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Abstract

To mitigate information asymmetry about borrowers in developing economies, digital lenders utilize machine-learning algorithms and nontraditional data from borrowers' mobile devices. Consequently, digital lenders have managed to expand access to credit for millions of individuals lacking a prior credit history. However, short-term, high-interest digital loans have raised concerns about predatory lending practices. To examine how digital credit influences borrowers' financial well-being, we use proprietary data from a digital lender in Kenya that randomly approves loan applications that would have otherwise been rejected based on the borrower's credit profile. We find that access to digital credit improves borrowers' financial well-being across various mobile-phone-based well-being measures, including monetary transaction volume, mobility, and social networks, as well as borrowers' self-reported income and employment. We further show that this positive impact is more pronounced when borrowers have limited access to credit, take loans for business purposes, and obtain more credit.

Keywords: Information Asymmetry, Big Data, Digital Loan, Digital Credit, Access to Credit, Financial Welfare, Financial Well-Being, Developing Economies, Mobile Phone Data

JEL Codes: D14, G21, G51, M40, M41, O16, O30, O55

1. Introduction

Extant literature documents that information asymmetry between lenders and borrowers significantly impedes credit provision. To mitigate information asymmetry, when issuing loans to corporate borrowers, financial institutions typically exploit various information channels, including financial statements, covenant compliance reports, analysts' reports, and business press articles (e.g., Balakrishnan & Ertan 2021; Bushman et al. 2017; Dou 2020; Dyreng et al. 2017; Vashishtha 2014; Call et al. 2022). With respect to household credit, lenders extensively rely on borrowers' credit scores, employment and income records, and banking history when making credit decisions (e.g., Experian 2023; Plaid 2023). Although these studies have advanced our understanding of how information asymmetry is resolved in credit markets, they primarily focus on developed economies with well-functioning financial and legal systems. In contrast, many developing economies lack well-performing formal institutions. Therefore, the majority of the households in these economies do not have credit scores, lack banking records, and are employed informally. This leads to their limited ability to borrow from the formal financial system (e.g., Beck et al. 2009; Akoten et al. 2006; Domeher and Abdulai 2011; World Bank 2022).

The emergence of digital lending in recent years has mitigated information asymmetry and reshaped the consumer credit market in many developing economies, including Egypt, Ghana, Kenya, the Philippines, India, and Mexico. To compensate for the lack of prior credit history or traditional credit scores from credit bureaus, digital lenders rely primarily on "nontraditional" data from individuals' mobile devices, including individuals' travel patterns, social networks, and transaction histories (e.g., Francis et al. 2017). Utilizing this data and machine-learning algorithms, digital lenders develop alternative credit scores, which allow them to extend credit to millions of individuals without prior access to credit (Blumenstock 2018a). Although digital lenders increase financial inclusion by mitigating information asymmetry about individuals without access to formal financial systems, there are substantial concerns that these lenders may engage in predatory lending practices and exacerbate borrowers' financial hardships (Center for Financial Inclusion 2020; Quartz 2021; Boston Review 2019). In this study, we examine whether digital loans, issued based on nontraditional digital information, enhance borrowers' financial welfare.[1]

While extant literature shows that access to credit leads to wealth creation (e.g., Buera et al. 2011; Beck et al. 2007; Bruhn and Love 2014), digital loans typically bear annualized interest rates of over 100%, which may impose a substantial financial burden on borrowers.[2] Borrowers of digital loans also tend to have low financial literacy and may be poorly informed regarding these loans' interest rates and late fees, potentially leading to overborrowing (e.g., Francis et al. 2017; Garz et al. 2021; Brailovskaya et al. 2023; Robinson et al. 2022).[3] Weak consumer protection for borrowers of digital loans further exacerbates these concerns (Garz et al. 2021; Robinson et al. 2022). Notably, recent research finds little evidence that digital credit has a positive impact on borrowers' welfare, though it documents some improvement in borrowers' subjective well-being and resilience to income shocks (Suri et al. 2021; Björkegren et al. 2022; Brailovskaya et al. 2023).

To examine our research question, we rely on a proprietary and anonymized database of digital loans in Kenya, which were originated by a large digital lender (the Lender hereafter) that served over 8 million borrowers worldwide, including more than 3 million borrowers in Kenya. Over the last decade, Kenya has experienced tremendous growth in digital lending, where by 2018 more than 25% of the Kenyan adult population had obtained at least one digital loan (Totolo 2018;

[1] We use *financial welfare* and *financial well-being* interchangeably throughout the paper.
[2] These high interest rates are comparable to the rates on payday loans in the US, which may be as high as 400% annualized (Consumer Financial Protection Bureau, 2022).
[3] Prior research also suggests that borrowers may be overly optimistic when obtaining short-term loans, which can further contribute to overborrowing (e.g., Ausubel 1991; Stango and Zinman 2009, 2011; Bryan et al. 2022).

Björkegren et al. 2022). The Lender administers its digital loans using a mobile app through which applicants submit their loan applications, fill out a loan application survey, and grant the Lender access to their mobile phone data. This research setting offers two important advantages in assessing the welfare benefits of digital credit. First, starting from April 2018, the Lender conducted an experiment in which it randomly approved loan applications that would have been rejected based on the borrower's credit score, as estimated by the Lender's proprietary credit scoring model.[4] This experiment allows us to address an important endogeneity concern that the Lender is more likely to approve loans to borrowers with better economic prospects, making it difficult to establish a causal relation between digital loans and borrowers' future financial welfare.

Second, measuring borrowers' financial well-being in developing economies is challenging because economic activities in these economies are mostly informal, such that there is little data on individuals' income and other welfare attributes. Census data is also largely unavailable or significantly outdated.[5] Therefore, to measure financial well-being, prior research on microfinance and digital credit relies primarily on self-reported household surveys, which are costly to conduct and are often done on a small scale. To overcome this data challenge, we rely on the emerging literature in computer science that shows that mobile phone data can be used to infer individuals' well-being (e.g., Blumenstock et al. 2015; Blumenstock 2014, 2016, 2018a,b; Luo et al. 2017; Aiken et al. 2022, 2023; Deng et al. 2021; Moro et al. 2021). To measure borrowers' welfare, we utilize the Lender's mobile phone data, which contains latent information about how borrowers communicate, their mobility patterns, and the financial transactions they engage in.

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[4] This type of experiment, often referred to as the reject inference methodology, is a common practice for credit risk modelers in the consumer credit industry (e.g., Crook and Banasik 2004; Banasik and Crook 2007; Bücker et al. 2013). By randomly approving loans rejected by the credit scoring model, the Lender aims to test the effectiveness of this model and to determine if there are opportunities to increase lending while maintaining an acceptable level of risk.

[5] The lack of data needed to assess individuals' economic conditions is referred to as "data deprivation" by the World Bank (2015).

Turning to our research design, borrowers who are randomly approved in the experiment serve as treatment borrowers in our sample, while control borrowers are those whose loan applications were rejected by the credit model and were not selected to receive credit as part of the experiment. Because of the random approval by the Lender, any difference between the treatment and control borrowers can only be due to the treatment (i.e., digital loans). However, we obtain borrowers' mobile phone and survey data on loan application dates and thus can measure changes in financial well-being only if a borrower decides to apply for a subsequent loan, raising self-selection concerns. To mitigate these concerns, we match treatment and control borrowers based on their creditworthiness and loan application dates. Specifically, we match a treatment borrower's *initial* loan (the first loan randomly approved by the Lender) with a rejected loan application of a control borrower and a treatment borrower's *last* application with a subsequent application of the control borrower, conditional on the control borrower not having been approved for a loan prior to this application. We require the loan application dates for the control borrower to fall within 30 days of the respective loan application dates for the treatment borrower, and the control borrower's credit score to be within a tight 0.05 range of the treatment borrower's credit score on the *initial* loan date (the credit score ranges from 0 to 1 according to the Lender's credit scoring model).

Our final sample consists of 20,092 loan applications for 5,023 unique treatment borrowers and 4,352 unique control borrowers (we match with replacement), spanning the period from April 2018 to January 2022. We conduct a difference-in-differences (DiD) research design with borrower and year-month fixed effects, which allows us to study the effect of digital loans on borrowers' financial well-being by comparing the changes in the financial well-being of treatment borrowers between their initial and last loan applications to those of control borrowers.

As discussed above, we follow a novel approach to measure financial well-being based on mobile phone data. First, we construct two measures of borrowers' monetary transactions—the monetary amounts mentioned in text messages (SMSs), averaged per transaction, and the average daily mobile banking (M-PESA) balance as reported in SMSs.[6] Second, because recent research documents that mobility is strongly associated with an individual's wealth, we construct two measures of borrowers' mobility—the number of unique cell towers passed by the borrower and the number of cities the borrower has traveled to. Third, we construct three measures of the extent and the strength of borrowers' social networks, as network attributes have been shown to reflect individuals' financial well-being. Specifically, we rely on the total number of borrowers' SMSs, the total number of unique phone numbers in their contacts list, and the proportion of people in their network who repaid loans to the Lender on time. Motivated by microfinance research that relies primarily on self-reported household surveys to measure borrowers' welfare and to support the robustness of our findings based on mobile phone data, we supplement our phone-based measures with borrowers' self-reported monthly income and employment status.

Our evidence suggests that, relative to control borrowers, digital lending improves treatment borrowers' financial well-being across all mobile phone measures we explore. Treatment borrowers experience an increase in their monetary transaction volume, have greater mobility, and command more extensive and stronger networks after they are randomly approved for digital loans. These effects are also economically significant. For example, relative to control borrowers, average monetary amounts per transaction are higher by 14.9% for treatment borrowers, these borrowers travel to 9.4% more cities, and they have 26.8% more SMS messages. Last, we find that treatment borrowers have 20.8% higher monthly income and are 23.5% more likely to be employed or self-employed after getting access to digital credit, further supporting a positive

[6] The data we use to measure an individual's financial well-being is not necessarily used by the Lender in the credit scoring model.

impact of digital credit on financial well-being.

Although these primary analyses rely on the matched sample of the initial and subsequent loan applications of the treatment and control borrowers and a tight fixed effect structure, to further address self-selection concerns, we obtained data through the Lender's mobile app installed by the borrower when applying for the loan (the App data hereafter). Because the App data is automatically collected over time regardless of whether a borrower applies for a subsequent loan, the analyses based on this data significantly mitigate the concerns associated with a borrower's decision to apply for more credit. However, we acknowledge that these analyses are subject to a self-selection concern arising from the fact that borrowers may select to uninstall the app.[7] To alleviate this concern, we match treatment and control borrowers based on their creditworthiness, loan application dates, and subsequent App data collection dates. Our analyses are limited to the monetary transaction volume and mobility measures as only those can be reconstructed based on the App data. We find results similar to our main analysis. This evidence indicates that our findings are unlikely to be attributed to borrowers' decision to apply for additional loans.

Next, to better understand the influence of digital lending on financial well-being, we examine borrower and loan characteristics that may strengthen this influence. First, we expect the impact of digital lending to be more pronounced for borrowers with limited access to credit (Bruhn and Love 2014; Di Maggio et al. 2022; Balyuk 2022). We proxy for the access to credit by whether borrowers have credit scores issued by a credit bureau, since these scores reduce information asymmetry and thus allow borrowers greater access to credit (e.g., Pagano and Jappelli 1993; An and Chan 2008; Karlan and Zinman 2010). Second, building on prior studies that show that loans issued with productive purposes are more likely to increase borrowers' income relative to loans

[7] Note that the self-selection issue of borrowers selecting to uninstall the Lender's app does not apply to our primary analyses given that borrowers in these analyses reapply for subsequent loans and thus must retain the Lender's app.

for nonproductive purposes (Imai and Azam 2012; Attanasio et al. 2015), we expect loans with business purpose, rather than personal purpose (e.g., consumption needs), to have a greater effect on financial well-being. We find some evidence in support of these two predictions. Last, we explore whether the influence of digital loans on borrowers' financial well-being is stronger when borrowers obtain more credit. Although we expect the beneficial effect of digital loans to increase with the amount of credit, we acknowledge that borrowers may overborrow. We find a stronger improvement in financial well-being when borrowers' total loan amounts are greater, further reinforcing the benefits of digital credit and mitigating concerns associated with overborrowing.

Our study makes several contributions. First, we contribute to the growing literature on fintech lending. Although prior studies show that this lending increases access to credit in developed economies (e.g., Hau et al. 2019; Di Maggio et al. 2022; Erel and Liebersohn 2022), there is still mixed evidence on the welfare effects of fintech credit. Di Maggio et al. (2022) find that fintech borrowers are less likely to default on credit card payments and have better credit scores. In contrast, Di Maggio and Yao (2021) show that these borrowers are more likely to default on their loans and tend to experience only a short-term reduction in the cost of credit, and Johnson et al. (2023) find that nonprime borrowers overpay and subsidize prime borrowers. We extend this research by exploring the welfare implications of digital loans, which have become a vital source of credit in developing economies. Although digital loans differ substantially with respect to their approval process, pricing, amount, and the regulatory environment from fintech personal loans in developed economies,[8] we show that by reducing information asymmetry fintech lending can be highly beneficial for borrowers typically rationed out of traditional financial services.

In this respect, we also contribute to the emerging literature on digital lending. The collective

[8] See Section 2 for a more detailed discussion of these differences, as well as the differences between digital loans and payday loans, and digital loans and microfinance loans in developing economies.

evidence from prior studies suggests that, despite the substantial demand for digital loans in developing economies, they have a modest effect on borrowers' welfare. Specifically, these studies show that while digital loans improve borrowers' subjective well-being (as measured by reduced depression and borrowers' satisfaction with their financial well-being) and households' resilience (Suri et al. 2021; Brailovskaya et al. 2023; Björkegren et al. 2022), they do not significantly affect many objective welfare attributes, including income, financial health, expenditures, and savings. We extend these studies by showing that access to digital credit can enhance borrowers' welfare across a variety of mobile-phone-based and self-reported welfare measures.

Our findings also add to the growing literature on household finance and consumer protection (e.g., Hayes et al. 2021; Law and Zuo 2021; Law and Mills 2019; Christensen et al. 2019; Nicoletti & Zhu 2023; deHaan et al. 2023; Dou and Roh 2023). Regulators in developing economies have recently introduced restrictions on digital lending or are considering curbing this lending due to the limited evidence of whether it benefits or exploits borrowers in these economies (e.g., Ilako 2019; Quartz 2021; Odueso 2022). We show that access to digital lending can enhance borrowers' welfare, especially for those without external credit scores and for those using digital credit for business purposes, potentially by providing borrowers with business opportunities that were previously unavailable. Furthermore, regulators express concerns that digital lenders might practice predatory lending by not being transparent about the interest and late fees they charge (e.g., World Bank 2021; Central Banking 2021; Central Bank of Kenya ACT 2021; German Development Institute 2021; Chherawala and Vaidya 2023).[9] Our research paves the way for future research on digital lenders' disclosure policies and how to design these policies to ensure

[9] The Central Bank of Kenya (Amendment) Act, 2021, which became effective on December 23, 2021, empowered CBK to license, regulate, and supervise digital credit providers to ensure a fair and non-discriminatory marketplace for access to credit. In August of 2022, the Reserve Bank of India (RBI) announced a similar regulatory framework for digital lenders in India, which restricts digital lending to businesses that are regulated by the RBI.

that digital credit positively impacts borrowers' financial well-being.

Last, we contribute to the emerging literature on alternative big data sources. Prior studies find that these sources, including social media data, crowdsourced data, satellite imagery, and customer transaction data, significantly enhance stock price informativeness, curtail managers' opportunistic behaviors, and shape institutional lending decisions (e.g., Jame et al. 2016; Bartov et al. 2018; Zhu 2019; Dichev and Qian 2022; Kang 2023). Additionally, big data allows researchers to measure important economic constructs, such as local informational advantages, local economic activities, production disruptions, consumer foot traffic, and the impact of managerial vocal cues (Hobson et al. 2012; Mayew and Venkatachalam 2012; Kang et al. 2021; Christensen et al. 2022; Li and Venkatachalam 2022; Noh et al. 2023). We add to this literature by highlighting that by facilitating greater access to credit, big data can be a critical tool in enhancing the financial well-being of borrowers lacking traditional financial records. Furthermore, while prior research on access to credit in developing economies largely relies on self-reported survey data, our study, to the best of our knowledge, is the first to show that mobile phone data can be used to measure objective aspects of borrowers' financial well-being.

Importantly, the implications of our research may extend beyond developing economies to developed ones, which also have millions of people without access to formal financial systems. For example, in the US, about 50 million people in 2017 were unbanked (FDIC 2018; Experian 2019). While various data regulation policies restrict the use of personal data in the US and Europe,[10] the debate on whether big data can serve as a tool for financial inclusion in developed economies is still ongoing (e.g., Federal Trade Commission 2016; Brookings Institution 2018; OECD 2021). Lenders and regulators should explore innovative approaches to leverage this data

[10] For example, see California Consumer Privacy Act (CCPA) that came into effect in 2020 in the US and the General Data Protection Regulation (GDPR) that was put into effect in 2018 in Europe.

to expand access to credit while also ensuring fair lending practices.

We acknowledge that our study has several limitations. We cannot measure the impact of digital credit on borrowers who are approved for credit in the normal course of business, that is, borrowers with higher creditworthiness. Regarding external validity, although our sample is limited to borrowers in Kenya, we believe it to be representative of borrowers in developing economies without traditional credit scores from credit bureaus and those without prior experience with formal financial systems. In addition, the greater impact of digital lending on the financial well-being of borrowers who have limited access to credit and those who use digital credit for business purposes is likely to apply to other settings. However, our findings may not necessarily generalize to developing countries with different institutional and regulatory environments. Furthermore, our data is obtained from a single digital lender, which may not be representative of other digital lenders. Thus, we caution against generalizing our results to other lenders that may encourage overborrowing or may not be sufficiently transparent regarding the fees they charge.

2. Institutional Background and Related Literature

2.1 Digital Lending

Financial inclusion is one of the primary issues in sub-Saharan Africa. In 2014, this region had 350 million unbanked individuals, accounting for 17% of the global total (OECD 2015). Over the last two decades, Kenya has become the epicenter for fintech innovation in sub-Saharan Africa that aims to increase access to financial products for these individuals. In 2007, telecom companies Safaricom and Vodafone launched the M-PESA project, which allows users to deposit, withdraw, transfer money, and pay for goods and services with their mobile phones (Saylor 2012). [11] In 2021,

[11] The project quickly spread across many African countries, including Tanzania, Mozambique, DRC, Lesotho, and Ghana, and became the most successful mobile money experiment in the region (CBK 2021). By 2014, mobile money ownership was substantially higher than bank account ownership in many African countries (e.g., Francis et al 2017).

81% of the Kenyan adult population had a mobile wallet account (Central Bank of Kenya 2021). Kenya has also experienced an exponential growth in digital lending since the first digital loan service—M-Shwari—was launched in 2012 through a partnership between the Commercial Bank of Africa and Safaricom.[12]

Digital lending generally works as follows. A loan applicant downloads the mobile app of the lender and fills out a short application on their mobile phone. The lender uses an automated system to process the applicant's information and assesses an applicant's creditworthiness primarily based on the data derived from their phones. If the loan application is approved, the loan is disbursed into the applicant's mobile wallet within minutes of submission.[13] Digital loans are typically short-term, ranging from less than one month to several months, and are small—from a few to several hundred US dollars. They also bear high interest rates, often exceeding 100% on an annualized basis (e.g., Francis et al. 2017; Robinson et al. 2022).

Despite digital loans being costly, a recent survey by the Digital Financial Services Association of Kenya (formerly known as Digital Lenders Association of Kenya) indicates that approximately 55.5% of Kenyan households depend on digital lending for business financing. Furthermore, 82.4% of respondents are willing to continue borrowing digital loans to invest in their businesses, and 62% of these borrowers go to digital lenders as their first borrowing option, even before asking family and friends (Digital Lenders Association of Kenya 2021). Prior studies also show that the return on micro-enterprises in credit-constrained developing economies may be very high (e.g., McKenzie and Woodruff 2006, 2008; Karlan and Zinman 2010; Dupas and

[12] While there is no official information on the number of digital lenders in Kenya, the Central Bank of Kenya (CBK) has received 381 applications for a license from digital lenders following regulations introduced in 2022, suggesting that this is the lower bound of digital lenders operating in Kenya (https://www.businessdailyafrica.com/bd/markets/capital-markets/digital-lending-gets-more-competitive-as-10-cleared-3954370). Our Lender is licensed by the CBK.

[13] Unlike Kenya where M-PESA is nearly omnipresent, in markets such as Mexico and the Philippines, most users pick up their loans in cash at bill pay or remittance centers.

Robinson 2013, Hussam et al., 2022), which further explains borrower's willingness to take on high-interest-rate digital loans. Digital credit is particularly valuable in Kenya because most businesses in the country are informal and insufficient access to affordable financing has been recognized as a main challenge for the informal economy (Federation of Kenyan Employers 2021).

In addition to typically having shorter duration and substantially higher interest rates, digital loans have three distinctive properties relative to more traditional microfinance loans (e.g., Björkegren et al. 2022). First, because digital loans do not require in-person interactions and are disbursed and repaid electronically, they have low transaction costs. In contrast, most microfinance loans involve large transaction costs, including costs related to travel to a bank branch, the wait time at the branch, and the time spent in group meetings.[14] These costs can be prohibitive for many individuals, especially in rural areas, leading to modest take-up rates, which are typically lower than 30% (Banerjee et al. 2015b; Francis et al. 2017). In comparison, the take-up rates on digital loans are substantially higher and range from about 34% to 70% (Robinson et al. 2022). Specific to Kenya, by 2018, more than 25% of the Kenyan adult population had obtained at least one digital loan, while less than 5% obtained microfinance loans (Totolo 2018; Björkegren et al. 2022).

Second, the evaluation of loan applicants' creditworthiness is automated and relies primarily on nontraditional digital data including mobile phone data, such as how applicants use mobile devices, their travel patterns and social networks, and their transaction history (e.g., Francis et al. 2017). Because this evaluation is not based on traditional credit scores generated by credit bureaus, digital loans grant access to credit to many individuals without any prior experience with a formal financial system or a verifiable history of financial transactions.[15] Third, digital loans are almost

[14] Even if a borrower wants to convert digital loans to cash and thus needs to travel to M-PESA (mobile money) agents, these agents are substantially more widespread than bank branches (i.e., Jack and Suri 2014).
[15] Three credit bureaus are licensed by the Central Bank of Kenya: Metropol Credit Reference Bureau Limited, Credit Reference Bureau Africa (TransUnion), and Creditinfo Credit Reference Bureau Kenya Limited.

instantaneous in their approval and disbursement.

Prior research finds mixed evidence regarding the economic benefits of microfinance (e.g., de Mel et al. 2008; Kaboski and Townsend 2012; Karlan et al. 2014; Angelucci et al. 2014; Augsburg et al. 2015; Meager 2019). For example, Banerjee et al. (2015a,b) find non-transformative effects of microcredit on households' well-being, including investments, income, consumption, women's empowerment, health, and education, while Karlan and Zinman (2011) find that microcredit has an adverse effect on borrower's business activities, employees, and subjective well-being. In contrast, Imai et al. (2010), Karlan and Zinman (2010), and Kaboski and Townsend (2011, 2012) find a positive influence of microcredit on household consumption, investment, income growth, and some aspects of mental health.[16]

There are also critical differences between digital loans in developing economies and personal loans issued by fintech lenders in developed economies (e.g., Di Maggio and Yao 2021; Di Maggio et al. 2022; Berg et al. 2022; Buchak et al. 2018). Digital lenders in developing economies are substantially less regulated than fintech lenders in developed economies. Digital loans in these economies are typically smaller and of shorter duration and have substantially higher interest rates. Furthermore, while digital loan borrowers in developing economies mostly do not have access to traditional financial services, a large number of borrowers who obtain credit from fintech lenders in developed economies have access to a wide range of financial products. The former borrowers are also significantly poorer and have much higher income volatility.

Digital loans also differ substantially from payday loans in developed economies. Payday loans are only given to employed borrowers (i.e., those with a paycheck) and those with an active account in a financial institution, while digital loans are mostly issued to borrowers without formal

[16] See Banerjee (2013) and Zinman (2014) for a comprehensive review of the microfinance literature.

employment and without access to a formal financial system. Additionally, the issuance of payday loans does not rely on sophisticated credit scoring models. Like the evidence on fintech lending and microfinance, the extensive literature on payday lending is inconclusive with respect to whether this lending exacerbates or alleviates borrowers' financial challenges (e.g., Zinman 2010; Melzer 2011; Morse 2011; Bhutta et al. 2015; Gathergood et al. 2019; Skiba and Tobacman 2019).

2.2 Evidence from Prior Research on Digital Credit

To the best of our knowledge, there is still limited research on the impact of digital credit on borrowers' welfare. Utilizing survey responses of borrowers in Nigeria, Björkegren et al. (2022) find that digital loans increase borrowers' subjective well-being, which is largely attributed to reduced depression (i.e., applicants report being less depressed). In contrast, they do not find that access to credit significantly affects any objective aspect of borrowers' welfare, including income, financial health, expenditures, or women's economic empowerment. There is also no evidence that larger loans have a stronger influence on either objective or subjective welfare attributes.

Suri et al. (2021) explore M-Shwari, one of the most popular digital loans in Kenya, and rely on administrative and survey data. The authors find that access to digital credit decreases the likelihood that households have to forgo an expense in the face of negative income shocks, thus improving households' resilience. However, the study finds no evidence that access to digital credit positively affects other welfare outcomes, such as savings and asset ownership.

Brailovskaya et al. (2023) examine a digital credit product called Kutchova in Malawi. Relying on self-reported borrower data, the authors find a positive effect of this product on one subjective measure of financial well-being ("are you satisfied with your financial well-being?"), but not on subjective measures of financial security, as well as no evidence of a positive impact on objective financial well-being measures, such as savings and borrower resilience. The authors complement these analyses with an intervention that enhances borrowers' financial literacy because the lender's late fees were not properly disclosed to borrowers. This intervention was successful in educating borrowers about fees and other risks associated with Kutchova loans and marginally improved loan repayments. However, surprisingly, it made the product more attractive to borrowers and increased loan demand, leading to overall higher default risk.

Although these studies suggest that digital loans have a rather modest effect on borrowers' welfare, in a recent survey of digital credit in developing economies, Robinson et al. (2022) highlight that this evidence is based on only a handful of products in specific markets and therefore call for more work in the digital credit area. To better understand the welfare impacts of digital credit, we examine a large sample of digital loans provided by the Lender in Kenya. In contrast to prior studies, we measure objective aspects of borrowers' financial well-being primarily using their mobile phone data. We supplement these mobile-based welfare measures with income and employment data, as self-reported by borrowers in loan application surveys.

2.3 Institutional Setting

We obtained data from the Lender that leverages advanced data science to provide digital loans to individuals in developing economies. The Lender acquires customers using a mix of offline and digital marketing tools and digital onboarding channels, such as radio campaigns, social media advertising campaigns, SMS campaigns, and referrals. Customers apply for digital loans through the Lender's mobile app, in which they submit their loan applications, fill out a loan application survey, and grant the Lender access to their mobile phone data in accordance with the Lender's Privacy Policy. Utilizing these data and machine-learning algorithms, the Lender generates a credit score for each applicant to decide whether credit should be extended. Rejected borrowers can reapply after a 30-day grace period.

Customers typically apply for the Lender's loans to satisfy capital needs for their small informal businesses, such as grocery and clothing stalls, and farming, as well as to cover medical, educational, housing, and transportation expenses. According to the Lender's internal analyses of their loans in Kenya, the average loan amount is 7,610.78 Kenyan shillings (KSH), which is equivalent to $75.35; the maximum first loan amount is 4,000 KSH (equivalent to $39.6) and the maximum loan limit is KSH 50,000 (equivalent to $495.6). The average loan duration is 27.6 days and the average interest rate is 13.67% over this duration (APR of 180.78%).[17] The Lender also charges a one-time late fee of 8% of the total amount outstanding if a borrower fails to repay seven days past the due date; no additional late fees are charged and the interest rate does not accumulate beyond the original due date. Borrowers are informed of the interest rate and late fees at the loan application stage before a customer accepts a loan offer.

The overall portfolio default rate of the Lender, defined as the percentage of loans that are not paid one year past the due date, is relatively low at 5%.[18] The Lender reported defaulted borrowers to credit bureaus prior to April 2020 but stopped doing so afterward, in line with the CBK's directive that suspended reporting of borrowers' negative credit information as part of the COVID-19 relief efforts.[19] The Lender employs several approaches to motivate timely loan payments. First, borrowers can apply again only after they repay their previous loan in full. Because the Lender is a large player in the digital market in Kenya, borrowers might not want to jeopardize their ability to rely on the Lender in case of future shocks to their income, such as a loss of employment. This policy of providing future credit conditional on prior loan repayment also

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[17] To convert Kenyan shillings to US dollars, we use the average exchange rate in 2018, which is the first year of our sample period (1 USD = 101 KSH).

[18] The default rates of the other large digital lenders in Africa range from 7% to 27% (Robinson et al. 2022).

[19] The CBK's directive covers all loans under 5 million KSH, which means that no negative credit information is reported with respect to any digital loan, given that these loans are very small. With respect to positive credit information, the Lender no longer reports it to credit bureaus because outstanding credit with digital lenders may adversely affect borrowers' credit score and their ability to borrow from banking institutions.

helps borrowers to avoid overborrowing. Second, the Lender accounts for borrowers' payment history when determining future loan amounts and interest rates, with the loan amount typically increasing for the subsequent loan by 1,000 to 3,000 KSH (equivalent to $9.9 to $29.7) for well-performing borrowers. Third, the lender has built a reputation as a reliable digital credit provider in Kenya. In contrast to many other lenders, the Lender does not use unethical shaming techniques to enforce repayments, such as notifying a borrower's friends and family when the borrower defaults. Furthermore, digital loans provided by the Lender often help borrowers in times of crisis, such as a medical emergency or acute business liquidity needs. Therefore, borrowers value their relationship with the Lender and reciprocate via loan repayments.[20]

To improve borrowers' understanding of the lending process, the Lender also provides educational tutorials. Every new customer receives an in-app financial-education content series, which provides financial tips on a weekly basis to help customers navigate the borrowing experience and make a plan for payment. In addition, the Lender provides a learning center in the app available to every customer, offering financial education content on topics like setting savings goals, building a family budget, and better managing overall financial standing. Importantly, the Lender does not sell any other products to the borrowers (i.e., there are no cross-selling opportunities available to the Lender) and does not sell borrower data to third parties.

3. Data, Sample, and Variables

3.1 Data Sources

We received from the Lender data that contains information on (1) the loan application, such as the application date, and terms if the loan has been approved; (2) the mobile phone data of the

[20] Drexler and Schoar (2014) highlight the importance of lending relationships and reciprocity by showing that when relationship loan officers are on leave, borrowers are more likely to miss payments or default. In addition, as credit bureaus' coverage in Kenya is limited, especially since April 2020, relationship-switching costs for borrowers are very high, further supporting the importance of retaining a relationship with the Lender (Sutherland 2018).

applicant, such as the connections of the applicant and location data; and (3) the applicant's self-reported monthly income, employment status, and loan purpose from the loan application survey. We obtain mobile phone data and loan application survey information as collected by the Lender on the loan application date. We also receive an applicant's credit score, as generated by the Lender's credit scoring model. All data items we have received are fully de-identified and anonymized, such that identifiable details of individual borrowers are not available to us. The Lender obtains all appropriate consents related to customer data from borrowers and users of its products and adheres to domestic and global data-handling and data protection standards.

3.2 Sample Selection

We investigate whether digital loans have financial well-being implications for borrowers. An inherent empirical challenge in addressing our question is endogeneity; that is, unobservable borrower characteristics explain both the Lender's decision to issue a loan and a borrower's future welfare. In other words, a concern is that the Lender's credit scoring model identifies borrowers who are expected to achieve positive economic outcomes in the future, regardless of whether they have access to digital loans. To address this identification challenge, we leverage the Lender's experiment that *randomly* approves loan applications that *would have otherwise been rejected* based on the borrower's credit score. To implement the random assignment, the Lender utilizes a standard random number generator available in Scala (i.e., scala.util.Random, Scala version 2.12). Borrowers are not informed that their application is randomly approved as part of the experiment.

This type of experiment, often referred to as the reject inference methodology, is a common practice in the consumer credit industry because it helps lenders to assess the accuracy of their credit models and reduce bias in training data for future modeling (e.g., Crook and Banasik 2004; Banasik and Crook 2007; Bücker et al. 2013). The Lender solely designed and conducted the experiment and collected the data during its normal business operations. We were not involved with the Lender's experiment and conducted our research using the data provided by the Lender following the completion of the experiment.[21]

Borrowers randomly selected and approved by the Lender serve as a treatment group in our sample. Because we obtain information collected by the Lender on loan application dates only, to measure changes in borrowers' well-being, we restrict our sample to borrowers who applied for more than one loan from the Lender. We begin our sample with 23,946 treatment borrowers with multiple loan applications over our sample period from April 2018 to January 2022 (the sample period starts when the Lender initiated the experiment). For each treatment borrower, we collect the initial loan, which is the first loan randomly approved by the Lender, and the borrower's last loan application, which can be approved or rejected.[22] We focus on the last loan application to measure changes in borrowers' financial well-being over a longer horizon because of the loans' short maturity. Given that our sample only includes borrowers who applied for multiple loans, our sample does not include borrowers who defaulted and thus cannot apply for a subsequent loan according to the Lender's policy (as discussed in Section 2.3).

Because treatment borrowers are randomly approved for the experiment by the Lender, any difference between the treatment and control borrowers – those whose loan applications were rejected by the credit model and were not selected to receive credit as part of the experiment – should be attributed to the treatment (i.e., access to digital credit). However, we can measure changes in borrowers' financial well-being only if a borrower decides to apply for a subsequent loan after her loan application was approved (treatment borrowers) or denied (control borrowers),

[21] Over our sample period, rejected borrowers who are randomly approved represent a negligible percentage of all rejected borrowers.

[22] Our results are robust to the inclusion of all subsequent loans rather than just the last loan.

raising self-selection concerns. To mitigate these concerns, we match treatment and control borrowers based on their creditworthiness and the dates on which they apply for digital loans. Specifically, we match a treatment borrower's initial loan with a rejected loan application of a control borrower and the treatment borrower's last application with a subsequent application of the control borrower, conditional on the control borrower not obtaining a loan from the Lender prior to this subsequent loan's application date. We perform the matching with replacement according to the following criteria: (1) the loan application date for a control borrower is within 30 days of the *initial* loan date for the treatment borrower; (2) a control borrower's credit score on the loan application date, as estimated by the Lender's credit scoring model, is within 0.05 range of the treatment borrower's credit score on the *initial* loan date; and (3) a control borrower's subsequent loan application date is within 30 days of the *last* loan application date for the treatment borrower. In Section 4.2.1, we discuss additional analyses that further address self-selection issues.

We successfully match 5,023 treatment borrowers with 4,352 control borrowers, such that our final sample includes 5,023 treatment-control pairs (our results are robust to matching without replacement). Because we incorporate two loan applications per borrower for each matched pair, our final sample consists of 20,092 loan applications.[23] Our treatment borrowers obtain 4.5 loans on average over the 158-day period between their initial and last loan application dates. Treatment loans have on average an amount of 3,675.00 KSH, which is equivalent to \$36.38, a duration of 27.44 days, and an interest rate is 15.00% over the loan duration (APR of 199.53%). The lower average loan amounts and higher interest rates for our sample of borrowers relative to these statistics for all loans in Kenya issued by the Lender are consistent with randomly approved

[23] An important benefit of retaining one observation in each of the pre- and post-period per borrower is that it alleviates a concern regarding potential serial correlation in difference-in-differences estimation when multiple observations are incorporated in the pre- and post-period (Bertrand et al. 2004).

borrowers having higher credit risk and therefore being rejected based on their credit score.

3.3 Variable Measurement and Descriptive Statistics

Emerging literature in computer science and developmental economics relies on mobile phone data to measure poverty and wealth at the individual level (e.g., Blumenstock et al. 2015; Blumenstock 2014, 2016, 2018a,b; Aiken et al. 2022, 2023).[24] These studies convincingly show that individuals' past mobile phone records, such as the history of transactions and patterns of travel, can be employed to measure their financial welfare.[25] Therefore, to measure our sample borrowers' welfare, we follow this novel approach and use mobile phone data. We supplement this data with borrowers' employment status and monthly income, as self-reported by borrowers in loan application surveys, because combining mobile phone data with survey-based measures can help estimate individuals' financial well-being more accurately (e.g., Aiken et al. 2022). We next discuss these measures in detail.

3.3.1 Monetary Transactions

Motivated by recent studies that utilize SMS data to estimate individuals' wealth (Blumenstock 2014, 2016, 2018a,b; Blumenstock et al. 2015; Aiken et al. 2022, 2023), we construct two measures of monetary transaction volumes. Our first measure is the monetary amounts mentioned in the borrower's SMSs, averaged per transaction (*SMS Amt*).[26] Our second measure is based on M-PESA, which is a dominant mobile banking service app in Kenya that allows users to store and transfer money through their mobile phones. We estimate the average daily M-PESA balance mentioned in the borrower's text messages (*SMS MPESA Amt*). These two

[24] As of 2018, 83% of adults in developing economies have a mobile phone (Brookings 2019), which allows for a very extensive coverage of households in these economies.

[25] Individual phone data can even be aggregated to accurately measure regional and national wealth and create detailed maps of the geographic distribution of wealth (e.g., Blumenstock et al. 2015; Aiken et al. 2022; Chi et al. 2022).

[26] We base *SMS Amt* on borrowers' incoming SMS messages. Monetary amounts in text messages are often related to invoice messages or transaction completion messages and are more objective when they are received by a borrower (that is, monetary amounts can be more easily manipulated when sent by a borrower).

outcome measures are generated by textually parsing each applicant's SMS texts available on their mobile phones as of the loan application date.[27]

Because loans are disbursed immediately after approval, and borrowers tend to use the loan funds on the loan application date according to the Lender's analysis, we exclude SMS messages received within 24 hours after the loan application for the measurement of both *SMS Amt* and *SMS MPESA Amt*. In the case of the *SMS Amt*, excluding messages received within these 24 hours helps us eliminate potential mechanical increases in the average transaction amount resulting from borrowers' immediate use of loan funds. With respect to *SMS MPESA Amt*, M-PESA sends texts to borrowers when their monetary balance changes, such as balance changes after the completion of a transaction. Therefore, by removing the 24-hour period, we can offset changes in the M-PESA balance due to the loan disbursement and subsequent use of funds by the borrower. Furthermore, for the estimation of the *SMS Amt* measure, we exclude SMSs received from the Lender to remove the impact from loan-related messages. Detailed variable definitions are reported in Appendix A.

3.3.2 Mobility

With billions of individuals carrying devices with fine-grained location information, global positioning system (GPS) information and network technologies have enabled researchers to better measure human mobility in developing economies (Gonzalez et al. 2008; Kwok 2009; Blumenstock 2012, 2016; Singh et al. 2015; Chi et al. 2022). Prior research suggests that mobility reflects an individual's wealth and is one of the strongest factors in predicting poverty (e.g., Blumenstock et al. 2015; Aiken et al. 2022; Deng et al. 2021; Moro et al. 2021). For instance, using mobile phone data, Frias-Martinez and Virsesa (2012) show that wealthier citizens travel to

[27] Mobile money is the most used and dominant financial service in Kenya (Central Bank of Kenya 2021). For example, in 2018, Kenyans transacted nearly half the equivalent of the country's gross domestic product (GDP) through their mobile phones (Central Bank of Kenya 2018). Therefore, borrowers' SMSs should reflect most of the monetary transactions they conduct.

more locations and for longer distances. Greater mobility may also be indicative of an individual's ownership of transportation assets (Blumenstock et al. 2015). Furthermore, Llorente et al. (2015) and Almaatouq et al. (2016) find that individuals' movement can reveal information about employment status: the unemployed tend to be less mobile and spend more time at their home location. Following this stream of literature, we employ two proxies to capture borrowers' mobility. First, we count the number of unique cell towers the borrower passes during the 30-day period preceding the loan application date (*#Cell Towers*).[28] Second, we count the number of cities the borrower has traveled to during this period *(#Cities)*.

3.3.3 Social Networks

Prior research shows that patterns of social networks derived from mobile phone data can be used to infer individuals' well-being (Eagle et al. 2010; Blumenstock et al. 2015; Blumenstock 2016; Luo et al. 2017; Aiken et al. 2022, 2023; Blumenstock et al. 2022; Chi et al. 2022). Social ties facilitate job opportunities and salary negotiations (Granovetter 1973; Burt 1992; Seidel et al. 2000), job mobility (Podolny and Baron 1997), entrepreneurial process (Dubini and Aldrich 1991), upward income mobility (Chetty et al. 2022), and connects people with complementary resources and information (Burt 1992). Thus, more extensive and stronger networks are likely to lead to borrowers' greater business opportunities, and in turn, reflect their greater financial well-being.[29]

We employ three complementary proxies for borrowers' social networks. Our first measure

[28] We acknowledge that due to data limitations the measurement window for mobility measures differs from that for measures of monetary transactions and social networks (discussed subsequently), with the latter two sets of measures being estimated based on all information accumulated on the borrower's phone prior to the loan application date (versus mobility measures that are based on information accumulated over the 30-day period prior to this date). Nevertheless, our research design captures changes in financial welfare of treatment borrowers from the initial to the last loan applications relative to respective changes for control borrowers, such that the estimation period of welfare measures should not affect our findings.

[29] While not the focus of our paper, networks also capture connected circles of friends, families, or colleagues, where people rely on mobile phone networks for support in cash or in kind (such as mobile money) in the aftermath of unexpected economic shocks, suggesting networks' important role in increasing financial resiliency (e.g., Blumenstock et al. 2016).

relies on the total number of incoming and outgoing text messages stored on the borrower's mobile phone (*SMS Count*). Similar to the construction of *SMS Amt*, we exclude SMS messages received from the Lender as well as SMS messages received within 24 hours after the loan application to remove the impact on *SMS Count* from the messages related to loan disbursements and the immediate use of loan funds. Further reflecting on the extent of social networks, the second measure counts the total number of unique phone numbers in the borrower's contacts list (*Network Ppl Number*). The third network measure attempts to capture the economic strength of a borrower's network because economically stronger networks are likely to be more effective in facilitating business opportunities and providing financial support (e.g., Blumenstock et al. 2016; Chetty et al. 2022). To measure the strength of a borrower's network, we estimate the proportion of the people in their network that repaid loans to the Lender on time out of the total number of network people (*Network Repaid*). All measures are estimated on the loan application date.

3.3.4 Self-Reported Monthly Income and Employment Status

Last, we follow prior studies that employ surveys to measure individuals' welfare (e.g., Kaboski and Townsend 2012; Imai and Azam 2012; Bruhn and Love 2014; Banerjee et al. 2015a,b). We incorporate a measure of a borrower's monthly income (*Monthly Income*) and an employment status (*Employed*), which is an indicator variable that takes the value of one if a borrower is employed or self-employed, and zero otherwise. Both measures are based on borrowers' self-reported data in the loan application survey.

3.3.5 Descriptive Statistics

Table 1 presents descriptive statistics.[30] With respect to *monetary transaction* proxies, the

[30] To better assess an economic magnitude of continuous variables used in our analyses, we discuss their mean values based on their original values before taking the log-transformation. However, because these variables are log-transformed in the empirical analyses, we report the descriptive statistics for log transformed values in Table 1.

mean values of *SMS Amt* and *SMS MPESA Amt* are 1,346 and 2,289 Kenyan shillings, respectively, which correspond to $13.3 and $22.6 US dollars. In terms of our measures for *mobility*, the average borrower in our sample passes 3.49 cell towers (*#Cell Towers*) and travels to 1.74 cities (*#Cities*) in the 30-day period prior to the loan application date. Regarding our proxies for *social networks*, borrowers have on average 493 text messages on their phones (*SMS Count*). Borrowers also have 203 people in their contacts list (*Network Ppl Number*). The mean values of a borrower's network economic strength indicate that 65% of people in the borrower's network repaid their loans from the Lender on time *(Network Repaid)*. Last, the average monthly income (*Monthly Income*) is 28,490 Kenyan shillings, which is the equivalent of $282.[31] Also, 42% of borrowers are either employed or self-employed (*Employed*). In addition, following prior research, we estimate two measures associated with digital lending (Björkegren et al. 2022; Robinson et al. 2022). The first measure proxies for the strength of a borrower's relationship with the lender based on the duration of this relationship (*Days First App*). The mean value of *Days First App* is 496, implying that 496 days elapsed since a borrower's first loan application with the Lender. The second measure is the credit score estimated by the Lender's credit scoring model on the loan application date (*Lender Credit Score*); the mean value of this variable is 0.79.

4. Results

4.1 The Effects of Digital Lending on Financial Well-Being

To isolate the effect of digital lending on borrowers' financial well-being, we employ a DiD research design using the following specification:

$$\begin{aligned} \textit{Financial Well-Being} = \beta_0 + \beta_1\, \textit{POST} + \beta_2\, \textit{POST} \times \textit{TREAT} + \textit{CONTROLS} + \\ \textit{Borrower fixed effects} + \textit{Year-Month fixed effects} + u \end{aligned} \qquad (1)$$

[31] The average monthly income in Kenya was $586.1 in 2018. The substantially lower average monthly income for our sample borrowers is consistent with digital loans being issued primarily to low creditworthiness borrowers without access to the formal financial system.

where *Financial Well-Being* is one of the proxies for a borrower's monetary transactions, mobility, social networks, *Monthly Income*, or *Employed*, as defined previously. *POST* is an indicator variable that takes the value of one for the last loan application of the treatment borrowers and their matched loan applications of the control borrowers, where initial loans for treatment borrowers and their matched loan applications of control borrowers are assigned the value of zero. *TREAT* is an indicator variable that takes the value of one for treatment borrowers, and zero otherwise. By design, the mean values of *TREAT* and *POST* are 0.5. We expect β_2 to be positive if access to a digital loan increases a borrower's financial welfare. We control for the strength of a borrower's relationship with the Lender (*Days First App*) and its creditworthiness (*Lender Credit Score*).[32] We include borrower fixed effects to control for unobservable time-invariant differences between treatment and control borrowers, thus further mitigating self-selection concerns. We further include year-month fixed effects to control for macroeconomic attributes (e.g., unemployment). We also cluster standard errors at the borrower and year-month level.[33] Our research design allows us to compare the changes in the financial well-being of treatment borrowers between their initial and last loan applications to those of control borrowers.[34]

We start by exploring whether access to digital lending affects borrowers' monetary transaction volume. Table 2 reports the results of these analyses, where we estimate Model (1) without and with control variables. In columns (1) and (2), we employ the *SMS Amt* measure and find in both specifications a positive and significant coefficient on the interaction term *POST* TREAT*, suggesting that access to digital lending increases the volume of borrowers' monetary

[32] We winsorize all continuous variables at the 1% and 99% level to mitigate potential influence of data outliers.
[33] Our results are robust to excluding borrower fixed effects and to performing the analyses with clustering standard errors at borrower level only.
[34] We recognize that we are unable to perform a pre-trend analysis in our DiD estimation because we have a limited number of loan applications in the pre-period for both treatment and matched control borrowers. However, we believe that the random approval in the experiment of loan applications that would have been rejected otherwise alleviates the concern over the difference in pre-trends between treatment and control borrowers.

transactions. Economically, in the post-period, average monetary amounts per transaction are higher by 14.9% for treatment borrowers relative to control borrowers. In columns (3) and (4), we find similar results using *SMS MPESA Amt*. Economically, in the post-period, treatment borrowers have an 8.2% higher average daily M-PESA balance relative to that of control borrowers.[35]

Next, we examine the impact of digital lending on borrowers' mobility and report the results in Table 3. Relying on *#Cell Towers,* in columns (1) and (2), we show that access to digital lending enhances borrowers' mobility: the coefficient on *POST*TREAT* is positive and significant. Economically, in the post-period, treatment borrowers pass 63.6% more cell towers relative to control borrowers.[36] In columns (3) and (4), we report similar results when using *#Cities*. In the post-period, treatment borrowers travel to 9.4% more cities relative to control borrowers.[37]

Our following analyses based on social network measures corroborate previous findings (Table 4). In columns (1) and (2), we explore the effect of digital credit on the extensiveness of borrowers' social networks by employing *SMS Count*. The positive and significant coefficient on *POST*TREAT* suggests that access to digital credit leads to more extensive networks. Economically, in the post-period, treatment borrowers have 26.8% more SMS messages relative to control borrowers. In columns (3) and (4), we find similar results using *Network Ppl Number*. Economically, in the post-period, treatment borrowers have 2.9% more people in their networks

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[35] We measure economic significance based on specifications that includes control variables for all our tests. Furthermore, the sum of the coefficients on *POST×TREAT* and *POST* is positive and statistically different from zero in both columns (2) and (4) (p-value = 0.000 and 0.005, respectively), which indicates that treatment borrowers have higher average monetary amounts per transaction and higher average daily M-PESA balance in the post- relative to the pre-period.

[36] The high economic significance of this effect is explained by a relatively very low number of cell towers in Kenya, as Kenya is substantially lagging behind in the development of telephone and internet connection (Robertson 2020). Our sample borrowers use on average 3.49 cell towers, with 66.6% higher number of cell towers corresponding to 2.21 additional cell towers used by treatment borrowers.

[37] Similar to the analyses in Table 2, the sum of the coefficients on *POST×TREAT* and *POST* is positive and statistically different from zero in columns (2) and (4) (p-value = 0.000 and 0.000, respectively). This evidence suggests that treatment borrowers have greater mobility in the post- relative to the pre-period based on both mobility measures.

relative to control borrowers. In columns (5) and (6), we focus on the economic strength of a borrower's network using *Network Repaid* and find that access to digital credit leads to stronger networks. Economically, in the post-period, treatment borrowers have a 5.6% higher proportion of people in their network who paid their digital loans on time relative to control borrowers.[38]

Last, we supplement the preceding analyses utilizing mobile-phone-based measures of borrowers' financial well-being with borrowers' monthly income and employment outcome measures collected from the loan application survey. As we report in columns (1) and (2) of Table 5, the coefficient on *POST*TREAT* is positive and significant, which indicates that access to digital loans increases borrowers' monthly income. In terms of economic significance, relative to control borrowers, treatment borrowers have 20.8% higher monthly income in the post-period.[39] In columns (3) and (4), we use *Employed* as an outcome measure and show that access to digital credit improves borrowers' employment outcomes.[40] Economically, in the post-period, treatment borrowers are 23.5% more likely to be employed or self-employed relative to control borrowers.[41]

Collectively, our findings suggest that digital lending improves borrowers' well-being across all mobile-phone-based measures we explore, including borrowers' monetary transactions, mobility, and social networks. These findings are reinforced by the evidence that access to digital loans increases borrowers' monthly income and leads to a higher likelihood of employment.

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[38] The sum of the coefficients on *POST×TREAT* and *POST* is positive and statistically different from zero in columns (2), (4), and (6) (p-value = 0.000, 0.094, and 0.011, respectively), suggesting that treatment borrowers have more extensive and stronger networks in the post- relative to the pre-period.

[39] The sum of the coefficients on *POST×TREAT* and *POST* is positive and statistically different from zero in column (2) (p-value = 0.000), suggesting that treatment borrowers have higher income in the post- relative to the pre-period.

[40] We continue to use the OLS model to estimate the effects on *Employed* because the Logit model does not converge due to our tight fixed effect structure. Nonetheless, our results continue to hold when using the Logit model without fixed effects.

[41] The negative and significant coefficients on *POST* in columns (3) and (4) suggest that control borrowers have lower employment probability in the post period, potentially due to not being able to get access to credit. Importantly, the sum of the coefficients on *POST×TREAT* and *POST* is positive and statistically different from zero in column (4) (p-value = 0.000), suggesting that treatment borrowers are more likely to be employed in the post- relative to the pre-period.

4.2 Robustness Tests

4.2.1 Self-Selection Issue

To address self-selection concerns due to borrowers' decision to apply for subsequent loans, our primary analyses rely on the matched sample of the initial and subsequent loan applications of the treatment and control borrowers and employ a tight fixed effect structure. To further address these concerns, we use data obtained through the Lender's mobile app, which is installed by the borrower during the loan application process. Because the App data is collected over time *regardless of* whether a borrower applies for a subsequent loan, the analyses based on this data significantly mitigate these self-selection concerns. The App data is collected by the Lender on a monthly basis and allow us to reconstruct monetary transaction and mobility welfare measures used in our tests in Tables 2 and 3 (the App data does not allow to estimate social network measures as well as borrowers' income and employment, which are obtained from self-reported surveys).[42]

While App data analyses are unaffected by borrowers' decision to apply for subsequent loans, we acknowledge that borrowers may select to uninstall the Lender's app. To mitigate this concern, we match treatment and control borrowers based on their creditworthiness, loan application dates and subsequent App data collection dates. Similar to our main sample, for each treatment borrower we collect the initial loan, which is the first loan randomly approved by the Lender, and match this loan with a rejected loan application of a control borrower. For each of these matched pairs, we collect the monthly App data for the 12 subsequent months (if available) and match the last available App data of the treatment borrower with the subsequent App data of the control borrower, conditional on the control borrower not obtaining a loan from the Lender prior to the collection date of the subsequent App data.

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[42] Although the data is collected monthly, some months are missing for some borrowers, potentially due to borrowers turning off internet data connectivity on their device.

We perform the matching with replacement according to the following criteria: (1) the loan application date for a control borrower is within 30 days of the *initial* loan date for the treatment borrower; (2) a control borrower's credit score on the loan application date, as estimated by the Lender's credit scoring model, is within 0.05 range of the treatment borrower's credit score on the *initial* loan date; and (3) a control borrower's subsequent App data is collected within 30 days of the collection date of the treatment borrower's *last* App data. We begin the App data sample with 42,186 treatment borrowers for which the Lender collected App data for more than one month following the first loan application over our sample period from April 2018 to January 2022.[43] We successfully match 10,155 treatment borrowers and construct 10,155 matched treatment-control pairs. As we retain two observations per borrower for each matched pair, the App data sample consists of 40,620 observations. The average number of days between the initial loan application date and the last App data collection date is 235 days.

Panel A of Table 6 reports descriptive statistics for the App data sample. The mean values of *SMS Amt* and *SMS MPESA Amt* are 1,299 and 1,724 Kenyan shillings, respectively, which are equivalent to $12.86 and $17.6 US dollars.[44] Regarding the mobility features, average borrowers pass 3.9 cell towers (*#Cell Towers*) and travel to 1.69 cities in the 30-day period before the App data is collected. The mean value of *Days First App* is 309, implying that 309 days elapsed since a borrower's first loan application with the Lender.

We re-estimate Model (1) using the App data sample and report the results of these analyses in Panel B of Table 6. We do not control for *Lender Credit Score* because the credit score is

[43] We start with a larger number of treatment borrowers than the starting number of borrowers in the main sample because the App data is collected on a monthly basis, so we do not restrict our sample to borrowers who applied to multiple loans from the Lender to measure changes in borrowers' well-being.

[44] Similar to our main analyses, we discuss the mean values of continuous variables based on their original values before taking the log-transformation.

estimated by the Lender only when borrowers apply for a loan and thus is not available when the App data is collected subsequent to a loan's application. Across all four well-being measures, we continue to find a positive and significant coefficient on the interaction term *POST*TREAT*, consistent with our previous findings that digital lending enhances borrowers' monetary transaction volume and mobility. Economically, in the post-period, relative to control borrowers, treatment borrowers have average monetary amounts per transaction that are higher by 24.1% and 4.4% higher average daily M-PESA balance. Treatment borrowers also pass 39.1% more cell towers and travel to 4.6% more cities in the post-period. These findings based on App data that is collected continuously suggest that the selection issue in our primary analyses related to borrowers' decision to apply for subsequent loans is unlikely to explain the effect of digital lending on borrowers' welfare.

Furthermore, the App data–based analyses allow us to shed some light on whether the impact of digital loans on borrowers' well-being is short-term. While the average number of days between the initial and last loan application in our main sample is 158 days, the average number of days between the initial loan application date and the last App data collection date is 235 days, which suggests that the welfare effects we observe are sustained over a longer time. To further support this inference, in untabulated analyses we require the borrowers in the App data sample to have at least 9 months of data after the first loan application date (in this subsample there are on average 310 days between the initial loan application date and the last App data collection date). We continue to find similar results across all welfare measures.

4.2.2 Heterogeneous Treatment Effects

Recent studies suggest that DiD estimates with two-way fixed effects can be biased when the treatment effects exhibit heterogeneity over time and across groups (e.g., Baker et al. 2022;

Goodman-Bacon 2021).[45] While we employ a matched sample DiD research design where the treatment effect is homogeneous for each matched pair, the timing of treatment is staggered across the matched pairs. Therefore, we follow de Chaisemartin and D'Haultfoeuille (2020) and examine whether the negative weights have a significant influence on our DiD estimates. We find that the negative weights are less than 0.5% for all of our main analyses (untabulated). We further estimate (1) the minimal value of the standard deviation of the treatment effect across the treatment groups and time periods under which our DiD estimate and the average treatment effect on the treated could have opposite signs, and (2) the minimal value of the standard deviation of the treatment effect across treatment groups and time periods under which our DiD estimate could be of a different sign than the treatment effect in all the treatment groups and time periods (de Chaisemartin and D'Haultfoeuille 2020). We show that our DiD estimate falls within the acceptable distribution using the two standard deviation measures. We conclude that treatment effect heterogeneity is unlikely to influence our findings.

5. Cross-Sectional Variations in the Effect of Digital Lending

To further explore the impact of digital credit on financial well-being, we focus on borrower and loan characteristics that are likely to heighten this impact. We start with borrowers' ability to access credit. Bruhn and Love (2014) show a more sizable effect of access to credit on borrowers in areas with lower preexisting bank penetration. Di Maggio et al. (2022) find that the "invisible primes" (i.e., borrowers with low credit scores and short credit histories) are most positively affected by fintech lending. Similarly, Balyuk (2022) finds that the effect of fintech loans is more pronounced for more credit-constrained borrowers. Building on these studies, we expect borrowers

[45] The staggered DiD with two-way fixed effects estimate the weighted sum of the treatment effects in each time and group level. If already treated units serve as controls, their treatment effects will be subtracted from the DiD estimate, leading to negative weights. The negative weights can cause estimated treatment effects to have the opposite sign of the average treatment effect on the treated (Goodman-Bacon 2021).

with more limited access to credit to be affected to a greater extent by digital loans.

To test this prediction, we rely on TransUnion data to identify whether a borrower has a credit score from a credit bureau, as having an external credit score should reduce information asymmetry and allow borrowers greater access to credit (e.g., Pagano and Jappelli 1993; An and Chan 2008; Karlan and Zinman 2010; Campello et al. 2011). We partition our sample based on whether a borrower has *TransUnion*'s credit score on the day of its first loan application and re-estimate Model (1) for all financial well-being measures we employ in Tables 2–5.[46] As we report in Panel A of Table 7, for eight out of the nine measures, the coefficients on the interaction term *POST x TREAT* are positive and significant in the *Without Credit Score* subsample. Furthermore, for *SMS Count*, *Network Repaid, Monthly Income,* and *Employed*, the coefficients on *POST x TREAT* are significantly higher for the *Without Credit Score* partitions than for the *With Credit Score* partitions (p-value = 0.000, 0.012, 0.051, and 0.000, respectively). This evidence suggests that digital loans have substantial welfare potential for "invisible" borrowers.

We also perform the analyses using a borrower's age as an additional proxy for access to credit because younger borrowers have shorter credit histories and are typically more likely to be credit rationed (e.g., Jappelli 1990; Hayashi 1985). We do not find that younger borrowers benefit to a greater extent from digital loans (untabulated). Women also typically have more limited access to credit in developing economies (e.g., Diagne et al. 2000; Banerjee 2013). Similar to Karlan and Zinman (2011) and de Mel et al. (2009), we do not find that the impact of the access to credit on financial well-being is more pronounced for female borrowers (untabulated).

In the next set of analyses, we explore how the loan purpose—whether the loan is obtained

[46] Although we measure access to credit based on TransUnion data only, there is typically a substantial overlap in the coverage of different credit bureaus (Forbes 2021). Moreover, TransUnion is the dominant credit bureau in Kenya, further mitigating concerns associated with the measurement of the access to credit based on the TransUnion data only.

for business or personal purpose (for example, for consumption or healthcare needs)—is associated with financial well-being. Prior literature in microfinance emphasizes the importance of loans for productive purposes, such as investments and business creation, and shows that these loans are more likely to decrease borrowers' poverty and increase their income relative to loans for nonproductive purposes (Imai and Azam 2012; Banerjee et al. 2015; Attanasio et al. 2015). Motivated by this evidence, we expect that digital loans used for business purposes have a stronger effect on borrowers' welfare relative to other loans. To test this prediction, we partition our sample based on whether a borrower self-reports in the loan application survey that the loan is obtained for a business or personal purpose. As we report in Panel B of Table 7, we find evidence consistent with our expectations: for all well-being measures except *SMS MPESA Amt*, the coefficients on the interaction term *POST x TREAT* are positive and significant in the *Business Purpose* partitions. For *#Cell Towers, Network Repaid, Monthly Income*, and *Employed* the coefficients on *POST x TREAT* are also significantly higher for the *Business Purpose* than for the *Personal Purpose* partitions (p-value = 0.011, 0.008, 0.019, and 0.096, respectively). Importantly, these loan-purpose-based findings suggest that digital loans potentially increase borrowers' financial well-being by providing borrowers with business opportunities not available to them otherwise.

In the final set of our cross-sectional tests, we focus on the amount of digital credit obtained by borrowers. So far, the primary tests in Tables 2–5 as well as in cross-sectional tests in Panels A and B of Table 7 suggest that access to digital credit enhances borrowers' welfare. These findings motivate us to predict that the beneficial effect of digital credit will be stronger when borrowers have access to a greater amount of credit. However, we acknowledge that larger loan amounts may indicate overborrowing, thus leading to adverse consequences on their welfare. We examine these arguments by partitioning our sample based on whether a treatment borrower's total amount of digital credit from the Lender is above or below the sample median.[47] As we report in Panel C of Table 7, we find that, for eight out of the nine well-being measures we employ, the coefficients on the interaction term *POST x TREAT* are positive and significant in the *High Loan Amount* partitions. Furthermore, for all these measures except *#Cities* and *Network Repaid*, the coefficients on *POST x TREAT* are significantly higher for the *High Loan Amount* partitions than for the *Low Loan Amount* partitions. In untabulated analysis, instead of partitioning our sample based on the total loan amount, we partition it based on the total number of digital loans obtained by treatment borrowers and find similar results. Thus, the effect of digital credit is more pronounced when borrowers receive greater funds, mitigating concerns associated with overleveraging.

Overall, our analyses in Table 7 reinforce the positive financial welfare effects of digital credit by providing some evidence that this credit is more beneficial for borrowers with limited access to credit, for borrowers who utilize digital loans for business purposes, and when borrowers obtain larger amounts of digital credit.

6. Conclusion

In many developing economies, the absence of borrowers' formal financial history and employment records exacerbates information asymmetry between borrowers and lenders and significantly limits households' ability to access credit. To mitigate this information asymmetry, digital lenders apply machine-learning algorithms to alternative data, primarily from mobile devices, bypassing the need for traditional credit scores. This has led to the tremendous growth of digital lending over the past decade in many developing countries around the world and has enabled millions of individuals without prior credit history to secure loans. However, this boon is

[47] We partition treatment borrowers based on total loan amounts aggregated over the post-period excluding the last loan. Because control borrowers do not obtain digital credit, we assign these borrowers to the *High Loan Amount* (*Low Loan Amount*) partition if their matched treatment borrower obtains above (below) median total loan amounts.

not without its pitfalls. Critics highlight that, in the absence of robust regulation, some digital lenders impose exorbitant interest rates without properly informing borrowers about these rates and late fees, imposing a further burden on poor households.

To examine the welfare impact of digital lending, we exploit an experiment conducted by the Lender in Kenya that randomly approves loans from the pool of applicants rejected based on its credit model. Using measures of borrowers' monetary transactions, mobility, and social networks based on mobile phone data and borrowers' income and employment collected from the self-reported survey, we find that access to digital credit improves borrowers' financial well-being. Additional analyses provide some evidence that digital lending has a greater impact on the financial well-being of borrowers who lack external credit scores, those who use digital credit for business purposes, and those who borrow larger loan amounts. Overall, our findings suggest that digital credit can play a positive role in financial inclusion and well-being.

The evidence we provide has important implications for regulators who consider how to design policies that carefully balance consumer protection with greater access to credit through digital loans. These policies are particularly important because the informal sector plays a vital role in job creation and poverty reduction in developing economies, and poor access to credit is one of the main challenges faced by this sector (e.g., IMF 2020; World Bank 2020).[48] Thus, by allowing for greater business opportunities in the informal sector, digital credit has the potential to contribute to the higher growth of developing economies.

[48] For example, in Kenya in 2019, the informal sector accounted for 83% of total employment and 90.7% of new job creation.

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APPENDIX A
Variable Definitions

Variable		Definition
Days First App	=	The natural logarithm of the number of days between the date of the borrower's first loan application and the date of the loan application under consideration.
Employed	=	An indicator variable equal to one if the borrower is employed or self-employed, as reported in the loan application survey, and zero otherwise.
Monthly Income	=	The natural logarithm of the monthly income reported in the loan application survey.
Network Ppl Number	=	The natural logarithm of the total number of unique phone numbers in the borrower's contacts list.
Network Repaid	=	The natural logarithm of the proportion of the people in the borrower's network that repaid loans to the Lender on time out of the total number of network people.
POST	=	An indicator variable equal to one for the last loan applications of the treatment borrowers and their matched loan applications of the control borrowers, whereas initial loans for the treatment borrowers and their matched loan applications of the control borrowers are assigned the value of zero.
SMS Amt	=	The natural logarithm of the average monetary amounts mentioned in the borrower's incoming SMS messages prior to the loan application date. SMS messages received from the Lender as well as SMS messages received within 24 hours following the loan application are excluded from the estimation.
SMS Counts	=	The natural logarithm of the total number of incoming and outgoing text messages of the borrower prior to the loan application date. SMS messages received from the Lender as well as SMS messages received within 24 hours following the loan application are excluded from the estimation.
SMS MPESA Amt	=	The natural logarithm of the average daily M-PESA balance mentioned in the borrower's incoming SMS messages prior to the loan application date. SMS messages received within 24 hours following the loan application are excluded from the estimation.
Lender Credit Score	=	The natural logarithm of the credit score as estimated by the Lender's credit scoring model on the loan application date.
TREAT	=	An indicator variable equal to one if the loan applicant was randomly approved by the Lender, and zero otherwise.
#Cell Towers	=	The natural logarithm of the number of unique cell towers passed by the borrower during the 30-day period preceding the loan application date.
#Cities	=	The natural logarithm of the number of cities the borrower has traveled to during the 30-day period preceding the loan application date.

TABLE 1
Descriptive Statistics

This table provides descriptive statistics for the main variables used in our analyses. All variables are defined in Appendix A.

	N	Mean	Median	SD
SMS Amt	16,656	5.69	5.53	1.69
SMS MPESA Amt	14,746	6.53	6.91	2.32
#Cell Towers	20,092	0.97	0.70	0.72
#Cities	20,092	0.48	0.70	0.41
SMS Counts	20,092	5.75	6.01	1.95
Network Ppl Number	20,092	4.18	5.15	2.93
Network Repaid	20,092	-0.57	-0.34	0.87
Monthly Income	20,092	9.83	9.90	1.22
Employed	20,092	0.42	0.00	0.49
Days First App	20,092	5.77	5.86	1.28
Lender Credit Score	20,092	-0.23	-0.19	0.12

TABLE 2
The Effects of Digital Lending on Monetary Transaction Volume

This table examines the effects of access to digital lending on borrowers' monetary transaction volume. In columns (1) and (2), we measure the borrower's monetary transaction volume using the average monetary amounts mentioned in the borrower's incoming SMS messages prior to the loan application date (*SMS Amt)*. In columns (3) and (4), we measure the applicant's monetary transaction volume using the average daily M-PESA balance mentioned in the borrower's incoming SMS messages prior to the loan application date (*SMS MPESA Amt)*. We include borrower and year-month fixed effects; p-values in parentheses are based on standard errors clustered at the borrower and year-month level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

	SMS Amt		*SMS MPESA Amt*	
	(1)	(2)	(3)	(4)
POST	0.103***	0.098***	0.003	0.008
	(0.015)	(0.015)	(0.023)	(0.023)
POST x TREAT	0.153***	0.149***	0.066**	0.082**
	(0.025)	(0.028)	(0.028)	(0.031)
Days First App		0.031**		-0.012
		(0.013)		(0.010)
Lender Credit Score		-0.027		0.142
		(0.113)		(0.105)
Borrower FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.805	0.805	0.909	0.909
Observations	16,656	16,656	14,746	14,746
Model	OLS	OLS	OLS	OLS

TABLE 3
The Effects of Digital Lending on Mobility

This table examines the effects of access to digital lending on borrowers' mobility. In columns (1) and (2), we measure the borrower's mobility using the number of unique cell towers passed by the borrower during the 30-day period preceding the loan application date (*#Cell Towers*). In columns (3) and (4), we measure the borrower's mobility using the number of cities the borrower has traveled to during the 30-day period preceding the loan application date (*#Cities*). We include borrower and year-month fixed effects; p-values in parentheses are based on standard errors clustered at the borrower and year-month level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

	#Cell Towers		*#Cities*	
	(1)	(2)	(3)	(4)
POST	0.063***	0.074***	-0.002	0.001
	(0.017)	(0.017)	(0.010)	(0.010)
POST x TREAT	0.603***	0.636***	0.084***	0.094***
	(0.019)	(0.020)	(0.011)	(0.011)
Days First App		-0.007		0.001
		(0.008)		(0.005)
Lender Credit Score		0.348***		0.113***
		(0.064)		(0.033)
Borrower FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.438	0.440	0.290	0.291
Observations	20,092	20,092	20,092	20,092
Model	OLS	OLS	OLS	OLS

TABLE 4
The Effects of Digital Lending on Social Networks

This table examines the effects of access to digital lending on borrowers' social network. In columns (1) and (2), we measure the borrower's social network using the total number of incoming and outgoing text messages of the borrower prior to the loan application date (*SMS Count*). In columns (3) and (4), we measure the borrower's social network using the total number of unique phone numbers in the borrower's contacts list on the loan application date (*Network Ppl Number*). In columns (5) and (6), we measure the borrower's social network using the proportion in the borrower's network that repaid loans to the Lender on time out of the total number of network people (*Network Repaid*). We include borrower and year-month fixed effects; p-values in parentheses are based on standard errors clustered at the borrower and year-month level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

	SMS Count		*Network Ppl Number*		*Network Repaid*	
	(1)	(2)	(3)	(4)	(5)	(6)
POST	0.250***	0.246***	-0.014*	-0.012*	-0.010	-0.003
	(0.026)	(0.025)	(0.007)	(0.007)	(0.016)	(0.015)
POST x TREAT	0.255***	0.268***	0.023***	0.029***	0.035	0.056**
	(0.026)	(0.028)	(0.008)	(0.011)	(0.022)	(0.022)
Days First App		0.082***		0.002		-0.007
		(0.025)		(0.002)		(0.010)
Lender Credit Score		0.296***		0.074		0.215***
		(0.099)		(0.047)		(0.071)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.823	0.824	0.991	0.991	0.461	0.461
Observations	20,092	20,092	20,092	20,092	20,092	20,092
Model	OLS	OLS	OLS	OLS	OLS	OLS

TABLE 5
The Effects of Digital Lending on Monthly Income and Employment Outcome

This table examines the effects of access to digital lending on borrowers' monthly income and employment outcome. In columns (1) and (2), we report the results using the borrower's self-reported monthly income (*Monthly Income*). In columns (3) and (4), we report the results using the borrower's employment outcome based on whether the borrower is employed or self-employed (*Employed*). We include borrower and year-month fixed effects; p-values in parentheses are based on standard errors clustered at the borrower and year-month level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

	Monthly Income		*Employed*	
	(1)	(2)	(3)	(4)
POST	-0.015	-0.015	-0.086***	-0.084***
	(0.024)	(0.023)	(0.015)	(0.015)
POST x TREAT	0.206***	0.208***	0.227***	0.235***
	(0.027)	(0.028)	(0.034)	(0.034)
Days First App		0.005		0.005
		(0.012)		(0.004)
Lender Credit Score		0.027		0.100***
		(0.104)		(0.025)
Borrower FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.329	0.329	0.892	0.892
Observations	20,092	20,092	20,092	20,092
Model	OLS	OLS	OLS	OLS

Table 6
The Effects of Digital Lending on Borrowers' Well-being Using the App Data Sample

This table examines the effects of access to digital lending on borrowers' well-being using the App data collected, regardless of whether a borrower applies for a subsequent loan through the Lender's mobile app installed by the borrower when applying for the loan**.** Panel A provides descriptive statistics and Panel B reports the results of the analyses. We include borrower and year-month fixed effects; p-values in parentheses are based on standard errors clustered at the borrower and year-month level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: Descriptive Statistics – App data

	N	Mean	Median	SD
SMS Amt	28,666	5.04	4.96	1.85
SMS MPESA Amt	19,131	6.02	6.25	1.99
#Cell Towers	40,620	0.68	1.13	1.57
#Cities	40,620	0.43	0.70	0.44
Days First App	40,620	5.51	5.71	0.79

Panel B: Main Analyses – App data

	SMS Amt	*SMS MPESA Amt*	*#Cell Towers*	*#Cities*
	(1)	(2)	(3)	(4)
POST	0.158***	0.040	-0.173***	-0.108***
	(0.031)	(0.026)	(0.053)	(0.013)
POST x TREAT	0.241***	0.044**	0.391***	0.046***
	(0.038)	(0.021)	(0.038)	(0.009)
Days First App	0.002	-0.024	-0.072*	-0.003
	(0.035)	(0.023)	(0.042)	(0.012)
Borrower FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.804	0.913	0.390	0.253
Observations	28,666	19,131	40,620	40,620
Model	OLS	OLS	OLS	OLS

TABLE 7
Cross-Sectional Variations in Borrower and Loan Characteristics

This table examines whether the effects of access to digital lending vary with the borrower and loan characteristics. Panel A reports the results for sample partitions based on whether a borrower has an external credit rating from a credit bureau (TransUnion). A borrower is assigned to *Without Credit Score* partition if the borrower does not have an external credit score on the date of the first loan application; otherwise, the borrower is assigned to *With Credit Score* partition. Panel B reports the results for sample partitions based on the loan purpose. A borrower is assigned to *Business Purpose* partition if the borrower reports in the loan application survey that she obtains the loan for a business purpose; otherwise, the borrower is assigned to *Personal Purpose* partition. Panel C reports the results for sample partitions based on the loan amount. We calculate total loan amounts obtained by each treatment borrower aggregated over the post-period excluding the last loan. A treatment borrower and her matched control borrower are assigned to *High Loan Amount* partition if the treatment borrower obtains above median total loan amounts; otherwise, they are assigned to *Low Loan Amount* partition. We report the coefficients on *POST x TREAT* for each outcome variable from Table 2 to Table 5 (other coefficients are not reported for brevity). We include borrower and year-month fixed effects; p-values in parentheses are based on standard errors clustered at the borrower and year-month level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: External Credit Score

Coefficients on *POST x TREAT* for each outcome variable	*With Credit Score* (1)	*Without Credit Score* (2)	*Difference* (2) - (1)
SMS Amt	0.135***	0.117**	-0.018
	(0.047)	(0.051)	(0.395)
SMS MPESA Amt	-0.028	0.078	0.106*
	(0.052)	(0.047)	(0.069)
#Cell Towers	0.642***	0.646***	0.004
	(0.042)	(0.031)	(0.463)
#Cities	0.097***	0.092***	-0.005
	(0.022)	(0.021)	(0.437)
SMS Count	0.040	0.327***	0.287***
	(0.044)	(0.057)	(0.000)
Network Ppl Number	0.023***	0.040*	0.017
	(0.008)	(0.021)	(0.232)
Network Repaid	-0.025	0.093**	0.118**
	(0.032)	(0.039)	(0.012)
Monthly Income	0.165***	0.280***	0.115*
	(0.039)	(0.057)	(0.051)
Employed	0.113***	0.300***	0.187***
	(0.032)	(0.032)	(0.000)

Panel B: Loan Purpose

Coefficients on *POST x TREAT* for each outcome variable	*Personal Purpose* (1)	*Business Purpose* (2)	*Difference* (2) - (1)
SMS Amt	0.105*	0.166***	0.061
	(0.062)	(0.040)	(0.227)
SMS MPESA Amt	0.120*	0.048	-0.072
	(0.064)	(0.036)	(0.153)
#Cell Towers	0.551***	0.665***	0.114**
	(0.040)	(0.023)	(0.011)
#Cities	0.090***	0.099***	0.009
	(0.023)	(0.014)	(0.367)
SMS Count	0.260***	0.248***	-0.012
	(0.045)	(0.031)	(0.410)
Network Ppl Number	0.017	0.024**	0.007
	(0.022)	(0.011)	(0.377)
Network Repaid	-0.017	0.084***	0.101***
	(0.037)	(0.027)	(0.008)
Monthly Income	0.102*	0.254***	0.152**
	(0.058)	(0.035)	(0.019)
Employed	0.207***	0.228***	0.021*
	(0.036)	(0.035)	(0.096)

Panel C: Loan Amount

Coefficients on *POST x TREAT* for each outcome variable	*Low Loan Amount* (1)	*High Loan Amount* (2)	*Difference* (2) - (1)
SMS Amt	0.096**	0.186***	0.090*
	(0.039)	(0.042)	(0.065)
SMS MPESA Amt	0.018	0.127**	0.109**
	(0.030)	(0.048)	(0.028)
#Cell Towers	0.597***	0.671***	0.074**
	(0.030)	(0.024)	(0.019)
#Cities	0.101***	0.087***	-0.014
	(0.014)	(0.017)	(0.248)
SMS Count	0.112***	0.407***	0.295***
	(0.033)	(0.041)	(0.000)
Network Ppl Number	0.013	0.044**	0.031*
	(0.011)	(0.017)	(0.074)
Network Repaid	0.060**	0.043	-0.017
	(0.030)	(0.030)	(0.336)
Monthly Income	0.113***	0.303***	0.190***
	(0.040)	(0.043)	(0.002)
Employed	0.119***	0.341***	0.222***
	(0.027)	(0.046)	(0.000)