Tetteh *Financial Innovation* (2023) 9:102
https://doi.org/10.1186/s40854-023-00507-0

Financial Innovation

RESEARCH

Open Access

Local digital lending development and the incidence of deprivation in Kenya

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Abstract

In the developing world, vulnerable communities often lack access to regular income sources to cope with unforeseen events. Recent advancements in financial technology have enabled microcredit to be delivered via digital platforms. Although digital credit may quicken remote access to consumer credit without the need for collateral, little is known about its contribution to the welfare of underserved communities. This study examines the effects of local digital lending development on deprivation and explores the implications of these effects on rural inhabitants. The results show a negative association between local digital lending development and food deprivation on one hand and health deprivation on the other. The evidence suggests that local digital lending development can reduce the probability of food and health deprivation. Furthermore, the evidence reveals that inhabitants of rural communities benefit more from digital lending development. This study recommends the decentralization of financial inclusion policies as a pathway to promote digital lending at the local level.

Keywords: Microfinance, Fintech, Digital lending, Deprivation

JEL Classification: G21, I31, O16, O33, O55

Introduction

Access to microcredit is viewed as a panacea for improving the welfare of the poor in developing countries (Dahal and Fiala 2020; Imai et al. 2010; Karlan and Zinman 2011; van Rooyen et al. 2012). This is because poor households and communities often lack access to flexible sources of income to cope with negative shocks such as illness or the death of household members.

While microcredit is instrumental in coping with negative shocks, the delivery of microloans via conventional channels, such as microfinance institutions, is not instant. In most cases, this may require physically commuting to branches of financial service providers. However, such commute may result in high transaction costs, especially in developing countries where bank branches are few (Beck et al. 2009; Francis et al. 2017; Jack and Suri 2014) thereby posing a barrier to accessing quick loans. The costs associated with financial transactions, coupled with conditions for loan acquisition, including collateral or prescriptions regarding how loans should be used often discourage consumers from accessing microcredit (Francis et al. 2017; Stefanelli et al. 2022). Consequently, those who reside in rural communities and poor neighborhoods are excluded from accessing formal financial services (Demirgüç-Kunt et al. 2018).

In the developing world, the recent advancements in financial technology (Fintech) and proliferation of mobile phones (Aker and Mbiti 2010) have led to innovative financial products, such as digital credit. In collaboration with commercial banks, Fintech companies are extending microcredit in the form of digital credit to consumers beyond traditional channels using digital platforms. Digital credits are distinct from traditional credit channels because they can be accessed remotely and instantaneously via mobile phones and apps within seconds or a day without collateral, and the processing of loans, including credit scoring, is automated (Chen and Mazer 2016; Pelletier et al. 2020). For example, digital credit offered by mobile network operators may rely on the transaction records of telecommunication consumers to build credit scores, which are fundamentally useful in determining the creditworthiness of potential borrowers (Dalton et al. 2019; Pelletier et al. 2020).

Digital credit is easily accessible to consumers and can help individuals and households cope with negative shocks. Nonetheless, there is a growing concern about the high interest rates that accompany short-term digital credits[1] and the probability of such loans leading to overindebtedness (Wamalwa et al. 2019; Wang et al. 2021) with potential consequences for welfare. Despite these concerns, there is limited empirical evidence of the impact of digital credit on welfare, especially in rural communities that are more likely to be financially excluded. Therefore, the main objective of this study is to fill this research gap by examining whether local digital lending development influences welfare and if this effect is favorable to rural communities.

This study investigates the relationship between local digital lending development and deprivation in Kenya. This study focuses on Kenya because of its leading role in mobile financial services in Africa (Suri 2017). Using the 2016 and 2019 FinAcess surveys, I first estimate a local digital lending development indicator that captures the ease with which digital credit can be accessed in a particular county, an administrative region in Kenya.[2] Local digital lending development is expected to facilitate easy access to digital credit and enable the management of risks that lead to deprivation. Second, this study relates the local digital lending development variable to the likelihood of individuals reporting the presence of deprivation in their households. Specifically, this study focuses on food and health deprivation to reflect the contribution of local digital lending development to the attainment of the United Nations Sustainable Development Goals (SDGs) 2 and 3. For example, SDG 2 seeks to enable countries to end hunger and achieve food security, whereas SDG 3 targets the promotion of healthy lives and well-being worldwide. Furthermore, this study examines whether digital lending development benefits rural communities.

The estimations from the multilevel regression show a negative association between local digital lending development and food deprivation on the one hand and health deprivation on the other. The evidence suggests that local digital lending development

[1] A typical example is M-Shwari, a digital loan product in Kenya, which attracts about 7.5 per cent facilitation fee (Suri et al. 2021).

[2] Kenya has a total of 47 counties which were created by the 2010 Constitution to drive local governance and development at the local level (Hope 2014). In this paper county and region are used interchangeably.

can reduce the probability of food and health deprivation. The results also show that rural dwellers gain more from this effect than their urban counterparts. These results are robust to the inclusion of individual, household, and regional characteristics and the application of an instrumental variable multilevel estimation approach to account for endogeneity. This study recommends the decentralization of financial inclusion policies as a pathway to promote digital lending at the regional or local government level.

This study contributes to the growing body of literature on mobile money and microfinance. The mobile money literature focuses largely on remittances as the main mechanism through which mobile money adoption enhances welfare. An exception is a study by Ahmed and Cowan (2021) which shows that mobile money improves the use of formal healthcare services, and this effect appears to be driven by informal borrowing. Suri et al. (2021) also moved beyond the remittance channel of mobile money by investigating the impact of M-Shwari, a digital loan product, on households' resilience to shocks in Kenya. This study contributes to literature by examining the effects of local digital lending development on deprivation. It also adds to the local financial development literature which primarily focuses on traditional financial services (Guiso et al. 2004) by focusing on local digital lending development. The rationale is to offer evidence to influence financial inclusion policies at the local government level. This study also examines the implications of digital lending development for underserved communities, with a specific focus on rural areas.

The remainder of this study proceeds as follows. The next section reviews related literature, including a brief background on digital lending in Kenya. "Data and key variables" section describes the data and main variables used in the analysis. In "Estimation strategy" section, I discuss the proposed estimation strategy. "Results" section presents the results, including the research implications, and "Conclusion" section provides the main conclusions.

Literature review

Digital lending development and why it matters for welfare

Financial development refers to the ease with which individuals in need of external financing can access credit (Guiso et al. 2004). Local financial development focuses on within-country variations in financial development and can be measured using indicators of credit or bank branches (Fafchamps and Schündeln 2013; Guiso et al. 2004). This study draws on the literature on local financial development to create an indicator of local digital lending development that captures the ease with which individuals can access digital credit in a particular administrative region. At the center of this measure is the digitalization of microloans (digital credit), which is defined in this study as the use of digital technologies, including financial technologies, to provide microloans.

The digitalization of microloans can influence the attitudes and perceptions of borrowers toward microloans (Langley et al. 2019). For example, borrowers may perceive digital credits as free money and not as debt, especially when these loans are easily available via digital channels without the need for collateral (Chen and Mazer 2016; Langley et al. 2019). In this case, digital credit can contribute to overindebtedness by enabling borrowers to take up loans that they do not need, which may affect welfare. For example, the repayment burden of microloans can increase borrowers' stress levels leading to adverse effects on welfare (Ibrahim et al. 2021).

Digital credit can equally improve welfare, especially when such loans are used to meet the daily needs of borrowers, such as food and healthcare. Literature suggests that access to flexible sources of microloans can enable individuals or households to respond to unexpected financial events or emergencies (Ibrahim et al. 2021). When faced with health emergencies, access to microloans can enhance individuals' ability to pay for health services, leading to better health outcomes (Bhuiya et al. 2018). Access to flexible credit can also safeguard individuals against shocks that could lead to food deprivation (Islam et al 2016). Microloans have become an important avenue through which people can manage risk, especially during emergencies. Karlan and Zinman (2011) find that microcredit positively affects access to informal financing, improves the capacity to cope with risks, and enhances the strength of community ties.

Related literature

A growing body of literature suggests that digital technology contributes to economic outcomes, especially in developing countries (Xie et al. 2022b). Investments in payment and money transfer technologies for example have led to lower transaction costs in payment services (Kou et al. 2021). Digital technology promotes business model innovation and simultaneously provides the infrastructure for the emergence of digital lending platforms (De Crescenzo et al. 2022; Stefanelli et al. 2022; Wolfe et al. 2021; Xie et al. 2022a). In Sub-Saharan Africa, the successful deployment and adoption of mobile money have led to the delivery of financial services, including microloans, via mobile phones, with potential welfare implications.

Jack et al. (2013), for example, reveal that households with mobile money users have a higher propensity to receive remittances within their networks than households without mobile money. The study also shows that households with access to mobile money have better access to credit and emergency transfers than non-mobile money households signaling that mobile money may provide some level of insurance for users. In a related study, Jack and Suri (2014) show that mobile money enables households to share risk during negative shocks. Evidence indicates that households without mobile money experience a significant reduction in consumption during adverse shocks compared to households with mobile money (Jack and Suri 2014). Similarly, Riley (2018) finds that mobile money users can mitigate the reduction in consumption during a rainfall shock. However, this study finds no spillover effects of mobile money use.

Suri and Jack (2016) document the impact of mobile money adoption on poverty reduction in Kenya. This study demonstrates that mobile money contributes to poverty reduction by two percentage points. This effect is driven by improvements in financial resilience, savings, and labor market participation (Suri and Jack 2016). Furthermore, evidence suggests that mobile money has the potential to improve access to health insurance (Ahmed and Cowan 2021; Obadha et al. 2020). Ky et al. (2018) show that mobile money adoption increases the probability of individuals, especially vulnerable groups, to save toward health emergencies. Outside Kenya, Munyegera and Matsumoto (2016) provide evidence supporting the impact of mobile money adoption on household welfare in rural Uganda. This study reveals that mobile money use positively influences per capita consumption, with remittances as the main mechanism. Recent studies also corroborate the welfare impact of mobile money in Ghana, Burkina Faso, and Togo (Afawubo et al. 2020; N'dri and Kakinaka 2020; Peprah et al. 2020).

This study also contributes to the literature on microfinance and welfare. Suri et al. (2021) investigate the impact of M-Shwari, a digital loan product, on households' resilience to shocks in Kenya. This study shows that households with access to M-Shwari are less likely to forego expenses while facing negative shocks.

A review of eight impact evaluation studies by Dahal and Fiala (2020) shows that microfinance has no or minimal impact on welfare. This study concludes that the data employed by previous studies lack sufficient statistical power to identify the effect of microfinance on recipients. A similar review was conducted on selected studies in Sub-Saharan Africa by van Rooyen et al. (2012). These findings suggest that microfinance has positive and negative effects. Specifically, the study reveals that access to microfinance tends to have a positive impact on the health of the poor, as does access to food (van Rooyen et al. 2012).

Empirical evidence outside Sub-Saharan Africa indicates that microfinance has contributed to improvements in food access and dietary diversity (Bidisha et al. 2017). However, Islam et al. (2016) argue that the relationship between microfinance and food access is potentially non-linear, and such effects may become invisible or even negative in the short-term but positive in the long-run. Additionally, Bhuiya et al. (2018) find a significant and positive relationship between microfinance and access to health services, such as antenatal care, diarrhea treatment, and malaria treatment, but the effect of microfinance on access to medicine is negative.

Despite the contributions of previous studies, we do not know whether those who reside in regions with easy access to digital credits are better off compared to those who reside in regions with limited access to digital credits. Therefore, it would be interesting to examine the relationship between local digital lending development and deprivation. Based on the literature, this study hypothesizes that digital lending development can reduce food and health deprivation, given that it facilitates easy access to credit. It is expected that rural inhabitants will benefit more from local digital lending development, given its potential to overcome financial inclusion barriers in rural areas. This study also acknowledges that digital lending development can undermine welfare, especially when these loans lead to overindebtedness.

Background on digital lending in Kenya

Following the launch of the Kenyan M-Pesa in 2007 by Safaricom, a mobile network operator, the country emerged as a global leader in providing mobile money services. Mobile money is a financial innovation that enables consumers to conduct financial transactions, such as money transfers, savings, and bill payments, using their mobile phones without the need to open a bank account with financial institutions (Suri 2017).

The successful deployment of mobile money services has provided the necessary infrastructure for the development of complementary and innovative financial products, including digital credits, which are largely offered by commercial banks in partnership with mobile network operators.

The first digital credit product in Kenya, M-Kesho, was launched in 2010 as a partnership between Safaricom and the Equity Bank with the sole objective of enabling consumers to withdraw money, save, and access microloans using their mobile phones (FSD Kenya 2016). Although M-Kesho was unable to achieve a high adoption rate, it provided the necessary experimentation for the subsequent development of Kenya's digital lending landscape (Wamalwa et al. 2019). Consequently, in 2012, Safaricom, in collaboration with the Commercial Bank of Africa (CBA) launched M-Shwari, which has become one of Kenya's most successful digital lending platforms (Kaffenberger et al. 2018). A year after its deployment, M-Shwari attracted approximately 5 million subscribers (FSD Kenya 2016), and disbursed microloans valued at approximately KSh 7.8 billion (Kaffenberger et al. 2018). Loan disbursements often range between KSh 100 to KSh 10,000 with a loan repayment period of 30 days and a facilitation fee of about 7.5 percent (Suri et al. 2021). Since 2014, Kenya has witnessed the proliferation of mobile phone- and app-based digital lending products such as KCB M-Pesa, Equity Eazzy, M-Coop Cash, Branch, and Tala (Kaffenberger et al. 2018).

The provision of digital loans championed by Fintech companies provides new possibilities for examining the implications of such loans for welfare. Therefore, this study assesses the development of digital lending, operationalized as the provision of digital loans via mobile phones or apps by Fintech companies, banks, or both, and its implications for welfare.

Data and key variables

This study combined data from the 2016 and 2019 FinAccess surveys in Kenya. The FinAccess surveys are repeated cross-sectional surveys that provide demand-side information on the use of financial services among Kenya's adult population. The surveys were conducted using a unique household sampling framework based on the 5th National Sample Survey and Evaluation Program designed to yield a national representative sample. The household was considered the basic sampling unit, in which one individual aged 16 years and older was randomly selected from a roster of all eligible members in each household. Overall, the 2016 FinAccess survey targeted 10,008 households, of which 8665 respondents were successfully interviewed, leading to a response rate of about 87 percent. Similarly, the 2019 FinAccess survey achieved a response rate of 89 percent, resulting in 8669 observations from an initial target of 11,000. The surveys were spearheaded by the Central Bank of Kenya, the Kenyan National Bureau of Statistics, and the Financial Sector Deepening Trust of Kenya.

Dependent variables

This study employs two main outcome variables to capture household deprivation. The first outcome variable is food deprivation, which is measured using a dummy variable that equals 1 if individuals report that any member of their household has often or sometimes gone without food, and 0 otherwise. The second outcome variable of interest is health deprivation, that equals 1 if respondents report that any member of the household has often or sometimes gone without medicine or needed medical treatment, and 0 otherwise. The choice of dependent variables was based on the extant welfare literature. Access to food and healthcare, for example, is considered a basic requirement in almost every community and has been used extensively in previous studies as an indicator of welfare (Bhuiya et al. 2018; Bidisha et al. 2017; van Rooyen et al. 2012).

Main independent variable

The main independent variable of interest is an index of local digital lending development. Following the methodology of Guiso et al. (2004)[3] a novel digital lending development index was constructed at the local level by estimating the likelihood of an individual i to access digital credit in region (county) *j* using the specification below:

$$digital\ credit_{ij} = \boldsymbol{a}_0 + \boldsymbol{a}_1 X_{ij} + \delta_j + \varepsilon \tag{1}$$

where digital credit is a dummy variable equal to 1 if the individual is currently or is used to accessing mobile banking loans or digital loans via mobile phones or apps and 0 otherwise. X_{ij} is a vector of individual and household characteristics expected to affect the decision to access digital credit. These variables include location in a rural area, household size (in logs), age (in logs), gender (female), income (in logs), mobile money/mobile banking account ownership, bank account ownership, mobile phone ownership, and educational level (at least secondary education). $\boldsymbol{a}_0$ and ε are the constant and error term, respectively.[4] The estimation also includes regional dummies δ_j which correspond to the 47 counties of Kenya to enable the computation of the local digital lending development indicator. Mombasa County was set as the reference county and was therefore omitted from the regression. Following this, 46 counties were retained to compute the local digital lending development indicator. The marginal effects associated with the 46 regional dummies were extracted and normalized using the min–max method. Thus, the final indicator was computed as follows:

$$loc\_digital\_lending_j = \frac{\varphi_j - min_j(\varphi)}{max_j(\varphi) - min_j(\varphi)} \tag{2}$$

where $loc\_digital\_lending_j$ is the local digital lending development indicator of region j. φ_j is the marginal probability of accessing digital credit in region j. $min_j(\varphi)$ and $max_j(\varphi)$ are the observed minimum and maximum effects across the 46 regions. The final values lie between 0 and 1, with higher values corresponding to higher achievements in digital lending development at the regional level.[5] The estimates for the probability of accessing

[3] Guiso et al. (2004) use this methodology to examine the relationship between local financial development at the regional level in Italy to predict micro-level entrepreneurial activities including new business formation, firm entry, competition, and firm growth. A recent study also adopts this approach to examine the effect of informal competition at the local level on the innovativeness of firms (Avenyo et al. 2021). Similarly, Guzmán-Cuevaset al. (2009) adopt a regional approach to study how firms' characteristics are shaped by the level of development of the region in which they are located.

[4] Analysis is conducted with standard errors clustered at the regional level to control for within-region error correlation.

[5] The choice of an aggregate measure of digital credit at the local level is in line with the study objective and is preferred to an individual-level measure. Note that, only one respondent is selected per household. So, in this case, it will not be ideal to attribute digital credit at the individual level to household level outcome given that a respondent without digital credit may be living in the same household with someone who has digital credit but not captured by the survey.

Table 1 Estimates of local digital lending development where higher values correspond to higher achievement

Region	Digital lending development score	Region	Digital lending development score
Muranga	1.00	Siaya	0.655
Kiambu	0.988	Kisumu	0.655
Kakamega	0.898	Trans Nzoia	0.635
Bungoma	0.882	Kilifi	0.620
Nyandarua	0.847	Embu	0.620
Vihiga	0.831	Homa Bay	0.620
Machakos	0.827	Nandi	0.612
Kitui	0.820	Narok	0.612
Kwale	0.816	Nyamira	0.604
Makueni	0.776	Lamu	0.592
Kericho	0.773	Samburu	0.592
Kajiado	0.761	Kisii	0.569
Nairobi	0.757	Taita Taveta	0.529
Uasin-Gishu	0.749	Tana River	0.522
Nyeri	0.741	Turkana	0.522
Busia	0.741	Meru	0.482
Nakuru	0.722	Migori	0.482
Baringo	0.706	Isiolo	0.447
Laikipia	0.698	Tharaka Nithi	0.435
Kirinyaga	0.678	Marsabit	0.392
Bomet	0.678	Garissa	0.204
Elgeyo Marakwet	0.667	Mandera	0.169
West Pokot	0.663	Wajir	0.00

digital credit are presented in Table 9 in the "Appendix", and the local digital lending development indicator is presented in Table 1.

Descriptive statistics of main variables

Tables 7 and 8 in the "Appendix" present definitions of the variables and summary statistics, respectively. The descriptive statistics in Table 8 shows that approximately 30 percent and 29 percent of respondents in the sample experienced food and health deprivation, respectively, in their households. Additionally, approximately 57 percent of the respondents live in rural areas. Table 8 also reveals that approximately 14 percent of respondents have access to digital credit, while approximately 70 percent currently own mobile money or mobile banking accounts. Compared with account ownership, access to digital credit is relatively low signaling that the latter is still in the early stages of development. Table 1 presents the values of digital lending development associated with various administrative regions in Kenya. Muranga, Kiambu, Kakamega, Bungoma, and Nyandarua occupy the top positions in local digital lending development. However, Wajir County scored lowest in local digital lending development. The following sections test the extent to which the observed regional variations in local digital lending development affect household deprivation.

Estimation strategy

This study examines the relationship between local digital lending development and the prevalence of food and health deprivation in households. The data structure is such that individual-level observations are nested within regions. Given this hierarchical structure, it is anticipated that contextual factors, in this case, regional factors, and not only individual-level factors may condition the likelihood of household deprivation. In addition, individuals in the same region may share similar characteristics owing to location-specific factors, such as shared history, economic opportunities, and adverse shocks. In this case, observations are likely to be clustered within regions, thereby violating the assumption of independence in linear or binary regression models (Guo and Zhao 2000). An empirical strategy that does not account for the multilevel nature of the data will underestimate the standard errors, leading to biased estimates (Hox 2010). Accordingly, this study employs a multilevel probit model to simultaneously account for individual and contextual factors that affect deprivation while adjusting for clustering, leading to accurate estimates of the standard errors.

Formally, the probability of individual i located in region j reporting the presence of deprivation $\left(Y_{ij}\right)$ is modelled as a function of a set of covariates, including the local digital lending development indicator, using the following latent response model:

$$Y_{ij}^{*} = \beta_0 + \beta_1 X_{ij} + \beta_2 loc\_digital\_lending_j + \beta_3 \lambda_j + u_j + \varepsilon_{ij} \tag{3}$$

$$Y_{ij} = \left\{ \begin{array}{ll} 1, & if\ Y_{ij}^{*} > 0 \\ 0, & otherwise \end{array} \right\} \tag{4}$$

where, Y_{ij} represents the binary outcome variable of interest (food and health deprivation). $loc\_digital\_lending_j$ is the local digital lending development variable (regional-level variable), and β_2 is the parameter of interest to be estimated. u_j captures the random effect at the regional level and it is assumed to be normally distributed with mean 0 and variance σ_u^2 while ε_{ij} is the individual level error term which has a mean 0 and a fixed variance of 1. Vector X_{ij} indicates individual and household characteristics (Level 1 variables). This study controls for household size (in logs), location in a rural area, respondents' educational level, age (in logs), gender, monthly income (in logs), bank account ownership, and wealth status. Furthermore, wealth status was computed using principal component analysis. The computation of the wealth score is based on five dummy variables that reflect households' access to amenities, such as access to flush toilets, piped water, electricity/solar for lighting, electricity, or gas/LPG for cooking, if the number of habitable rooms in a household is more than three. These variables, which provide some indication of wealth, are restricted to five variables owing to the availability of consistent information across the 2016 and 2019 FinAccess household surveys. The wealth score is estimated using the first principal component, which has an eigenvalue of 2.1.[6] Subsequently, the wealth score is normalized using the min–max method, and values lie

[6] As a rule of thumb, the first principal component is selected because it is the only component with an eigenvalue larger than 1. The PCA estimates are not reported. However, the final estimate in the form of wealth score is captured in the summary statistics table in the "Appendix".

between 0 and 1, where 1 indicates a higher wealth status. Additionally, the estimations account for other credit channels, including loans from banks and microfinance institutions (formal loans), government and employers (other loans), and informal loans.

Finally, vector λ_j denotes the regional level controls. This study controls for baseline extreme poverty levels (in logs)[7] and the total number of deaths reported (in logs) at the regional level. It is expected that respondents in poverty-endemic regions will be more prone to report that their households have gone without food or medical treatment. Additionally, a high incidence of death in a region is a risk factor that has the potential to affect deprivation. This study controls for Gross County Product (GCP) per capita, the equivalent of Gross Domestic Product per capita at the regional level, to account for local economic development. Furthermore, the analysis controlled for regional size, including land and water areas covered by each region (sq km). Land availability is crucial for agricultural production. Regional-level control variables were obtained from relevant statistical reports of the Kenyan National Bureau of Statistics (KNBS 2017, 2018, 2019). These variables are for 2015, which coincides with the baseline data employed in the analysis.

To ascertain the implications of local digital lending development for rural communities, the local digital lending variable is allowed to interact with the variable Rural using the following specification:

$$\begin{aligned} Y_{ij}^{*} = \beta_0 + \beta_1 X_{ij} + \beta_2 Rural_{ij} \\ + \beta_3 loc\_digital\_lending_j + \beta_4 \big(Rural_{ij} \\ \times loc\_digital\_lending_j\big) + \beta_5 \lambda_j + u_j + \varepsilon_{ij} \end{aligned} \tag{5}$$

where the interaction term β_4 is the main parameter of interest.

Prior to the estimations, the intra-class correlation coefficient (ICC) was estimated for the baseline model using Eq. (3) without covariates (empty model). This captures the proportion of variance attributable to group structure (Hox 2010). The ICC values range from 0 to 1. In this case, an ICC equals 1 means that 100 percent of the variance in household deprivation is explained by differences between regions, whereas an ICC of 0 implies that there is no such effect. The computation followed the following specifications.

$$ICC = \frac{\sigma_u^2}{\sigma_u^2 + 1} \tag{6}$$

where σ_u^2 is the variance of the random intercept (regional-level variance component). However, the variance of the individual error term was fixed at 1, as indicated previously.

[7] Extreme poverty is defined as "households and individuals whose monthly adult equivalent total consumption expenditure per person is less than KSh 1954 in rural and peri-urban areas and less than KSh 2551 in core-urban areas"(KNBS 2018 p 44). KSh = Kenyan Shilling.

Results

This section provides the multilevel regression results for the relationship between local digital lending development and food deprivation on the one hand and health deprivation on the other. First, the effect of local digital lending development on food deprivation is presented. Second, this section presents the results of the relationship between local digital lending development and health deprivation. Third, this study provides the differential effects for rural and urban communities. Subsequently, I present the results of robustness checks using an instrumental variable (IV) technique within a multilevel regression framework. Finally, the research and policy implications of the findings are discussed.

Local digital lending development and food deprivation

This subsection establishes whether local digital lending development, which is expected to provide easy access to digital credit, affects the likelihood of food deprivation.

Table 2 presents the average marginal effects of the relationship between local digital lending development and food deprivation, based on multilevel probit estimations. Note that the estimations follow a two-step approach in which the local digital lending development variable was first estimated using Eq. (1). To obtain robust standard errors, the multilevel regression estimations adjust for standard errors using cluster bootstrapping with 400 replications.[8] Column (1) presents the null model, in which the estimation is restricted to the dependent variable without independent variables, to enable the computation of the ICC. The estimate in Column (1) shows an ICC of 0.172. This suggests that approximately 17 percent of the variance in food deprivation can be attributed to regional differences. Column (2) shows the results when Level 1 controls are included in the model in addition to the local digital lending development variable. Finally, Column (3) provides the complete model, which is the preferred model, in which regional-level covariates are included as additional controls.

The results in Column (2) show a negative and significant relationship between the local digital lending development variable and food deprivation; this effect is statistically significant at the 1 percent significance level. This effect is robust to the inclusion of regional controls, as indicated in Column (3). This implies that residents of regions with high digital lending development are less likely to report food deprivation in their households. The marginal effects in Column (3) suggest that, on average, a point increase in the local digital lending development indicator (on a scale of 0–1) decreases the probability of food deprivation by 0.4 percent points. These results are consistent with the literature on financial development, which indicates that local financial development affects economic outcomes (Fafchamps and Schündeln 2013; Guiso et al. 2004). Within the context of digital credit, the evidence presented in this study shows that the development of digital lending at the local level can be beneficial in engendering food access. One possible explanation is that local digital lending development can facilitate easy access to digital credit, thereby enabling financially constrained households to access credit to meet their

[8] The clusters correspond to the regions (counties).

Table 2 The effect of local digital lending development on food deprivation

	(1) Null model	(2) Level 1 controls	(3) Level 2 controls
Log of age		0.072***	0.071***
		(0.012)	(0.012)
Female		− 0.019***	− 0.019***
		(0.007)	(0.007)
At least secondary education		− 0.089***	− 0.088***
		(0.008)	(0.008)
Log of household size		0.016**	0.016**
		(0.007)	(0.006)
Wealth score		− 0.151***	− 0.149***
		(0.017)	(0.017)
Log of income		− 0.031***	− 0.030***
		(0.002)	(0.002)
Bank account		− 0.065***	− 0.065***
		(0.011)	(0.011)
Formal loans		− 0.034**	− 0.034**
		(0.015)	(0.015)
Other loans		− 0.004	− 0.004
		(0.020)	(0.019)
Informal loans		0.052***	0.052***
		(0.010)	(0.010)
Rural		0.027**	0.027**
		(0.011)	(0.011)
Local digital lending		− 0.392***	− 0.382***
		(0.041)	(0.094)
Log of reported death			0.039
			(0.026)
Log of total size			0.006
			(0.013)
Log of extreme poverty			0.031
			(0.023)
Log of GCP per capita			− 0.080
			(0.059)
Regional variance (σ_u^2)	0.208	0.117***	0.085***
	(0.044)	(0.022)	(0.017)
ICC	0.172	0.105	0.079
Year dummy	No	Yes	Yes
No. of observations	17,311	16,176	16,176
Number of regions	47	46	46

The Table reports average marginal effects. The outcome variable, food deprivation, equals 1 if any member of the household has sometimes or often gone without food. The main independent variable is local digital lending development which is the regional level effect of the likelihood to access digital credit. Standard errors are adjusted via cluster bootstrapping with 400 replications. Robust standard errors are in parentheses

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

daily household needs such as food. Additionally, easy access to quick loans via digital platforms can improve households' resilience to adverse income shocks that are likely to lead to food deprivation (Suri et al. 2021). This line of reasoning is consistent with earlier studies demonstrating that access to flexible sources of credit can affect welfare (Ibrahim et al. 2021; Jack et al. 2013; Munyegera and Matsumoto 2016).

The control variables yielded interesting results. Evidence suggests that household size can increase the likelihood of food deprivation. Similarly, the likelihood of food deprivation increases with age. The results further indicate that individuals living in households with better access to amenities (wealth scores) are less likely to report food deprivation. Similarly, females, those with bank accounts, and those with at least secondary education are less likely to report food deprivation in their households. Furthermore, as expected, the results show a negative relationship between income and food deprivation on the one hand, and formal loans and food deprivation on the other. However, respondents with access to informal loans are more likely to report food deprivation.

While these results are not the focus of the study, the positive relationship between location in rural areas and food deprivation is of particular interest, given that it provides evidence suggesting that location matters for welfare. This evidence implies that households in rural areas are more likely to experience food deprivation than those located in urban areas.[9] This is primarily because residents in urban areas may have better access to economic opportunities and, therefore, are less vulnerable to income shocks.

Local digital lending development and health deprivation

The analysis follows the same estimation strategy. The estimations are conducted using a multilevel probit regression, where the outcome variable, health deprivation, is regressed on the local digital lending development indicator; the results are presented in Table 3. Column (1) shows the null model, with its associated ICC estimated to be 0.114. This suggests that approximately 11 percent of the variance in health deprivation is attributable to regional factors. Columns (2) and (3) present the average marginal effects, where the estimations are extended to include level 1 and level 2 controls, respectively. The results show a significant negative relationship between local digital lending development and health deprivation. This effect is statistically significant at the 1 percent significance level, implying that households in regions with high local digital lending development are less likely to experience health deprivation. Specifically, Column (3) shows that, on average, a point increase in the local digital lending development index reduces the probability of health deprivation by 0.4 percent points. This effect is similar to that observed for food deprivation.

A possible explanation is that local digital lending development can enable easy access to digital credit, thereby increasing households' ability to access quick loans to pay for health services during unexpected events or health emergencies. This result is consistent with previous studies that demonstrated the potential effects of innovative financial products on healthcare (Ahmed and Cowan 2021; Ky et al. 2018; Obadha et al. 2020; Suri et al. 2021).

[9] The location of respondents gives an indication of where the household is located given that the household was used as the primary sampling unit. In this case if respondent is in rural area, it simply suggests that the household is located in rural centre as well.

Table 3 The effect of local digital lending development on health deprivation

	(1) Null model	(2) Level 1 controls	(3) Level 2 controls
Log of age		0.087***	0.087***
		(0.009)	(0.009)
Female		− 0.007	− 0.007
		(0.006)	(0.006)
At least secondary education		− 0.076***	− 0.077***
		(0.008)	(0.009)
Log of household size		0.021***	0.021***
		(0.006)	(0.006)
Wealth score		− 0.149***	− 0.149***
		(0.017)	(0.017)
Log of income		− 0.025***	− 0.025***
		(0.002)	(0.002)
Bank account		− 0.063***	− 0.063***
		(0.013)	(0.013)
Formal loans		− 0.020	− 0.020
		(0.013)	(0.013)
Other loans		0.022	0.022
		(0.020)	(0.020)
Informal loans		0.063***	0.063***
		(0.010)	(0.011)
Rural		0.018*	0.018*
		(0.010)	(0.010)
Local digital lending		− 0.291***	− 0.380***
		(0.064)	(0.083)
Log of reported death			0.041**
			(0.019)
Log of total size			− 0.006
			(0.011)
Log extreme poverty			0.002
			(0.018)
Log GCP per capita			− 0.073*
			(0.042)
Regional variance (σ_u^2)	0.129***	0.078***	0.062***
	(0.028)	(0.012)	(0.010)
ICC	0.114	0.072	0.059
Year dummy	No	Yes	Yes
No. of observations	17,300	16,167	16,167
Number of regions	47	46	46

The Table reports average marginal effects. The outcome variable, health deprivation, equals 1 if any member of the household has sometimes or often gone without medicine or medical treatment. The main independent variable is local digital lending development which is the regional level effect of the likelihood to access digital credit. Standard errors are adjusted via cluster bootstrapping with 400 replications. Robust standard errors are in parentheses

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

The control variables also show significant results. Individual-level controls, such as education, access to amenities (wealth score), income, GCP per capita, and bank account ownership, show negative and significant relationships with health deprivation.

However, the likelihood of health deprivation tends to increase with age, household size, and number of reported deaths in the region. Those with informal loans are more likely to report health deprivation in their households. Similarly, rural dwellers are more likely to experience health deprivation in their households than urban inhabitants, indicating that the former are more vulnerable than the latter.

Does local digital lending development benefit rural communities?

Urban areas are considered advantageous because they are the epicenters of economic opportunities, including the provision of financial services. By contrast, rural areas are disproportionately disadvantaged in the provision of financial services (Beck et al. 2009) and often have inadequate economic opportunities. This subsection highlights the implications of local digital lending development for rural communities. To achieve this objective, this study presents the differential effect of local digital lending development on food deprivation on one hand and health deprivation on the other.

First, I estimate the interaction between location in rural areas and local digital lending development using Eq. (5) to ascertain whether local digital lending development is favorable to rural dwellers. The coefficient estimates of the interaction term are presented in Table 10 in the "Appendix". To compute the differential effect more precisely, I estimate the average marginal effects of local digital lending development for rural and urban residents. This approach is preferred because the computation of the interaction effects in nonlinear models is nontrivial and cannot be simply deduced from the coefficient associated with the interaction term (Ai and Norton 2003). With this approach, the interaction effect (cross-partial derivative effect) can be easily estimated as the difference in the marginal effect of local digital lending development on the conditional probability that food or health deprivation equals 1 between rural and urban areas (Karaca-Mandic et al. 2012).

The results of the differential effects are presented in Table 4. Column (1) shows the results when the dependent variable is food deprivation, whereas column (2) indicates the results for health deprivation. As shown in column (1), the effect of local digital lending development on food deprivation for rural dwellers is − 0.437, compared to − 0.274 for urban areas. This suggests that, on average, rural dwellers benefit more from such development than urban dwellers, with a difference of approximately 16.3 percentage points. As indicated in the previous section, rural communities are more likely to suffer from food deprivation. So, in this case, local digital lending development can facilitate the extension of microcredit via digital platforms to areas where these credits are needed the most leading to more significant effects.

Column (2) shows the health deprivation estimates. The results reveal that for inhabitants of rural communities, the effect of local digital lending development on health deprivation is − 0.400, whereas the effect for those in urban communities is − 0.344. This implies that, on average, rural dwellers benefit more from such development than urban inhabitants, although the difference is marginal (5.6 percentage points) compared with earlier estimates for food deprivation. This finding suggests that local digital lending development is instrumental in reducing food deprivation in rural communities.

Table 4 Differential effects of local digital lending development for rural and urban dwellers

	(1) Food deprivation	(2) Health deprivation
Urban	− 0.274***	− 0.344***
	(0.095)	(0.089)
Rural	− 0.437***	− 0.400***
	(0.100)	(0.086)
Regional variance (σ_u^2)	0.084***	0.062***
	(0.017)	(0.010)
ICC	0.077	0.058
Year dummy	Yes	Yes
Controls	Yes	Yes
No. of observations	16,176	16,167
Number of regions	46	46

The Table reports average marginal effects. Estimation is carried out using Eq. (5). Standard errors are adjusted for via cluster bootstrapping with 400 replications. Robust standard errors are in parentheses

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

Robustness checks

This study further checks for the robustness of the results by addressing potential endogeneity concerns. One may argue that the inhabitants of developed regions may suffer less from deprivation owing to the presence of good economic opportunities including easy access to digital credit. In addition, omitted variable bias cannot be entirely ruled out in the analysis, especially given the complex nature of the study, for which both regional- and individual-level controls must be considered. In this case, the baseline estimates may be biased because of endogeneity. To correct for this potential source of bias, a two-step estimation procedure was followed, which is similar to the approach of Rivers and Vuong (1988) but, in this case, applied within a multilevel framework. First, I regress the endogenous variable, local digital lending development, on the regional-level controls, together with an instrumental variable, using the specification below:

$$loc\_digital\_lending_j = \gamma_0 + \gamma_1 \lambda_j + \gamma_2 z_j + \omega_j \tag{7}$$

where $loc\_digital\_lending_j$ is the local digital lending development variable, λ_j is a vector of regional-level covariates, z_j is the instrumental variable, and ω_j is the error term. For the instrumental variable, I use the average distance to the nearest mobile money agent at the regional level which is expressed in kilometers. The distance to mobile money agents is estimated using 2014 geospatial data on mobile money agents combined with household location information from the FinAccess survey.[10] The geospatial data on mobile money agents was sponsored by the Bill and Melinda Gates Foundation and accessed through the FinMark Trust (insight2impact). Mobile money agents are at the center of the digital financial revolution in Kenya. For example, these agents are contact points for mobile money registration, cash deposits, and withdrawals. Previous studies have employed distance to mobile money agents as an instrument for mobile

[10] The latitude and longitude information of the 2018 FinAccess survey were used to estimate the distance to mobile money agents.

money adoption (Jack and Suri 2014; Ky et al. 2018). Proximity to mobile money agents is expected to influence local digital lending development given that mobile money deployment provides the necessary infrastructure for the development of other innovative products, such as digital credit.

Second the residual θ_j from the reduced form Eq. (7) is added as an additional regressor in the multilevel probit model using the following specification:

$$Y_{ij}^{*} = P_0 + P_1 X_{ij} + P_2 loc\_digital\_lending_j + P_3 \lambda_j + P_4 \theta_j + u_j + \varepsilon_{ij} \tag{8}$$

$$Y_{1ij} = 1\left[Y_{ij}^{*} > 0\right] \tag{9}$$

where X_{ij} is a vector of level 1 controls, λ_j is a vector of regional-level covariates, u_j is the random effect, and ε_{ij} is the individual error term. A major advantage of the procedure in Eq. (8) is that the t statistics on θ_j provides a simple test of endogeneity. Thus, it tests the null hypothesis that the local digital lending variable is exogenous: $H_0 : P_4 = 0$. However, a major drawback of this method is that it is based on strong assumptions and if exogeneity is rejected ($P_4 \neq 0$) the test statistics and standard errors may be biased (Wooldridge 2002). As an alternative approach, I estimate a linear probability model (LPM) using two-stage least squares (2SLS). This approach is preferred because it is straightforward and provides an equally accurate estimation of the average effect (Wooldridge 2002). In this case, I estimate a linear probability model where instead of the residual, the outcome variables are regressed on the predicted values of the endogenous variable from the first-stage regression (Eq. 7), as expressed below:

$$Y_{ij} = Q_0 + Q_1 X_{ij} + Q_2 \widehat{digital}_j + Q_3 \lambda_j + v_j + e_{ij} \tag{10}$$

where $\widehat{digital}_j$ is the predicted value of local digital lending development, v_j is the regional-level random effect, and e_{ij} is the Level 1 error term (for a similar empirical strategy see Clément and Piaser 2021). To obtain accurate standard errors, the multilevel estimations adjusted for standard errors through cluster bootstrapping with 400 replications.

Table 11 in the "Appendix" presents the first-stage results. As expected, the instrumental variable significantly predicts local digital lending development. Thus, regions with a high average distance from mobile money agents tend to have lower digital lending development, and vice versa. Table 5 presents the second-stage results of the instrumental variable regression. Columns (1) and (2) report the average marginal effects of local digital lending development on food and health deprivations, respectively, using multilevel probit models. The evidence shows that local digital lending development significantly reduces the probability of food deprivation on the one hand and health deprivation on the other. Columns (3) and (4) of Table 5 provide the results for food and health deprivation using the LPM. The results confirm the baseline estimates, suggesting that local digital lending development matters for both food and health deprivations.

It is worth noting that in both columns (1) and (2) the test statistics on the residual (Θj) is not statistically significant therefore the null hypothesis that local digital lending development is exogenous cannot be rejected. This confirms that the baseline estimations are not biased because the evidence suggests that the main independent variable of interest is not endogenous. Nonetheless, Table 6 presents the results for the interaction between digital lending development and location in rural areas. For ease of interpretation, this analysis is carried out using the LPM. The estimates for food deprivation are shown in column (1), and the results for health deprivation are presented in column (2). These results are consistent with earlier estimations, indicating that those residing in rural communities benefit more from local digital lending development, especially in terms of food access.

Research implications of findings

This study advances the literature on local financial development (Fafchamps and Schündeln 2013; Guiso et al. 2004) by developing an indicator of local digital lending development and further relating this indicator to the incidence of deprivation. Bernards (2022) notes that the development of digital finance in Kenya follows existing patterns of uneven development that can be traced back to the colonial financial infrastructure, where urban areas are favored over rural areas. For example, a recent study suggests the existence of financial inclusion gap between urban and rural areas in developing countries (Demirgüç-Kunt et al. 2021). This implies that any attempt to resolve the rural–urban divide in digital finance should first address the contextual factors that inhibit the provision of digital financial services in rural areas. Bernards (2022) argues that even if digital finance leads to welfare gains, such gains are likely to be unevenly distributed in ways that reflect existing patterns of development. However, this study demonstrates that local digital lending development matters for welfare, particularly in rural areas compared to urban areas. This finding is consistent with previous studies showing that digital financial services tend to favor disadvantaged segments of society (e.g., Ky et al. 2018).

Bateman et al. (2019) identified digital lending-related overindebtedness as a major concern in Kenya. This is because digital loans are easily accessible and can be redirected to risky ventures such as gambling (Bateman et al. 2019). This is particularly true when borrowers perceive digital loans as free money and not debt (Langley et al. 2019). Wang et al. (2021) note that digital credit providers often use credit rating techniques to classify borrowers into different credit grades. In this case, borrowers with worse credit grades are charged higher interest rates given that they have a higher default risk. The high interest rates associated with digital credit, especially for those with worse credit scores, can equally increase borrowers' repayment burden, leading to overindebtedness. Nonetheless, digital loans can improve welfare, especially when they are used to meet consumers' daily needs. This study acknowledges that easy access to digital credit and the high interest rates associated with such loans can increase the repayment burden of borrowers, with significant implications for welfare (Langley et al. 2019; Stefanelli et al. 2022). For example, if left unchecked, the negative effects of overindebtedness can undermine the benefits of digital lending. However, this has not been tested empirically in this study.

Overall, the results of this study are consistent with the literature on microfinance and welfare. This confirms previous studies showing that microfinance can significantly

Table 5 The effect of local digital lending development on food and health deprivations; robustness test

	Multilevel probit model		**Multilevel LPM (2SLS)**	
	Food deprivation	**Health deprivation**	**Food deprivation**	**Health deprivation**
	(1)	**(2)**	**(3)**	**(4)**
Log of age	0.071***	0.087***	0.078***	0.093***
	(0.012)	(0.009)	(0.014)	(0.010)
Female	− 0.019***	− 0.007	− 0.018***	− 0.007
	(0.007)	(0.006)	(0.007)	(0.006)
At least secondary education	− 0.088***	− 0.077***	− 0.090***	− 0.077***
	(0.008)	(0.009)	(0.008)	(0.008)
Log of household size	0.016**	0.021***	0.015**	0.018***
	(0.006)	(0.006)	(0.007)	(0.006)
Wealth score	− 0.149***	− 0.149***	− 0.092***	− − 0.105***
	(0.017)	(0.017)	(0.018)	(0.013)
Log of income	− 0.030***	− 0.025***	− 0.032***	− 0.026***
	(0.002)	(0.002)	(0.003)	(0.003)
Bank account	− 0.065***	− 0.063***	− 0.057***	− 0.056***
	(0.011)	(0.013)	(0.010)	(0.012)
Formal loans	− 0.034**	− 0.020	− 0.028**	− 0.019*
	(0.015)	(0.013)	(0.013)	(0.011)
Other loans	− 0.004	0.022	− 0.001	0.017
	(0.020)	(0.020)	(0.014)	(0.017)
Informal loans	0.052***	0.063***	0.055***	0.065***
	(0.010)	(0.011)	(0.009)	(0.010)
Rural	0.027**	0.018*	0.031***	0.018*
	(0.011)	(0.010)	(0.012)	(0.010)
Local digital lending	− 0.433*	− 0.442**		
	(0.257)	(0.191)		
Residual (θ_j)	0.069	0.082		
	(0.268)	(0.189)		
$\widehat{digital}_j$			− 0.503*	− 0.474*
			(0.286)	(0.256)
Log of reported death	0.045	0.048*	0.051	0.050
	(0.043)	(0.029)	(0.045)	(0.034)
Log total size	0.004	− 0.008	0.006	− 0.009
	(0.011)	(0.011)	(0.015)	(0.015)
Log of extreme poverty	0.034	0.006	0.034	0.010
	(0.027)	(0.020)	(0.031)	(0.025)
Log of GCP per capita	− 0.075	− 0.067	− 0.101	− 0.087
	(0.070)	(0.046)	(0.078)	(0.055)
Constant			1.165	1.025
			(0.972)	(0.712)
Regional variance (σ_u^2)	0.085***	0.062***	0.010	0.008
	(0.018)	(0.011)	(0.002)	(0.002)
Year dummy	Yes	Yes	Yes	Yes
No. of observations	16,176	16,167	16,176	16,167
Number of regions	46	46	46	46

Columns (1) and (2) report the average marginal effects. Columns (3) and (4) are coefficient estimates from the linear probability model. Standard errors are adjusted for via cluster bootstrapping with 400 replications. Robust standard errors are in parentheses

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

Table 6 Differential effects of local digital lending development. Robustness test

	(1) Food deprivation	(2) Health deprivation
Rural	0.202***	0.048
	(0.063)	(0.047)
$\widehat{digital}_j$	− 0.319	− 0.442*
	(0.282)	(0.253)
Rural #$\widehat{digital}_j$	− 0.263***	− 0.046
	(0.095)	(0.070)
Constant	1.156	1.023
	(0.945)	(0.709)
Regional variance (σ_u^2)	0.010	0.008
	(0.002)	(0.002)
Controls	Yes	Yes
Year dummy	Yes	Yes
No. of observations	16,176	16,167
Number of regions	46	46

The Table reports coefficient estimates of the interaction between digital lending development and derivation (food and health). The estimation is carried out using a linear probability model (multilevel). Standard errors are adjusted for via cluster bootstrapping with 400 replications. Robust standard errors are in parentheses

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

influence access to food (Bidisha et al. 2017). Also, this study corroborates earlier studies suggesting that microfinance positively affects access to healthcare (Bhuiya et al. 2018). Consistent with Suri et al. (2021), this study highlights digital credit as an important channel through which mobile phone-related financial innovations influence welfare. This is a clear departure from the mobile money literature, which largely focuses on remittances as the main mechanism through which mobile money affects household outcomes.

Future studies can explore the interplay between local digital lending development and the repayment burden of borrowers, and the implications of this effect on welfare. This will influence financial inclusion policies at the local government level. In addition, this study lays the foundation for future studies to explore the effect of local digital lending development on other economic outcomes that have not been addressed in this study, such as entrepreneurship, firm performance, and multidimensional well-being. Furthermore, this study focuses on Kenya and does not assume that the results are generalizable across Sub-Saharan Africa. However, other countries can learn from the Kenyan experience in the provision of digital financial services and apply this to suit their local contexts. Future studies can extend this analysis to other countries in Sub-Saharan Africa to obtain more generalizable results.

Conclusion

This study examines the relationship between local digital lending development and the incidence of deprivation, and explores the implications of this relationship for rural residents. This study demonstrates that local digital lending development has the potential to decrease the likelihood of food deprivation, especially in rural communities where such credit is mostly needed. Similarly, evidence suggests that the development of digital lending at the local level can reduce the probability of health deprivation. Although the empirical evidence on the impact of microfinance on welfare is mixed, this study provides additional evidence indicating that the provision of microloans via digital delivery channels can reduce the likelihood of deprivation, especially in rural communities.

On the policy front, this study provides insights into the welfare effect of local digital lending development at the household level, based on Kenyan data. This study recommends the decentralization of financial inclusion policies and the empowerment of local governments to lead financial inclusion initiatives, especially in rural areas. This study is expected to stimulate interest in the promotion of digital lending at the local government level, thereby shifting the conversation from centralization to the decentralization of financial inclusion policies. It is anticipated that decentralized financial inclusion policies will lead to a quick response to factors that inhibit financial inclusion at the local level, especially in rural communities. Local governments can lead financial literacy and consumer protection initiatives to engender access to digital credit at the local level while simultaneously ensuring that easy accessibility to digital credit does not degenerate into overindebtedness. To achieve this, local governments should be encouraged to participate actively in the design and implementation of financial inclusion policies to promote inclusive development.

This study acknowledges that without the right policies in place, high interest rates and overindebtedness may undermine the positive effects of local digital lending development on welfare. Future studies could explore how the repayment burden can condition the relationship between local digital lending development and welfare. It will also be of policy relevance to explore the relationship between local digital lending development and other economic outcomes, such as multidimensional well-being, entrepreneurship, and firm performance in Sub-Saharan Africa.

Appendix

See Tables 7, 8, 9, 10, and 11.

Table 7 Definition of variables employed for the study

Variable	Description
Food deprivation	1 if any member of the household has often or sometimes gone without food
Health deprivation	1 if any member of the household has often or sometimes gone without medicine or medical treatment
Age	Age of respondent
Female	1 if the respondent is female
At least secondary education	1 is respondent has at least secondary education
Household size	Total number of household members
Rural	1 if the respondent resides in a rural area
Income	Monthly income of respondent in Kenyan shilling
Bank account	1 if respondent currently has savings or post bank, or current account with the bank
Mobile finance account	1 if respondent current has mobile money or mobile banking account
Mobile phone	I if respondent owns a mobile phone
Wealth score	Index capturing household access to amenities (variables include habitable rooms; Toilet; water source; lighting; and cooking fuel)

Table 7 (continued)

Variable	Description
Habitable rooms	1 if the number of habitable rooms in the household is more than 3
Toilet	1 if the main type of toilet facility is a flush toilet
Water source	1 if water is piped into dwelling/plots or yard
lighting	1 if the source of lighting is electricity or Solar
Cooking fuel	1 if the source of cooking fuel is electricity or Gas/LPG
Formal loans	1 if respondent currently or used to have loans from banks and microfinance institutions
Other loans	1 If respondent currently or used to have loans from government and employer
Informal loans	I if respondent currently or used to have loans from Sacco, money lenders, Chama, family/friends among others
Digital credit	1 if respondent currently or used to access mobile banking loans or digital loans via mobile phones or apps
Local digital lending	A continuous variable measuring local digital lending development
Reported death	Total number of reported deaths by county in 2015
Total size	Total land and water area by county (square kilometres)
Extreme poverty	2015 extreme poverty headcount rate by county
GCP per capita	2015 Gross County Product (Constant prices in KSh million) per capita
Ave distance MM	Average distance to nearest mobile money agents by county, 2014 estimates (in km)

Table 8 Summary statistics of variables employed for the analyses

	Obs.	Mean	Std. Dev.	Min	Max
Food deprivation	17,311	0.30	0.46	0	1
Health deprivation	17,300	0.29	0.46	0	1
Age	17,334	38.25	16.87	16	100
female	17,334	0.59	0.49	0	1
At least Secondary education	17,319	0.40	0.49	0	1
Household size	17,334	4.18	2.41	1	21
Rural	17,334	0.57	0.49	0	1
Income	16,695	13,013.94	131,556.20	0	2E+07
Bank account	17,334	0.25	0.43	0	1
Mobile finance account	17,334	0.70	0.46	0	1
Mobile phone	17,302	0.77	0.42	0	1
Wealth score	17,309	0.13	0.34	0	1
Habitable rooms	17,315	0.18	0.38	0	1
Toilet	17,331	0.11	0.31	0	1
Water source	17,334	0.26	0.44	0	1
lighting	17,333	0.55	0.50	0	1
Cooking fuel	17,332	0.13	0.34	0	1
Formal loans	17,334	0.09	0.28	0	1
Other loans	17,334	0.05	0.21	0	1
Informal loans	17,334	0.52	0.50	0	1
Digital credit	17,334	0.14	0.34	0	1
Local digital lending	16,778	0.66	0.20	− 1E − 08	1
Reported death	17,334	5728.66	5606.40	389	23,486
Total size	17,334	11,468.69	17,172.37	216	76,031
Extreme poverty	17,334	9.47	10.41	0.20	52.70
GCP per capita	17,334	11.14	0.46	10.21	12.25
Ave distance MM	17,334	3.85	4.68	0.12	19.32

Table 9 Marginal effect estimates for the probability of accessing digital credit

	Digital credit
Rural	− 0.019***
	(0.005)
Log of household size	0.001
	(0.003)
Log of age	− 0.052***
	(0.007)
Female	− 0.015***
	(0.004)
At least secondary education	0.039***
	(0.005)
Log of income	0.015***
	(0.002)
Bank account	0.048***
	(0.004)
Mobile money/mobile banking account	0.083***
	(0.011)
Mobile phone	0.060***
	(0.012)
Year dummy	Yes
Regional dummies	Yes
No. of observations	16,650

Estimation is based on Eq. (1). The dependent variable equals 1 if the respondent has access to digital credit. Robust Standard errors are in parentheses. Standard Errors are clustered at the regional level

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

Table 10 Interaction between local digital lending development and location in rural areas

	(1) Food deprivation	(2) Health deprivation
Rural	0.447***	0.165
	(0.145)	(0.123)
Local digital lending	− 0.967***	− 1.191***
	(0.326)	(0.312)
Rural # local digital lending	− 0.555**	− 0.163
	(0.237)	(0.196)
Constant	1.710	1.372
	(2.681)	(1.900)
Regional variance (σ_u^2)	0.084***	0.062***
	(0.017)	(0.010)
ICC	0.077	0.058
Year dummy	Yes	Yes
Controls	Yes	Yes
Observations	16,176	16,167
Number of groups	46	46

Dependent variables are food and health deprivation

The Table reports coefficient estimates. Standard errors are adjusted for via cluster bootstrapping with 400 replications. Robust standard errors are in parentheses

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

Table 11 First stage regression (OLS)

	(1) **Local digital lending development**
Log of reported death	0.077***
	(0.001)
Log total size	0.019***
	(0.001)
Log extreme poverty	0.073***
	(0.002)
Log of GCP per capita	0.084***
	(0.003)
Ave distance MM	− 0.028***
	(0.002)
Constant	− 1.075***
	(0.041)
Year dummy	Yes
Observations	16,778
R-squared	0.598

All variables are regional-level covariates. Robust standard errors in parentheses

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

Abbreviations

Fintech	Financial technology
FSD	Financial Sector Deepening Trust of Kenya
GCP	Gross County Product
ICC	Intraclass Correlation Coefficient
KNBS	Kenyan National Bureau of Statistics
LPM	Linear Probability Model
PCA	Principal Component Analysis
SDGs	United Nations Sustainable Development Goals

Acknowledgements
The author would like to thank Micheline Goedhuys, Maty Konte, Pierre Mohnen, and Davina Osei for their useful comments and support. The author also acknowledges financial support from the United Nations University—Maastricht Economic and Social Research Institute on Innovation and Technology (UNU-MERIT) as a PhD fellow.

Author contributions
I am the sole author of this paper and contributed to all aspects. The author read and approved the final manuscript.

Funding
No funding to report.

Availability of data and materials
The datasets supporting the findings of this study are available upon reasonable request.

Declarations

Competing interests
The author indicates there is no competing interests.

Received: 16 November 2022 Accepted: 27 April 2023
Published online: 21 August 2023

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