributable to the indirect effect mediated by land titles. While this number may seem small in comparison with the other coefficients, it is essential to highlight that the mortgage market in Rwanda was at its infancy during this time period. Before the arrival of mobile internet, around 0.6% of the loans in our sample were collateralized or defined as mortgages, while this proportion

[17] The Sobel-Goodman test is an application of the delta method. The idea is that when a mediator is included in a regression analysis with the independent variable, the effect of the independent variable is reduced and the effect of the mediator remains significant. The Sobel-Goodman test is a specialized t-test that provides a method to determine whether the reduction in the effect of the independent variable, after including the mediator in the model, is a significant reduction and therefore whether the mediation effect is statistically significant.

[18] These results are corroborated by the findings in Table B2 in 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.

grew to 2.8% by the end of the sample. We can convincingly argue that part of this growth emerged from the introduction of 3G internet and the facilitation of receiving a land title. An important implication of the mediation analysis is that the elasticity of construction investment to the availability of loans and mortgages is 1.8.[19]

6.2.2 Structural Estimation

Our second quantification exercise adopts a structural approach in line with Christensen et al. (2024). We specify a decision-theoretic framework to model credit choices and uses revealed preferences to estimate the parameters of interest.[20] The model compares individuals that have already decided to borrow and are comparing banks and MFIs to access credit. The utility from borrowing from a bank is modeled as the log amount of the loan granted:

$$u_{im}^{\text{bank}} = \theta_i + kD_m^{\text{land title}}$$

where θ_i represents the log of the loan amount granted by any financial institution to individual i in the absence of land titles; $D_m^{\text{land title}}$ is a variable denoting municipalities m with a high availability of land titles (we employ the *Rapid Completion* dummy as in Table **??**); and k captures the percentage increase in the loan amount granted by banks in municipalities with a more widespread adoption of the land title reform.

On the other hand, the utility from borrowing from a MFI is:

$$u_{im}^{\text{MFI}} = \beta\theta_i + \varepsilon_{im}, \quad \varepsilon_{im} \sim N(\delta_0 + \delta_1 3G_m, \sigma^2).$$

where β represents the weight individuals assign to the loan amount when borrowing from a MFI. The stochastic component ε_{im} introduces heterogeneity across individuals, driven by differences in mobile internet coverage $3G_m$ and the variance of the distribution σ^2. If $\delta_1 < 0$, greater 3G coverage tilts individuals' preferences toward banks, representing the direct effect of 3G technology on individual borrowing choices.

The indirect effect operates through the impact of 3G on the acquisition of land titles, which facilitates access to bank loans by providing collateral. This indirect effect κ is estimated via a 2SLS regression, where the land title dummy is regressed on 3G coverage.

Individuals choose to borrow from banks when $u_i^{\text{bank}} > u_i^{\text{MFI}}$. Given that $\nu_{im} := \frac{\varepsilon_{im} - \delta_0 - \delta_1 3G_m}{\sigma} \sim$

[19] In the mortgage market, an 80% increase in collateralized loans and mortgages due to the land titles implies that collateralized loans account for 2.2% of lending (80% × 2.8% = 2.2%). As 4% of the increase in building volume is mediated by land titles, the elasticity of construction investment to the availability of loans and mortgages is equal to 4%/2.2% = 1.8.

[20] The structural estimation is conducted on a collapsed version of the dataset, data are aggregated at the individual level and the examined period is after the introduction of internet.

$N(0,1)$, this is equivalent to:

$$\nu_{im} < \frac{(1-\beta)\theta_i + kD_m^{\text{land title}} - \delta_0 - \delta_1 3G_m}{\sigma}$$

. Thus, the probability of choosing a bank over a MFI is given by:

$$Pr\{\mathbb{I}_{\text{bank loan}} = 1\} = Pr\{\nu_{im} < \gamma_0 + \gamma_1 3G_m + \gamma_2 D_m^{\text{land title}} + \gamma_3\theta_i\} = \Phi(\gamma_0 + \gamma_1 3G_m + \gamma_2 D_m^{\text{land title}} + \gamma_3\theta_i),$$

where $\Phi(.)$ is the standard normal cumulative density function.

Under the normality assumption, we can estimate this model through a probit regression, where the dependent variable is a dummy for choosing a bank loan (or a collateralized bank loan) and the independent variables include the predicted value of the standardized 3G coverage, the land title dummy, and θ_i. As θ_i is missing when the measure of land titles is equal to one and the loan is granted by a bank, we generate a counterfactual value by subtracting the estimated $\hat{k}$ from the loan amount. $\hat{k}$ is obtained from a regression of the log of the loan amount on the land title dummy, respectively for bank loans and collateralized bank loans.

Using this structural approach, we decompose the total effect of mobile internet on bank loans into: i) the direct effect, computed as the marginal effect of 3G coverage from the probit regression, and ii) the indirect effect, calculated as the product between $\hat{\kappa}$ (the impact of 3G on land titles) and the marginal effect of land titles on the probability of choosing a bank loan.

Figure 5 and Table 8, panel B, report our estimates. Consistent with the results from the mediation analysis, we find that approximately 30% of the probability of receiving a bank loan can be attributed to the indirect effect facilitated by the acquisition of land as collateral, while the remaining 70% is attributed to the direct effect of mobile internet. When considering collateralized loans, the proportion of the effect mediated by land titles increases to 75% of the total effect, with the residual direct effect shrinking significantly.

7 Additional Evidence and Robustness

7.1 Alternative Mechanisms

An alternative channel through which land titles might affect banking and investment could be the reduction of uncertainty over land ownership resulting from the reform. This possibility is inspired by a substantial body of literature on the topic, recently expanded by the work of Adamopoulos et al. (2024). To explore this channel in depth, we utilize the comprehensive measures implemented by the Government of Rwanda to resolve ownership disputes and uncertainty. The reform was supported by "the large-scale mobilization of citizens, up to around 110,000 people, to assist in adjudicating disputes" (World Bank, 2020).

We digitized data from a 2014 district-level list of disputes from Kyewalabye (2014), which shows that the share of parcel disputes was minimal, averaging below 0.15% (Figure B4). To assess whether these disputes influenced the likelihood of receiving bank and MFI loans, we replicate the results from Table 3, incorporating an interaction between 3G coverage and the standardized share of disputes. As shown in Table B3, this interaction is small and statistically insignificant.

While this test does not rule out the significance of securing property rights, it suggests that uncertainty over ownership was not a critical issue in this context. The minimal level of disputes and the lack of a measurable effect on loan access indicate that other channels, such as the enhanced ability to use land as collateral, are more pivotal in explaining the reform's impact on financial access and investment.

In a second exercise, we examine whether the distribution of land titles is correlated with the underlying value of the land. While Table A1 indicates that urban municipalities experienced much larger effects than rural ones, we provide an additional test using geographic heterogeneity in land suitability for Rwanda's top two crops, coffee and tea. Figure B4 displays the suitability maps for these crops and points to a valuable lack of correlation and provide variation across different municipalities.

A model of land title demand would predict that the reduction in information costs from mobile internet rollout would yield greater benefits where the expected return on land is higher, hence a higher distribution of titles where land is more productive. We test this prediction in Table B4 by interacting the 3G coverage variable with the standardized suitability for coffee and tea. The results confirm that municipalities with higher suitability exhibit a significantly higher probability of surpassing the 50% threshold for the number of distributed titles.

7.2 Confounding Variables of 3G Coverage

Municipality characteristics. 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 B1 and includes: 2G coverage, to control for alternative mobile technologies; total population, urban population, and employed population, to control for demographic and economic features; the number of total bank branches, to control for bank physical infrastructures; and a dummy for the presence of a primary road, to controls for the level of connection of the municipality. Variables obtained from the 2012 Census are interacted with the dummy post-2010. Table B5 reports the estimates related to this augmented specification. The coefficients keep the same sign as in the baseline regressions and remain statistically significant.

We augment also the baseline model by incorporating province-by-time fixed effects to control for trends at the province level. Results remain qualitatively consistent with the baseline ones. However, the IV estimates suffer from reduced statistical power, likely due to the decreased variation in our instruments within provinces (Table B6).

Contemporaneous MFI Reform. In 2009, the government of Rwanda launched the Umurenge SACCOs (U-SACCOs) program, with the aim to boost up rural savings and increase financial inclusion. The program helped people to have access to credit through U-SACCOs, build credit history, and eventually access commercial 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 B7. Our coefficients remain unaffected, indicating that the effect of mobile internet on the probability of having a bank loan is orthogonal to the nationwide U-SACCO program.

High-Speed Fiber and Bank Supply. 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 crate a dummy variable for the presence of fixed broadband at the municipality level and add it to the main specifications. Results, reported in Table B8, are in line with the baseline ones.

We also check the sensitivity of our results on the collateral channel 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 generally associated to the functioning of banks and their branches (D'Andrea et al., 2023) and 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. (2022) and Barjamovic et al. (2019).[21] Results from this falsification test are reported in Table B9 and provide robust

[21] 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. 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

evidence in favor of the collateral channel as advocated in Section 6.

7.3 Alternative Model Specifications

We test the robustness of our main results estimating several modifications to the main 2SLS specification reported in Table 3.

Bank-municipality level analysis. We start by replicating our analysis on banking by aggregating data at the bank-municipality-year level. We estimate the following model:

$$Y_{bmt} = v + \beta_1 3G\ \widehat{Coverage}_{mt} + \alpha_{bm} + \phi_{bt} + \varepsilon_{bmt} \tag{4}$$

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, the average interest rate, and loans in default. Bank-municipality fixed effects (α_{bm}) account for unobserved time-invariant characteristics that may be specific to each bank-municipality pair, while bank-year fixed effects (ϕ_{bt}) capture common time-varying shocks that affect the bank in a particular year. Estimates, reported in Table B10, confirm those in the main text. A one standard deviation increase in 3G coverage is associated with a 13% increase in the number of loans granted, a similar increase in the number of borrowers switching from the microfinance sector, a 29% increase in total loan outstanding, and no significant effect on average interest rates and loans in default.

Including all borrowers. We make several modifications to the main 2SLS specification reported in Table 3. 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.[22] As a first robustness check, we test the sensitivity of our results to this choice. The estimated coefficient from the model considering the full sample are unaffected compared to the baseline ones (Table B11).

Alternative definition of the dependent variable. 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

variation for fiber deployment. The map of fiber-optic connections and post-colonial roads in Rwanda is presented in Figure B2 in the appendix.

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

bank (MFI) loan that takes value 1 from the first year in which the borrower has an outstanding loan with the lender. 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 (Table B12).

Alternative measures of 3G coverage. Moving to the share of 3G coverage in the municipality, in a first robustness test 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 B13. The setting, in the OLS framework, also allows for the application of the methodology introduced by Sun and Abraham (2021), which accounts for time heterogeneity in the treatment effect. 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 B14 and are in line with the baseline ones, with larger magnitudes.

Alternative versions of the instruments. 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 again qualitatively in line with the main ones, but larger in magnitudes (Table B15).

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. Imbens and Angrist (1994) show 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.[23] Recently, Mogstad et al. (2021) extend the framework of Imbens and Angrist (1994) and show that these results can be generalized if a partial monotonicity condition is satisfied.[24] We show that our estimates do not suffer from overidentification problems, and provide direct evidence of the validity of using multiple instruments. First, we follow

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

[24] The partial monotonicity condition is that the Imbens and Angrist (1994) 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 Imbens and Angrist (1994) 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

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 consistent with the main findings (Table B16).

Next, we replace lightning strikes and incidental coverage with predetermined geographical features that are inputs into these IVs: the altitude of the municipality and the percentage covered by wood, water, and sand. The results reported in Table B17 confirm the baseline ones, showing larger magnitudes and higher F-statistics (above 100).

Reduced form regressions. To conclude this series of tests on the 2SLS strategy, Table B18 presents reduced form regressions. Columns 1 and 2 display estimates when lightning strikes and incidental coverage are used as predictors. Columns 3 and 4 focus on altitude, wood, water, and sand coverage. Estimates from both IV strategies are consistent with our main specifications.

8 Conclusion

This paper examines how new technologies can reduce financial frictions and foster mortgage market development in low- and middle-income countries. Using comprehensive datasets on mobile connectivity and Rwanda's credit registry, combined with information from a national land reform, land records, and satellite-based measures of building volume, we causal evidence on the impact of mobile internet on banking and real estate investments. We find that the expansion of 3G coverage significantly improves access to land, which in turn enables individuals to secure bank credit by using land titles as collateral, thereby facilitating greater investment in construction.

Our findings reveal that expanded 3G coverage leads to a higher probability of obtaining a bank loan, a decrease in the likelihood of securing a microfinance loan, and no significant change in overall access to finance. Importantly, we observe a transition among borrowers from MFIs to banks, driven by the transformative role of mobile internet in fostering the land reform. This transition to bank credit is facilitated by the availability of land collateral.

Our research further highlights that mobile internet enhances construction investment by accelerating the distribution of land titles and promoting the use of land as collateral. Our estimates show that areas with better internet coverage experience faster land reform implementation and a greater number of land transactions. This, in turn, leads to increased use of land as collateral, as evidenced by a rise in the share of mortgaged lands and an associated growth in construction activity.

The mediation analysis and the results from a structural estimation emphasize the importance of land title availability in channeling the benefits of mobile internet towards banking and investment. Our results suggest that between about one third of the internet's impact on access to bank loans is due to land titles, with this magnitude raising to up to 80% for collateralized loans.

By illustrating how mobile internet, in combination with a property rights reform, alleviates financial frictions and help create a mortgage market, this study contributes to the literature on technology, property rights, and access to credit, while offering practical insights for policymakers seeking to harness digital tools to promote economic growth.

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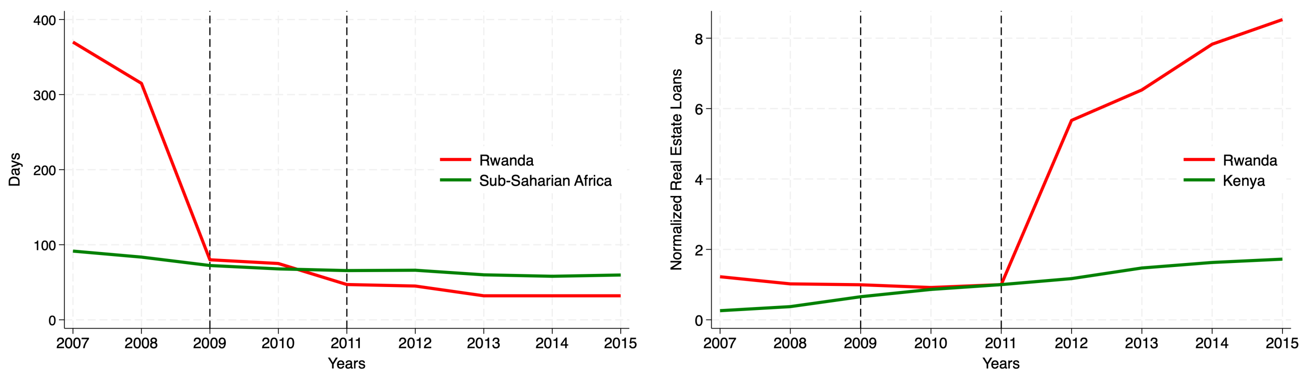
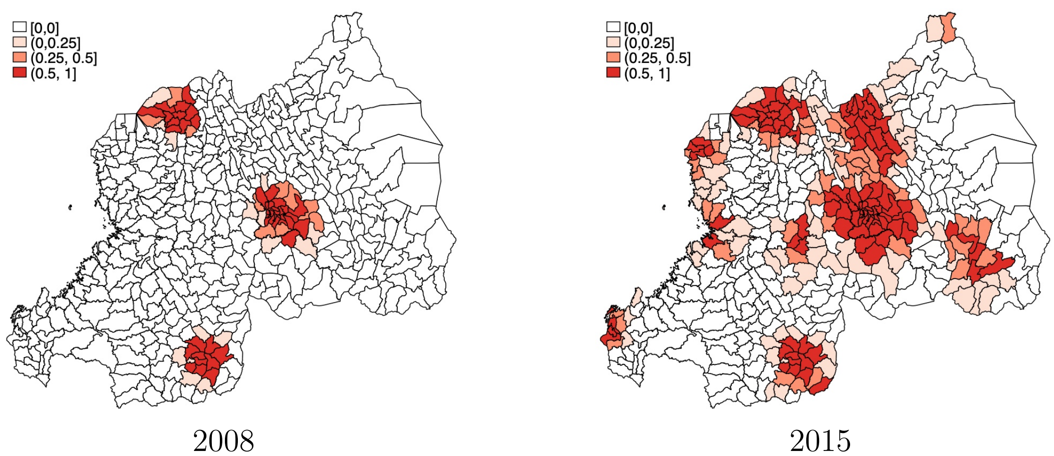
Figures

Figure (1) Registration Time for Land Titles and Mortgage Markets' Growth



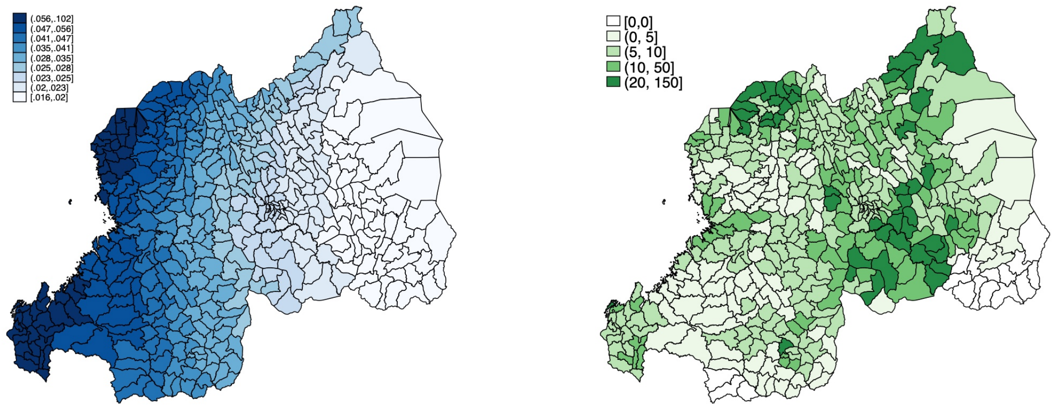
Notes: The left chart plots the average number of days to register a land transaction between 2007 and 2015. The red solid line represents Rwanda, while the green solid line shows the average across Sub-Saharan Africa countries. The vertical lines sign the years of the LT reform. Source: World Bank Doing Business. The right chart plots the amount of credit to the mortgage market between 2007 and 2015. The red solid line represents Rwanda, while the green solid line represents Kenya. The vertical lines sign the years of the LT reform. Source: IMF.

Figure (2) 3G Coverage in Rwanda



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

Figure (3) Cross-sectional Variation of Mobile Internet: Lightning Frequency and Incidental Coverage

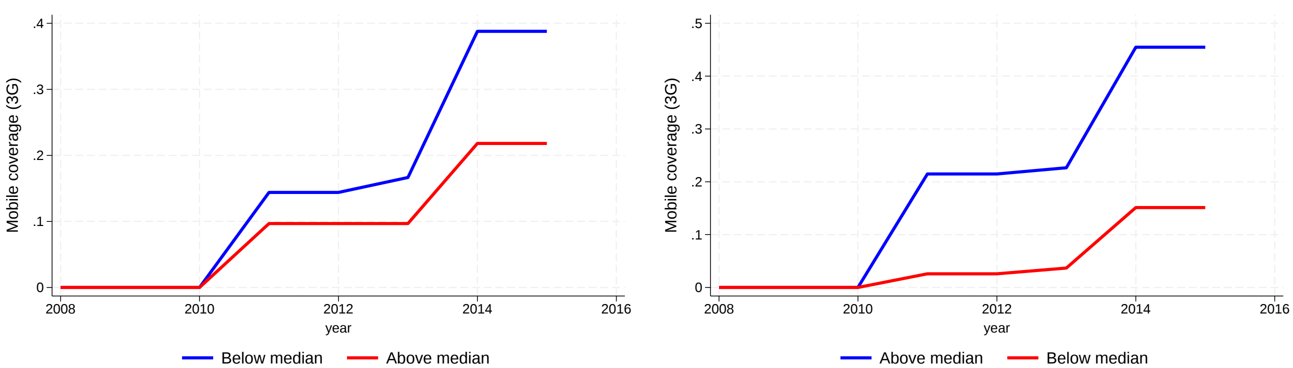


Lightning frequency

Incidental coverage

Notes: This figure shows the average frequency of lightning strikes and incidental coverage, by municipality in Rwanda. The left panel plots lightning frequency, a time-invariant indicator computed as the yearly average of strikes in the municipality, during the period 1998-2013. The right panel plots 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. Sources: GHRC and Björkegren (2019).

Figure (4) 3G Coverage, Lightning Frequency, and Incidental Coverage

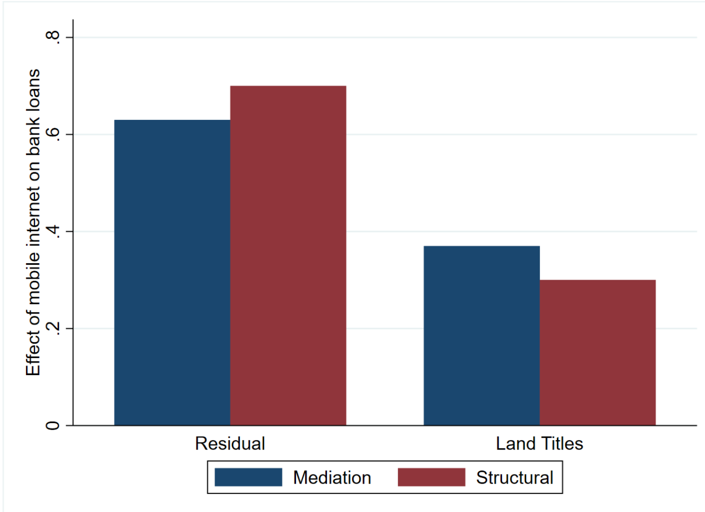


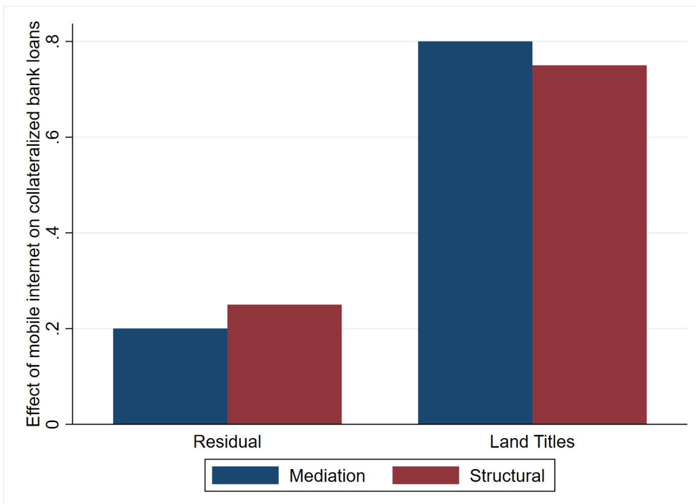
Lightning frequency

Incidental coverage

Notes: This figure provides visual evidence in support of the relevance of our instruments. The y-axis measures the 3G coverage. The left panel focuses on lightning strikes. 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. The right panel focuses on incidental coverage. 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 (5) Mediation Analysis and Structural Estimates





Notes: This figure plots the decomposition of the total effect of mobile internet on bank loans, on the top, and collateralized bank loans, on the bottom. 'Residual' refers to the direct effect of 3G coverage. 'Land titles' refers to the mediated effect by the availability of land titles. Results from the Sobel-Goodman mediation test are reported in blue, whereas estimates from the structural model are reported in red. The figure refers to the results presented in Table 8.

Tables

Table (1) Summary Statistics

	n	mean	sd	p50	min	max
	PANEL A: Access to 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
Interest rate	124,388	19.20	5.73	19.00	6.14	70.10
Past due	123,284	0.04	0.13	0.00	0.00	1.00
Collateral	128,639	0.12	0.32	0.00	0.00	1.00
	PANEL C: Land titles and Building volumes					
Fast Completion	2022	0.12	0.33	0.00	0.00	1.00
Number of transactions	2022	0.23	0.32	0.00	0.00	1.00
Share land mortgaged	337	0.01	0.03	0.00	0.00	0.23
Growth building volumes	337	0.25	0.12	0.24	0.00	0.58
	PANEL D: 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 E: 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), interest rates (in percentage terms), past due (as a share of outstanding amount), and collateral (a dummy variable indicating that the loan is secured). Panel C reports data on land titles and building volumes: a dummy variable indicating whether the number of land transactions in the municipality has reached 50% of the total in the first year of the reform, the log of the number of transactions, scaled by the total number of parcels, the share of land mortgaged, and the delta log of building volumes, evaluated between 2010 and 2015. Panel D shows the summary statistics for the main predictor: 3G Mobile coverage (and its related standardized measure). Finally, Panel E 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 Banking

	(1)	(2)	(3)	(4)	(5)
		Probability of		Probability of Switching	
	Any Loan	Bank Loan	MFI Loan	MFI to Bank	Bank to MFI
			PANEL A: OLS		
Std 3G coverage	0.002	0.018***	-0.017***	0.007***	-0.006***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)
Borrower FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	909165	909165	909165	514372	380974
Adj. R sq.	0.480	0.374	0.370	0.255	0.296
Mean Dep. Var.	0.284	0.136	0.164	0.010	0.034
S.D. Dep. Var.	0.451	0.343	0.370	0.100	0.181
			PANEL B: IVs		
Std 3G coverage	-0.002	0.034***	-0.036***	0.011***	-0.011**
	(0.006)	(0.012)	(0.012)	(0.003)	(0.005)
Borrower FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	909165	909165	909165	514372	380974
SW F-statistic	16.22	16.22	16.22	16.47	13.89
Mean Dep. Var.	0.284	0.136	0.164	0.010	0.034
S.D. Dep. Var.	0.451	0.343	0.370	0.100	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* (*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. *Probability* (*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* (*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. Panel A refers to OLS estimates. Panel B refers to 2SLS estimates. Obs. refers to the number of observations; Adj. R sq. is the adjusted R2; SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; 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 Land titles

	(1) Fast Completion	(2) Number of Transactions	(3) Fast Completion	(4) Number of Transactions
Std 3G coverage	0.173***	0.047***	0.147*	0.128***
	(0.020)	(0.007)	(0.080)	(0.036)
Estimation	OLS	OLS	IV	IV
Municipality FE	Yes	Yes	Yes	Yes
Borrower FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
SW F-statistic			19.19	19.19
Obs.	2022	2022	2022	2022
Adj. R sq.	0.577	0.804		
Mean Dep. Var.	0.122	0.229	0.122	0.229
S.D. Dep. Var.	0.327	0.316	0.327	0.316

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: *Fast Completion*, a dummy variable equal to one if the number of land transactions in municipality m has reached 50% of the total in the first year of the reform, and *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. 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. Obs. refers to the number of observations; Adj. R sq. is the adjusted R2; SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; 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 (5) Mobile Internet, Mobile Phones and Land Titles

	(1) Fast Completion	(2) Number of Transactions	(3) Fast Completion	(4) Number of Transactions
Std 3G coverage	0.025	0.022**	-0.018	0.089***
	(0.037)	(0.011)	(0.057)	(0.031)
Std 3G coverage × High mobile phone	0.222***	0.038***	0.459***	0.065*
	(0.037)	(0.014)	(0.086)	(0.038)
Estimation	OLS	OLS	IV	IV
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SW F-statistic			11.34	11.34
Obs.	2022	2022	2022	2022
Adj. R sq.	0.617	0.805		
Mean Dep. Var.	0.122	0.229	0.122	0.229
S.D. Dep. Var.	0.327	0.316	0.327	0.316

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: *Fast Completion*, a dummy variable equal to one if the number of land transactions in municipality m has reached 50% of the total in the first year of the reform; and *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. The main predictors are: *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t; and *Std 3G coverage* × *High mobile phone*, where the latter is a dummy variable equal to one if the district belongs to the top 25th percentile of mobile phones diffusion, 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 *High mobile phone*. Columns 1 and 2 refer to OLS estimates. Columns 3 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 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 (6) Mobile Internet and the Mortgage Market

	(1)	(2)	(3)	(4)
	Probability of		Probability of	
	Bank Collateral	Bank Mortgage	Bank Collateral	Bank Mortgage
Std 3G coverage	0.009***	0.003***	0.006**	0.008***
	(0.001)	(0.001)	(0.003)	(0.002)
Estimation	OLS	OLS	IV	IV
Municipality FE	No	No	No	No
Borrower FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SW F-statistic			16.22	16.22
Obs.	909165	909165	909165	909165
Adj. R sq.	0.499	0.512		
Mean Dep. Var.	0.015	0.016	0.015	0.016
S.D. Dep. Var.	0.12	0.125	0.12	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 as follows: *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. Obs. refers to the number of observations; Adj. R sq. is the adjusted R2; SW F-statistics reports the Sanderson-Windmeijer multivariate F-statistics; 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 (7) Mortgage Market and Residential Investments

	(1) Share of Land Mortgaged	(2) Growth Building Volumes	(3) Share of Land Mortgaged	(4) Growth Building Volumes
Std 3G coverage	0.024***	0.011**	0.017***	0.083*
	(0.003)	(0.005)	(0.005)	(0.035)
Estimation	OLS	OLS	IV	IV
SW F-statistic			18.52	7.87
Obs.	337	337	337	337
Adj. R sq.	0.528	0.613		
Mean Dep. Var.	0.014	0.248	0.014	0.248
S.D. Dep. Var.	0.034	0.123	0.034	0.123

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; and *Building volumes*, the delta log of building volumes in municipality m, between 2015 and 2010. 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. In columns 2 and 4 we control for the initial level of building volumes and population. 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. Standard errors, in parentheses, are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table (8) Mediation Analysis and Structural Estimates

	(1)	(2)	(3)
	Probability of		Growth
	Bank Loan	Bank Collateral	Building Volumes
		Panel A	
Sobel	0.013**	0.005**	0.003***
Aroian	0.013**	0.005**	0.003***
Goodman	0.013**	0.005**	0.003***
Indirect Effect (Collateral)	0.013**	0.005**	0.003***
Direct Effect (Mobile Internet)	0.021**	0.001	0.080**
Total Effect	0.034**	0.006^{+}	0.083**
Proportion Indirect	**37%**	**80%**	**3.6%**
		Panel B	
$\gamma 1$ (3G)	0.179*	0.033	
$\gamma 2$ (land title)	0.413***	0.535***	
$\gamma 3$ (θ)	0.121***	0.406***	
$\hat{k}$	0.256	0.052	
$\hat{\kappa}$	0.185	0.185	
$\hat{\delta}1$	-0.093	-0.026	
Indirect Effect	0.156	0.029	
Direct Effect	0.068	0.002	
Proportion Indirect	**30%**	**75%**	

Notes: This table reports estimates from the Sobel-Goodman mediation test, panel A, and the structural model, panel B. 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; *Building volumes*, the delta log of building volumes in municipality m, between 2015 and 2010. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. The mediation variable is *Fast Completion*, a dummy variable equal to one if the number of land transactions in municipality m has reached 50% of the total in the first year of the reform. In panel A, the first three rows report the Sobel, Aroian, and Goodman tests. The last row indicates the proportion of the total effect of mobile internet on the dependent variable that is mediated through land titles. In panel B, we report all the key parameters of the structural model and, in the last row, 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.

Online Appendix for: "Developing the Mortgage Market: Technology, Property Rights, and Banking"

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A Additional Evidence on Mobile Internet and Banking

A.1 Heterogeneity

We investigate whether the effect of mobile internet on accessing a commercial bank loan is heterogeneous along different dimensions.

We start by investigating the dynamics of the effect with an event study analysis. 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:

$$Y_{imt} = \nu + \sum_{k=-6}^{4} \beta_K I\{K_{mt} = k\} + \alpha_i + \phi_t + \varepsilon_{imt} \tag{5}$$

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 A1 shows the event study associated with the OLS regression. The graph demonstrates 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.

Next, 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 A1, panel

A.[25] We observe that the effect of 3G coverage appears to be larger in urban and wealthier areas, and where a physical bank branch is present. Although none of these differences are statistically significant, our findings suggest that the effect of mobile internet on accessing a commercial bank loan may be more pronounced in more 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 borrower characteristics and divide the sample based on the gender, marital status (single versus married), and age (young versus adult) of the borrower. The results of these tests are summarized in Table A1, panel B. We find that 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, implying that the adoption of mobile internet has broad positive implications, regardless of individual borrower characteristics.

A.2 Bank Loan Characteristics

By investigating the relationship between 3G coverage and loan characteristics, our analysis aims to shed light on how the availability of mobile internet influences the nature and extent of bank lending activities. We exploit the granularity of our data and present results at the individual borrower-bank-year level, focusing on borrowers who have access to bank loans. In this way, we examine the impact of mobile internet along the intensive margin of the credit relationship.[26]

Our findings are presented in Table A2, and show that a one standard deviation increase in 3G coverage is associated with an increase in outstanding loan amount by 6.5% (column 1). At the same time, we find no evidence of an effect on interest rates (column 2), i.e. borrowers with access to mobile internet show larger outstanding loan amounts without experiencing adverse effects on loan prices. These findings point to the beneficial role of mobile internet in enhancing borrowing opportunities and loan terms for individuals accessing commercial bank loans, and are corroborated by aggregate-level results in Table B10. Furthermore, we find no effects on the probability that the loan is past due (column 3), suggesting that mobile internet reducesing financial frictions.

As a second step, we focus on borrowers who initially have a loan with a MFI, exploring the heterogeneous effect of mobile internet on loan conditions for those who switched to a commercial

[25] A municipality is defined to be rural if the share of urban population is equal to zero. A municipality is poor if it is above the median of the poverty index.

[26] The panel dataset is unbalanced and based on outstanding relationships.

bank.[27] We estimate the following model:

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

where Y_{imt} measures either the amount of loan outstanding, the average interest rate, or the probability that the loan is past due for borrower i, in municipality m, in year t. The main predictors are: i) the standardized 3G coverage ($3G\ \widehat{Coverage}_{mt}$) in municipality m, at time t, instrumented by lightning strikes and incidental coverage; and ii) $3G\ \widehat{Coverage}_{mt}$ 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: 1) Z^{light}_{mt}, the standardized yearly average frequency of lightning Z^{light}_{m}, in municipality m, interacted with a dummy post-2010; 2) Z^{incid}_{mt}, the standardized average of incidental coverage Z^{incid}_{m}, in municipality m, interacted with a dummy post-2010; 3) Z^{light}_{mt} interacted with $Switcher_i$; and 4) Z^{incid}_{mt} interacted with $Switcher_i$.

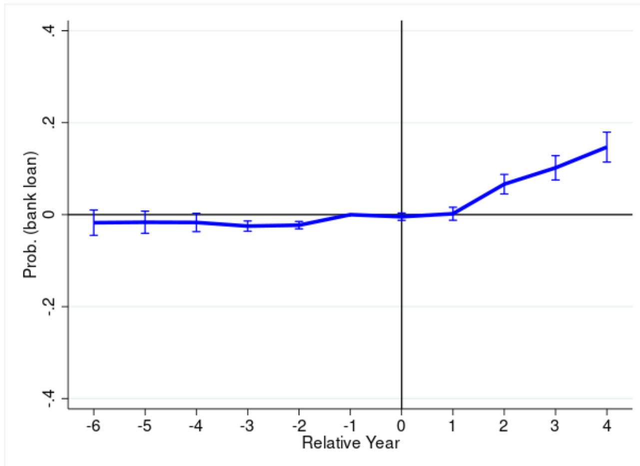
The results, presented in Table A2 (columns 4-6) highlight the role of mobile internet in facilitating and enhancing the loan conditions for switchers. Different from the borrowers keeping their relationships with MFIs, for whom access to the 3G internet has no effect, switchers experience a relative increase in loan outstanding and a significant decrease in the average interest rate, without any deterioration in loan performance.[28]

These results provide compelling evidence that mobile internet influences bank loan characteristics, particularly for switchers who benefit from better credit terms and improved financial opportunities.

[27] We consider borrower credit characteristics, without conditioning on having a loan with a formal bank.

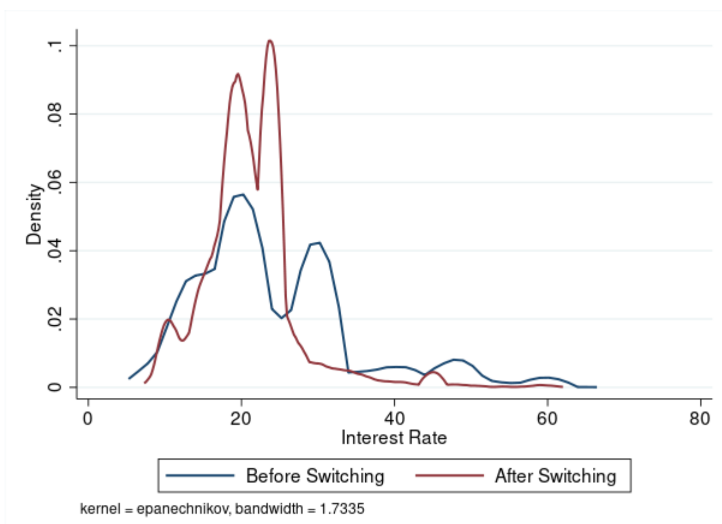
[28] Figure A2 in the appendix plots the distribution of interest rates for switchers, distinguishing between pre- and post-switching. The chart shows that borrowers in the upper tail of the distribution particularly benefit from becoming bank customers.

Figure (A1) 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.

Figure (A2) Distribution of interest rates for borrowers switching from MFIs 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.

Table (A1) 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.

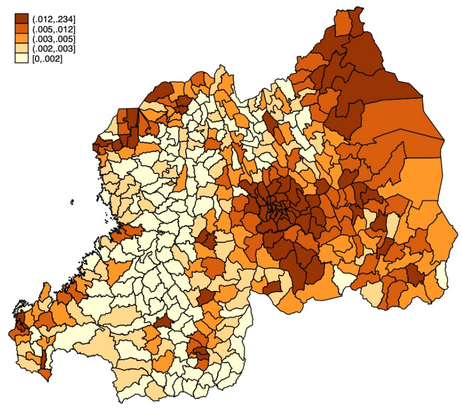
Table (A2) Mobile Internet and Bank Loan Characteristics

	(1) Volume of Loans	(2) Lending Rate	(3) Past Due Loans	(4) Volume of Loans	(5) Lending Rate	(6) Past Due Loans
Std 3G coverage	0.063**	0.154	-0.004	0.032	-0.077	-0.018
	(0.025)	(0.154)	(0.007)	(0.032)	(0.207)	(0.020)
Std 3G coverage				0.159***	-2.235***	-0.008
× Switcher				(0.054)	(0.660)	(0.022)
F-test (p-value)				0.001	0.001	0.010
Estimation	IV	IV	IV	IV	IV	IV
First MFI	No	No	No	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes	No	No	No
SW F-statistic	22.44	21.64	22.47	18.96	19.00	8.03
Obs.	104766	104423	106462	110391	79081	109613
Mean Dep. Var.	6.750	18.51	0.037	6.609	20.71	0.050
S.D. Dep. Var.	1.421	5.472	0.135	1.287	8.603	0.158

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; and *Past Due Loans*, a dummy taking unit value when the loan is past due and hence in a state of default. The main predictors are: *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t; and *Std 3G coverage* × $Switcher_i$, 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 (we refer to the share of past due amount in columns 3 and 6), S.D. Dep. Var. refers to the standard deviation of the dependent variable, and are reported for the natural logarithm of loan volume, the lending rate and the share of past due loans. 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.

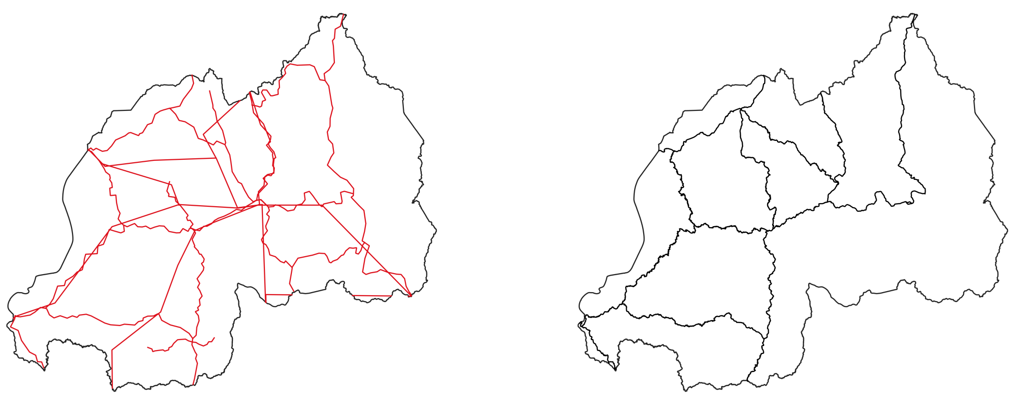
B Additional Figures and Tables

Figure (B1) Share of mortgaged land parcels



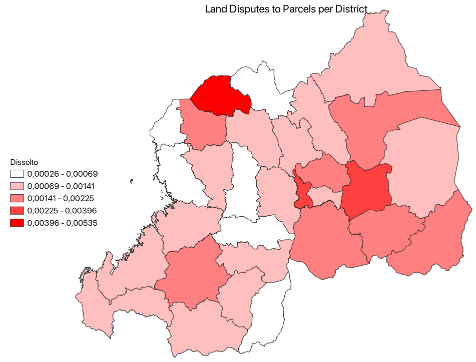
Notes: This figure plots the share of mortgaged land parcels, by municipality in Rwanda. Source: Land Management and Use Authority.

Figure (B2) Distribution of fiber-optic cables and post-colonial roads



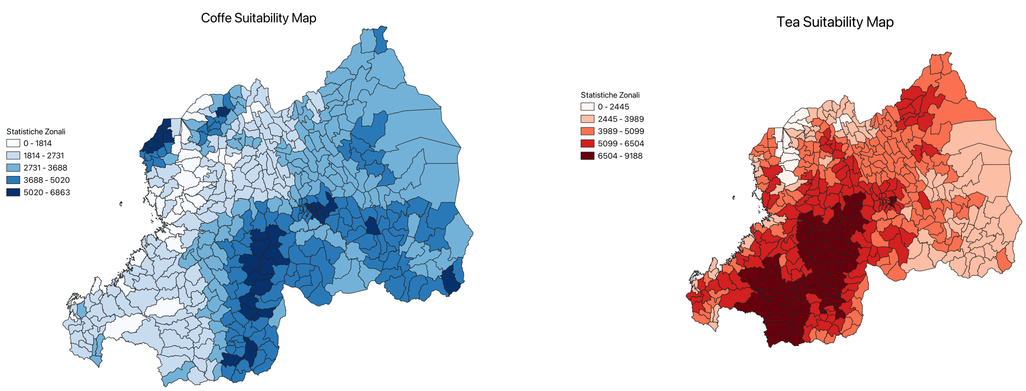
Notes: The left panel of the figure plots fiber-optic lines as in 2015. The public fiber was deployed in 2010, while private fiber complemented the main lines from 2014. The right panel plots surfaced roads as in 1975, from the Perry-Castañeda Library Map Collection.

Figure (B3) Share of Land Titles subject to Disputes



Notes: This figure reports the percentage of land titles subject to a dispute settlement action as of 2014. The average share of parcels subject to dispute is 0.146%, with a standard deviation of 0.111%. This dataset is available at the district level and is reported by Kyewalabye (2014).

Figure (B4) Land Suitability to Coffee and Tea



Notes: Both panels report statistics on land suitability elaborated by the Food and Agriculture Organization, FAO, in their GAEZ v4 Data Portal. The left panel presents the suitability measures for coffee, while the right those for tea.

Table (B1) 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 (B2) 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, *Fast Completion*, a dummy variable equal to one if the number of land transactions in municipality m has reached 50% of the total in the first year of the reform. 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.

Table (B3) Mobile internet and land disputes

	(1)	(2)
	Probability of	
	Bank Loan	MFI Loan
Std 3G coverage	0.042**	-0.035**
	(0.019)	(0.017)
Std 3G coverage × disputes	-0.018	-0.002
	(0.025)	(0.021)
Estimation	IV	IV
Borrower FE	Yes	Yes
Year FE	Yes	Yes
SW F-statistic	5.90	5.90
Obs.	909165	909165
Mean Dep. Var.	0.136	0.164
S.D. Dep. Var.	0.343	0.370

Notes: This table reports estimates from 2SLS as presented in equation (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. This variable has been interacted with the variable *disputes*, measuring the standardized share of land parcels subject to disputes in municipality m, during the year 2014. We instrument both variables 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; 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 (B4) Mobile internet and profitable lands

	(1)	(2)	(3)	(4)
	Fast Completion			
Std 3G coverage	0.118***	-0.059	0.159***	0.104*
	(0.030)	(0.101)	(0.020)	(0.061)
Std 3G coverage × coffee	0.051***	0.144***		
	(0.016)	(0.055)		
Std 3G coverage × tea			0.067***	0.082***
			(0.024)	(0.028)
Estimation	OLS	IV	OLS	IV
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SW F-statistic		12.52		17.04
Obs.	2022	2022	2022	2022
Adj. R sq.	0.584		0.587	
Mean Dep. Var.	0.122	0.122	0.122	0.122
S.D. Dep. Var.	0.327	0.327	0.327	0.327

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 variable is *Fast Completion*, a dummy variable equal to one if the number of land transactions in municipality m has reached 50% of the total in the first year of the reform. The main predictor is *Std 3G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. This is interacted with $coffe$ a standardized variable measuring the average suitability of municipality m to coffee, in columns (1) and (2); and is interacted with tea a standardized variable measuring the average suitability of municipality m to tea, in columns (3) and (4). Both are 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 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 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 (B5) Mobile internet and access to credit—Additional 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 2SLS as presented in equation (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 (B6) Mobile internet and access to credit—Province-specific time trends

	(1)	(2)	(3)	(4)
	Probability of			
	Bank Loan	MFI Loan	Bank Loan	MFI Loan
Std 3G coverage	0.012***	-0.018***	0.027	-0.049**
	(0.005)	(0.006)	(0.020)	(0.013)
Estimation	OLS	OLS	IV	IV
Borrower FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
SW F-statistic			11.63	11.63
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* 3*G coverage*, the standardized measure of 3G mobile coverage, in municipality m, at time t. We also 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 province by 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—Controlling for the U-SACCO program

	(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 2SLS as presented in equation (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—Controlling for broadband internet

	(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 2SLS as presented in equation (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) Broadband internet and land transactions

	(1) Fast Completion	(2) Number of Transactions
Std 3G coverage	0.162**	0.013***
	(0.082)	(0.037)
Fiber	0.002	-0.024
	(0.063)	(0.028)
Estimation	IV	IV
Municipality FE	Yes	Yes
Year FE	Yes	Yes
SW F-statistic	19.43	19.43
SW F-statistic	50.83	50.83
Obs.	2022	2022
Mean Dep. Var.	0.121	0.229
S.D. Dep. Var.	0.327	0.316

Notes: This table reports estimates from 2SLS as presented in equation (3), by using data at the municipality level. The dependent variables are as follows: *Fast Completion*, a dummy variable equal to one if the number of land transactions in municipality m has reached 50% of the total in the first year of the reform; and *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. 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). 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.

Table (B10) Mobile internet and aggregate bank characteristics

	(1) Number of Loans	(2) Number of Switchers	(3) Volume of Loans	(4) Lending Rate	(5) Past Due Loans
Std 3G coverage	0.130**	0.118***	0.285***	0.279	-0.012
	(0.065)	(0.034)	(0.091)	(0.287)	(0.017)
Estimation	IV	IV	IV	IV	IV
Bank-municipality FE	Yes	Yes	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes	Yes	Yes
SW F-statistic	15.97	15.97	15.62	15.70	15.97
Obs.	12695	12695	12459	12467	12695
Mean Dep. Var.	1.307	0.171	8.650	18.75	0.011
S.D. Dep. Var.	1.301	0.420	1.696	5.375	0.078

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; and *Past Due Loans*, the share of loans that are in past due and hence in a state of default. 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 (we refer to the share of past due amount in column 5), S.D. Dep. Var. refers to the standard deviation of the dependent variable, and are reported for the natural logarithm of loan volume, the lending rate and the share of past due loans. 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 (B11) 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 2SLS as presented in equation (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 (B12) Mobile internet and access to credit—Staggered dependent variables

	(1)	(2)
	Staggered	
	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 2SLS as presented in equation (3). The dependent variables are as follows: *Staggered* (*Bank Loan*), a dummy variable equal to one from the first year in which the borrower i, in municipality m, has an outstanding loan with a bank in year t, and zero otherwise; *Staggered* (MFI *loan*), a dummy variable equal to one from the first year in which the 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 (B13) Mobile internet and access to credit—Two-way fixed effects

	(1)	(2)	(3)	(4)
	Probability of			
	Bank Loan	MFI Loan	Bank Loan	MFI Loan
Dummy 3G	0.057***	-0.105***	0.094***	-0.110***
	(0.011)	(0.016)	(0.036)	(0.035)
Estimation	OLS	OLS	IV	IV
Borrower FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SW F-statistic			19.17	19.17
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 *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 (B14) 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	9.67	9.67	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 2SLS as presented in equation (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 (B15) Mobile internet and access to credit–Alternative 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 2SLS as presented in equation (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* 3*G 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 (B16) 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 2SLS as presented in equation (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* 3*G 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 (B17) Mobile internet and access to credit—Geographical instruments

	(1)	(2)	(3)	(4)
		Probability of		
	Bank Loan	MFI Loan	Bank Loan	MFI Loan
Std 3G coverage	0.048***	-0.049***		
	(0.009)	(0.009)		
Altitude			-0.021***	0.024***
			(0.006)	(0.006)
Wood			0.001	0.003
			(0.012)	(0.009)
Water			-0.008**	0.008*
			(0.003)	(0.004)
Sand			0.014***	-0.008***
			(0.001)	(0.001)
Estimation	IV	IV	OLS	OLS
Borrower FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SW F-statistic	861.54	861.54		
Obs.	906990	906990	906920	906920
Adj. R sq.			0.374	0.370
Mean Dep. Var.	0.136	0.163	0.136	0.163
S.D. Dep. Var.	0.343	0.369	0.343	0.369

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 four instruments: the mean altitude of the municipality m, and the percentage of its territory covered by wood, water and sand, all interacted with a dummy post-2010. In columns 3 and 4, we also provide the reduced form counterpart of this regression. 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 (B18) Mobile internet and access to credit—Reduced form

	(1)	(2)
	Probability of	
	Bank Loan	MFI Loan
Std Lightning	-0.013**	0.012**
	(0.006)	(0.006)
Std Incidental	0.003	-0.008*
	(0.004)	(0.004)
Estimation	OLS	OLS
Borrower FE	Yes	Yes
Year FE	Yes	Yes
Obs.	909165	909165
Adj. R sq.	0.372	0.369
Mean Dep. Var.	0.136	0.163
S.D. Dep. Var.	0.343	0.369

Notes: This table reports estimates from OLS as presented in equation (1). 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 predictors are: Z_{mt}^{light}, the standardized yearly average frequency of lightning Z_m^{light}, in municipality m, interacted with a dummy post-2010; and Z_{mt}^{incid}, the standardized average of incidental coverage Z_m^{incid}, in municipality m, interacted with a dummy post-2010. 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.