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Digital Credit, Financial Literacy and Household Indebtedness

*By Peter Wamalwa, Irene Rugiri & Julienne Lauler

Abstract

Easier access to credit has been emphasized to ease financial constraints that impede investments critical for improving earnings and alleviating poverty. This paper analyses the uptake of digital credit and its impact on household indebtedness in Kenya. The empirical results show that financial literacy reduces utilisation of digital credit. However, using conventional credit is preferred to digital credit. The empirical results also show that individuals using digital credit are more likely to sale household assets to repay their loan, have a higher number of loans and lower income compared to those using conventional credit or not using credit.

** Peter Wamalwa, Irene Rugiri and Julienne Lauler are affliated to the Central Bank of Kenya. All views expressed herein are their own and any errors and omissions are fully owned.*

1.0 Introduction

Expanding access to credit is one of the cornerstones of enhancing financial development, which has been shown to accelerate growth in income and alleviate poverty (Levine et. al, 2000, Clarke, et al., 2006).

Whereas access to credit from formal financial institutions such as commercial banks, microfinance institutions and savings and credit cooperative societies (Saccos) has improved, the digitally delivered micro-credit has significantly increased access and utilisation of credit to a large proportion of borrowers previously excluded from formal financial services in developing economies. Digitally-delivered micro-credit[1] is easily and conveniently obtained particularly for the previously financially excluded, however, it is expensive and short term relative conventional credit (CGAP, 2017).

The use of digital channels to provide loans has reduced transaction and information costs associated with lending, thereby driving demand and expanding the supply of credit. Financial institutions can leverage this technology to more efficiently screen for default risks, and households can more easily and affordably borrow (Gross & Souleles, 2001; Narajabad, 2012; Livshits, Sanchez, 2012). Access to digital credit, enables households and firms to invest in human and physical capital and shift to higher-skilled, high earning occupations (See, for example, Galor and Zeira, 1993; Banerjee and Newman, 1993; Lloyd-Ellis and Bernhardt, 2000, Jack and Sur, 2014). This not only increases income and

1 "Digitally-delivered micro-credit" or "digital credit" refers to unsecured cash loans in emerging markets that are obtained via digital channels (e.g. mobile phones or the Internet) without the involvement of a salesperson, that use digital channels for loan disbursement and collection, and that leverage digital data to make lending decisions via automated processes (CGAP, 2017). In Kenya, digital credit platforms include a range of prudentially regulated products provided through banks (e.g. M-Shwari, KCB M-Pesa, Equitel, M-Coop Cash), as well as an increasing number of non-bank products that are outside of the current regulatory framework.

wealth at the household and national levels but also reduce wealth inequality.[2]

However, the increase in digital credit uptake amid increasing default rates among borrowers has raised questions about the number of information consumers of digital credit to receive to inform their decisions to procure credit as well as the effect of digital credit on household indebtedness. These questions are more pertinent, especially for a majority of digital credit consumers, who may not make informed decisions due to limited financial literacy or disclosure of terms and conditions of credit, thereby predisposing borrowers to welfare-reducing credit or over-indebtedness.

There is no consensus in the literature on the effect of digital credit on household indebtedness and income outcomes. A growing literature shows that, on the one hand, access to consumer credit can improve household incomes by enabling consumption smoothing and access to emergency funds (see, for example: Morse, 2009; Morgan, Strain, & Seblani, 2007; Wilson, Findlay, Meehan Jr., Wellford, & Schurter, 2010; and Karlan & Zinman, 2010). On the other hand, a separate strand of literature shows that access to high-interest, short-term consumer credit can be detrimental to household earnings, often trapping borrowers in debt and exacerbating financial distress (Parrish & King, 2009; Baugh, 2015; CFPB, 2016; and Melzer, 2011).

Evidence also shows that financial distress as a result of easy to access credit is compounded by limited financial literacy (Lusardi and Tufano, 2008, 2015; Stango and Zinman, 2007; Johnson, Kotlikoff and Samuelson, 2001), or behavioural biases whereby borrowers prefer current to future consumption (O'Donoghue and Rabin, 1999; Stango and Zinman, 2009; Ausubel, 1991). Conversely, lenders can use superior information on borrowers to extend expensive re-financing loans (Bond et al., 2009). Hence, the effect of digital credit on household indebtedness is an open question to be investigated. Understanding the effect of digital credit on household indebtedness has become even more pertinent in developing economies, where regulatory frameworks for credit market and consumer protection lag behind technology and financial innovations that increase access to credit.

Therefore, this study uses data from the FinAccess Digital Credit Tracker Survey, 2017 and FinAccess Household Survey 2015-16 in Kenya to analyse the

2 The literature on the effect of financial sector development on macro-economic outcomes is vast, with "financial development" commonly measured as credit to the private sector by financial intermediaries. For the effect of financial development on growth, see, among others, Levine, Loayza, & Beck (2000), King & Levine (1993) and Rousseau & Wachtel (2000). For the effect of financial development on poverty reduction see, among others, Honohan, (2004) and Park and Mercado (2015). On the effect of financial development on income inequality see, among others, Buera, Kaboski, & Shin (2012), Clarke, Xu, & Zou (2006), Greenwood & Jovanovic, (1990), Galor and Zeira (1993) and Banerjee and Newman (1993).

digital credit uptake as well as the effect of digital credit on household indebtedness. To do this end, we first establish household characteristics that influence digital credit uptake. This enables us to disentangle the contribution of financial literacy to the uptake of digital credit. We then establish the impact of digital borrowing on household indebtedness. We estimate multinomial and binary response models to establish the household characteristics that influence the utilisation of digital credit. We also estimate the impact of using digital credit on household indebtedness.

The results from the multinomial and binary response models show that digital credit is preferred the most compared to either conventional credit or not using credit by male household heads, households with higher income, the employed and the self-employed. However, if households' heads are to choose between conventional credit and digital credit, conventional credit is preferred. The results also show that the educated are more likely to use digital credit than conventional credit, while the financially literate are less likely to use digital credit. Therefore, there is evidence that households utilise digital credit to ameliorate short term liquidity problems because it is easier to access, despite the high cost and short repayment period. The financially literate have the cognitive ability to make good credit consumption decisions. The results on the impact of digital credit on indebtedness indicate that digital credit increases the probability of debt distress by 0.22 and reduces income by about 16 per cent. This is due to small amount of loans advanced with short maturities and high-interest rates and fees that do not enable households to make long term indivisible investments, which have a dramatic impact on household income and wealth (Clarke, et al., 2006). However, households that have no access to either conventional or digital credit are the worst off. Hence, policy intervention geared towards enhancing access to credit should be cognisant of ease and convenience of access to digital credit and its lower contribution to income improvement relative to conventional credit.

This paper, by analyzing the utilisation of digital credit and its impact on household indebtedness, contributes to the literature on the impact of consumer credit offered through digital channels. We also shed light on whether digital credit bridges the financing gaps by enabling access to convenient, short-term credit rather than trapping borrowers in a cycle of borrowing and repaying at a high cost. Hence, this paper contributes to the debate on policy interventions related to digital credit, consumer protection and financial education.

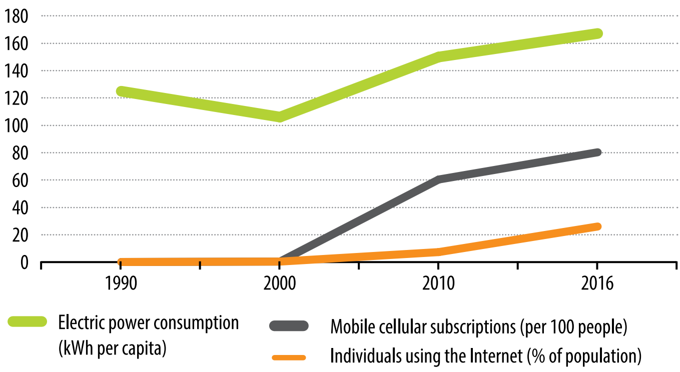
The remainder of this paper is structured as follows. Section 1 provides background on digital credit in emerging markets, with a focus on the rapid expansion of digitally-delivered credit in Kenya. Section 2 reviews relevant literature on the impact of consumer credit uptake on individual outcomes and explores the debate between welfare-enhancing and welfare-reducing credit. Section 3 details the empirical model, while Section 4 presents the results and Section 5 concludes.

2.0 Background: Digital Credit

Kenya, like other developing countries, has recorded tremendous progress in increasing mobile network coverage, internet penetration and electricity connectivity in recent decades (figure 1).

Mobile cellular subscriptions per 100 people, for instance, has grown from 0.4 in 2000 to 80.4 in 2016. This rapid telecommunication and energy infrastructure development, coupled with the global decline in cellphone prices, have been harnessed by the telecommunication companies to provide value-added services such as mobile money transfer services.

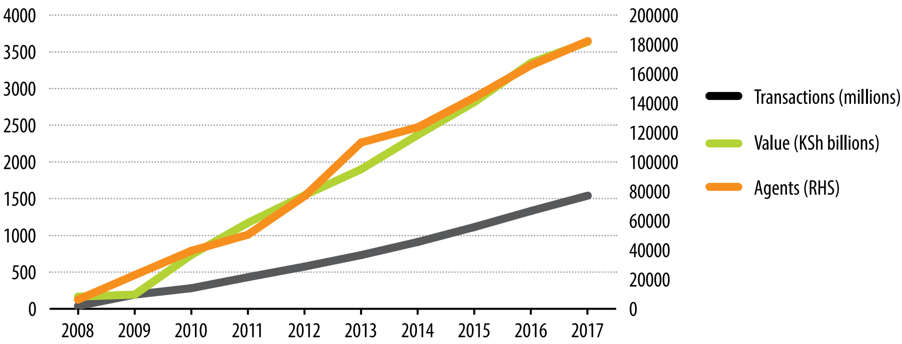
Figure 1: Telecommunication services penetration in Kenya 1990-2016



Source: World Development Indicators, 2016

The uptake of mobile money transfer services has increased rapidly in Kenya and the East African region in general. According to the Central Bank of Kenya, the amount transacted through real-time mobile-based payments increased from KSh 166 billion in 2008 to KSh 3,638.5 billion in 2017, while the number of mobile money agents has increased from 6,104 to 182,472 over the same period (**figure 2**).

Figure 2: Mobile Money Uptake in Kenya from 2008 to 2017



Source: Central Bank of Kenya

The success of mobile money transfer services in Kenya and other developing countries has been leveraged on to provide digital credit. In Kenya, the provision of digital credit began in 2010 with a joint venture between Safaricom and Equity Bank called M-Kesho, which leveraged the transactional rails of M-Pesa to offer full-fledged savings account to mobile money account holders, with no account opening fees, minimum balances or monthly charges. Small-scale loans ranging from KSh 100-5,000 were also available through the platform. Whereas the uptake of this product was poor, it laid the base for future innovations to deliver digital credit.

Since 2010, application-based digital credit providers and financial institutions have been providing unsecured credit by leveraging on telecommunication services, either independently or in collaboration with telecommunication companies. Initially, the uptake of digital credit was slow, between 2010 and the first quarter of 2015, due to supply-side constraints and ambiguity of the regulatory framework.[3] However, harmonization of the regulatory framework, especially the enactment of the National Payments Act in 2011 and complementary regulation in 2014, provided a conducive regulatory framework for providing digital credit. As a result, the number of new digital credit providers increased tremendously. **Table 1** below provides a breakdown of the digital credit products currently offered by commercial banks, along with product features.

3 Most of the digital credit providers were either unregistered or hence operated informally or were registered as money transfer service providers by the communication commission of Kenya (later renamed Communication Authority of Kenya) while financial institutions were registered and regulated by the Central Bank of Kenya.

Table 1: Mobile Banking Products Offered by Commercial Banks

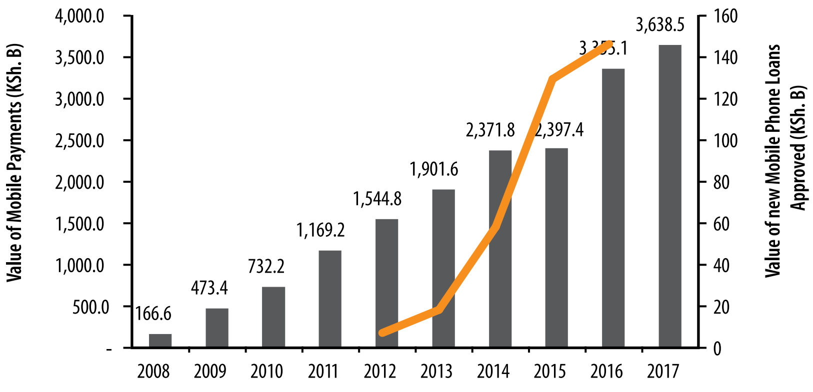
Bank	Product	Launch date	Product features	Eligible customers	Credit scoring process and data sources	Partnership model
KCB	KCB M-Pesa	March 2015	Loan product, Fixed or targeted savings accounts, inter-account funds transfer	All active M-Pesa customers	Instant credit scoring using data from Safaricom, M-PESA transactions	MNO (Safaricom) and Bank (KCB)
CBA	M-Shwari	Nov. 2012	Loan product, Deposit account	All active M-Pesa customers	Electronic KYC verification; instant credit scoring; data used for credit scoring includes KYC details from Safaricom, data related to airtime, airtime credit, M-PESA, length of time as a customer and M-Shwari behaviour.	MNO (Safaricom) and Bank (CBA)
Co-op Bank	M-Coop Cash	August 2014	Loans, savings	Eligible for Cooperative Bank customers only (need to have Coop PIN to access M-Coop Cash)	N/A	N/A
Equity Bank	Equitel	July 2015	Bank account access, funds transfer, Eazzy loans, Savings, make payments	Eligible for Equity customers only; to access loans, must have active Equity Bank account for at least 6 months and active Equitel line	Credit scoring based on past borrowing behaviour of customers; bank account data	Bank only (Equity Bank), through its subsidiary Finserve Africa Limited. Equitel is a mobile virtual network operator (MVNO) using Airtel Kenya network as a carrier.

Bank	Product	Launch date	Product features	Eligible customers	Credit scoring process and data sources	Partnership model
Barclays Bank	Timiza	March 2018	Transfer to/from M-Pesa, request and repay loans, savings, bill payments, disability and funeral insurance, airtime purchase, order Little Cab taxis	Eligible for all active M-Pesa users with a national ID; Timiza is a separate bank account *not linked* to Barclay's account	Credit scoring based on M-PESA transactions, previous credit usage (e.g. *Okoa Jahazi*), credit rating with the CRBs	Bank (Barclays), MNO (Safaricom), technology provider (Craft Silicon)

Source: Bank websites and informal interviews

It is estimated that there are about 22 bank and non-bank digital credit providers in Kenya with approximately 7 million subscribers (CGAP, 2017). However, these estimates are likely to be modest as more financial institutions are eager to capitalize on the mobile technology to introduce new products, and more financial technology firms (fintechs) attempt to provide consumer credit, besides savings and money transfer services. The total credit provided by commercial banks via mobile channels has increased from KSh 197.966 million in January 2013 to KSh 13,993.163 million in March 2018 (**Figure 3**). According to the 2017 FinAccess Digital Credit Tracker survey, 27 per cent (or more than 6 million)

Figure 3: Value of mobile payments and the value of new mobile phone loans approved



Source: Central Bank of Kenya

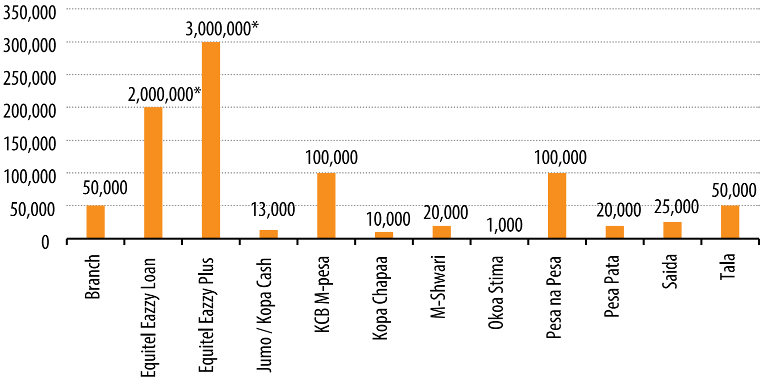
of Kenyans have used digital credit (FSD Kenya-CBK, 2018). Mobile credit services largely use mobile money transfer rails to dispense loans and for loan repayments. Hence, the tremendous increase in the value of mobile money transactions might be explained in part by the increase in the uptake of digital credit (**figure 2**).

Using mobile channels to advance loans opens access to credit among segments of the population which might have access to a mobile phone, but not formal financial institutions. The greater reach of instant, automated and remote lending technology enables these services to be accessed and utilised easily among under-served population segments. The fact that mobile credit products are easily accessible, further makes them useful to meet urgent or unanticipated needs such as late-night emergencies and working capital for urban micro-enterprises, which may not be met by conventional credit providers (Mazer and McKee, 2017).

A majority of digital credit providers target borrowers excluded in the formal financial sector, some who may have no existing banking relationship, thereby predisposing themselves to high-risk borrowers. To ascertain the risk profile of potential borrowers and amount of loan to be advanced, lenders assess mobile usage history, mobile money transaction records and use of airtime data from mobile network operators, and records with credit reference bureaus (CRBs), among other sources. In the absence of collateral or customer data, lenders reduce their exposure to risk by offering short term and low-value mobile credit, and by levying fees or interest rates that are relatively high as compared to conventional loans.

Figure 4 shows the maximum value of loans provided by selected digital credit providers. The loans range from KSh 1,000 to KSh 3 million. The average loan limit across all providers is KSh 449,000. Furthermore, 68 per cent of mobile loan accounts at commercial banks are for loans between KSh 100-5,000, while only 32 per cent of accounts are for loans more than KSh 5,000 (CBK, 2018). This shows that most mobile loans offered by commercial banks are micro-loans. These may be sufficient to ameliorate short-term liquidity problems for a household or to provide working capital for small businesses. However, low-value loans are unlikely to enable households or firms to make capital-intensive or long-term investments, which have higher returns and can increase the incomes and wealth of households.

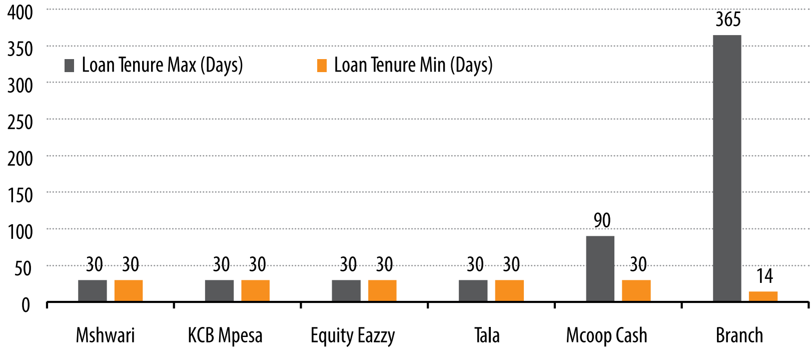
Figure 4: Maximum Loan Limit for Selected Mobile Credit Providers



Source: CGAP 2017 and digital credit providers * Not drawn to scale

Digital credit loans are also short term in nature. **Figure 5** shows that the maximum and minimum loan tenors for the five most-used digital credit products are 30 days, while two providers have loans tenors of between 90 days and one year.

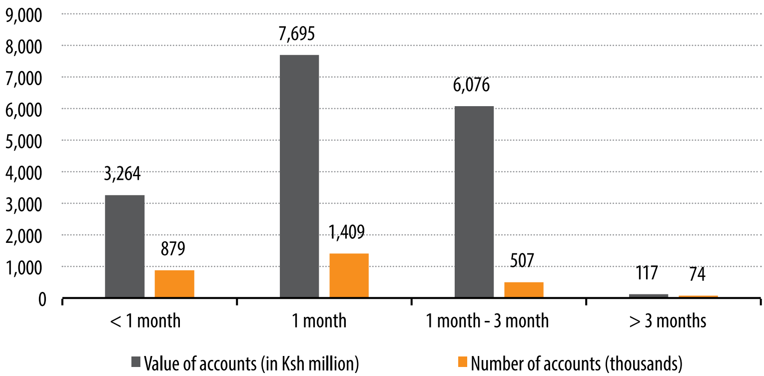
Figure 5: Maximum and Minimum Loan Tenures for Digital Credit Products (in Days)



Source: Others compilation from respective digital credit providers websites

Figure 6 further shows the number that 1409 thousand loans (about 80 per cent) of the total number of mobile loan accounts from commercial banks are one month or less in tenor. Similarly, 64 per cent of the total value of mobile loans from commercial banks is one month or less in tenor. The short-term nature of these products may inhibit their usage for finance longer-term and capital-intensive investment.

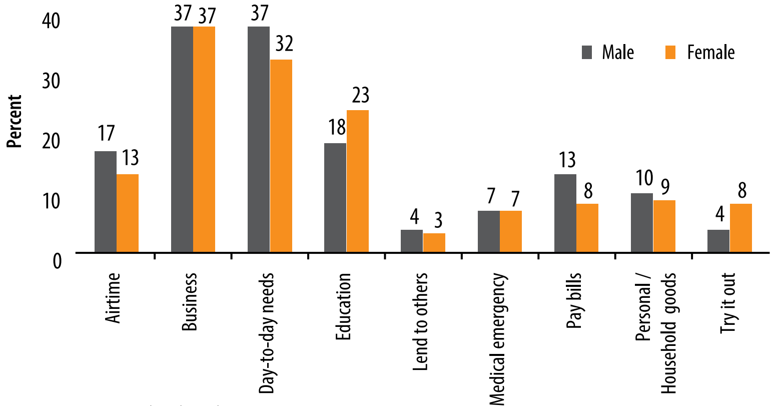
Figure 6: Number and Value of Mobile Banking Accounts by Loan Tenor



Source: CBK – July 2018

Indeed, the 2017 FinAccess Digital Credit Tracker survey shows that about 35 per cent of digital borrowers use digital loans to meet day-to-day needs, while 7 per cent use digital loans for medical emergencies and 9.5 per cent to buy personal or household goods. On the other hand, 37 per cent use digital loans for business purposes, which might include working capital needs or capital investments, while about 21 per cent use them for education, both of which can have long-term benefits (**Figure 7**). These suggest that borrowers are more likely to take digital loans to meet short-term financial needs, rather than for longer-term investment purposes. The long-term investment financed by digital credit, for instance, education, may compound household indebtedness because returns to education are realized way after the loans have fallen due.

Figure 7: Reasons for Taking Digital Credit by Gender (%)



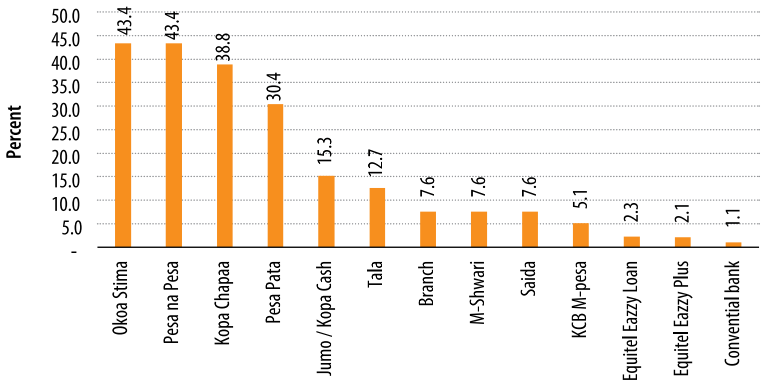
Source: FinAccess Digital Credit Tracker Survey 2017

The risks associated with unsecured digital lending necessitate lenders to reduce their risk exposure by charging fees and interest rates that are relatively high as compared to conventional loan products. A survey of digital credit products in Kenya shows that monthly percentage interest rates range from 2.1 per cent to 43.4 per cent, while monthly interest rate conventional loans average 1.3 per cent (**figure 8**). On average, the monthly percentage interest rate on digital loans exceeds the lending rate for conventional loans, while some digital credit providers have a variable interest rate on loans.[4] This indicates that digital credit despite being easily accessible and enables borrowers to meet financial needs, it is more expensive than conventional credit. The high fees and the interest rate on digital credit can reduce household income over time, particularly if borrowers are taking loans for non-productive purposes and thus the returns on investments financed by digital loans may be insufficient to cover loan obligations when they fall due.

Despite the fact that digital credit is easy to access and meets unanticipated needs, the short tenure, ease of access and the high cost of digital credit may exacerbate debt distress, especially when credit is used for non-productive purposes. In addition, digital borrowers who experience difficulties in repaying their loans within the short time frame may borrow from other lenders to repay their loans or may

4 While most of these loans are short term, and the customer will not be paying on it for a full month, monthly interest rate is still the most effective way to standardize costs and compare loans to alternative options. A distribution of minimum, maximum loans and fees and interest rate on loans is in the appendix

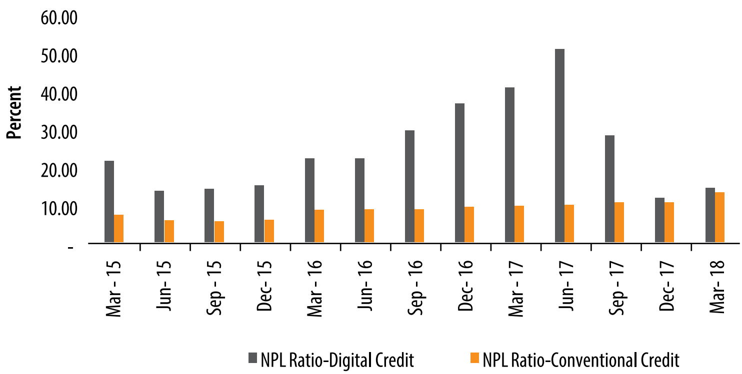
Figure 8: Maximum Monthly Interest rate for Selected Digital Credit Providers and Conventional Loans (%)



Source: CGAP 2017 and digital credit providers

default, occasioning an adverse listing by the credit reference bureaus. This can reduce their ability to access additional or higher-value loans in the future. Indeed, digital non-performing loans (NPL) to digital credit ratio for commercial bank averaged at 21 per cent between March 2015 and March 2018, which is relatively high as compared to the banking industry average NPL ratio of 10.2 per cent (**figure 9**).

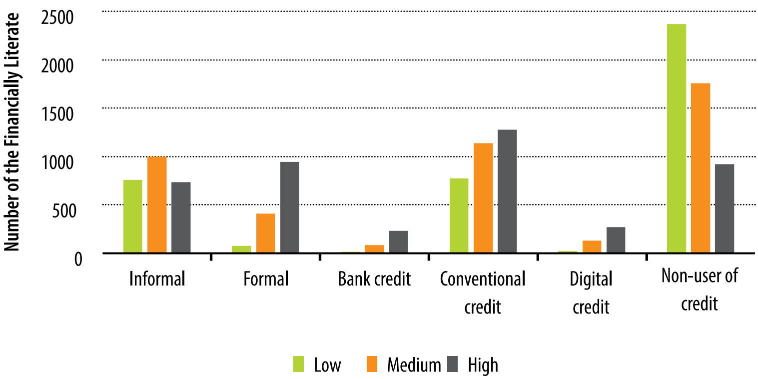
Figure 9: NPL Ratio for Conventional and Digital Credit, 2015-2018



Source: CBK

Despite the NPL ratio for digital loans reducing drastically from June 2017, it remains significantly higher than that for conventional loans. This implies that a larger proportion of digital borrowers' default as compared to conventional credit borrowers. This may be due to poor screening of borrowers and weak under-writing of digital loans as compared to conventional loans. It may also reflect the high-interest rates charged by mobile lending platforms as compared to conventional loans. These factors might be compounded by poor financial literacy, or borrowers not having adequate information on terms and conditions of loans when making borrowing decisions. The financially literate understand the terms and conditions of credit, and hence, make apt credit consumption decisions. Furthermore, they can negotiate and obtain credit on favourable terms, which minimise debt distress. The highly financially literate tend to utilise conventional credit, while a majority of the least financially literate either do not use credit or use informal credit, which is more often expensive than conventional credit (figure 10).

Figure 10: Financial literacy and credit utilisation



Source: FSD-Kenya

The increased utilisation of digital credit, among consumers with low financial literacy amid high non-performing loans, have elevated financial stability risks as well as predisposing consumers to indebtedness. These risks have brought into focus the amount of information provided to digital credit consumers to inform their borrowing decisions and the impact of digital credit on household indebtedness. Yet, a plethora of empirical literature has focused on the impact of conventional credit. Hence, this study attempts to shed some light on the impact of digital credit usage on consumer indebtedness.

3.0 Review of relevant literature

The impact of credit utilisation on household indebtedness can be explained by the tradeoff that borrowers inadvertently make between current consumption and future consumption, albeit with either a higher or lower income depending on the impact of credit on capital accumulation. Thus, credit utilisation can either have a neutral or positive impact on households' consumption and income growth (McCarthy, 1997; Bacchetta and Gerlach, 1997; Ludvigson, 1999).

The life-cycle hypothesis developed by Ando and Modigliani (1963) posits that credit smoothens fluctuations of consumption by enabling households to consume more than their current income when income reduces below permanent level, reduces consumption when income is high when loans are repaid. This implies that indebtedness of households increases when income is low and reduces when income is high. Hence, the young who tend to have little income accumulate debt to undertake investment, which then reduces as more wealth is accumulated over their entire. Therefore, on aggregate current debt accumulation decision have no effect on overall household indebtedness. However, a growing body of literature shows that consumer credit can improve household welfare by facilitating access to economic opportunities, consumption smoothing, and access to emergency funds (Raijas et al., 2010; Morse, 2009; Morgan, Strain, & Seblani, 2007; Wilson, et al, 2010; and Karlan & Zinman, 2010). Payday lending in the U.S., for example, has been shown to bridge liquidity gaps and enable individuals to overcome sporadic shocks to their finances, which enables investment in income enhancing activities.

However, the rise of technology-driven, unsecured consumer lending has increased household indebtedness and reduced ability of consumers to smoothen fluctuations in income and consumption. For example, empirical evidence abounds on increased unsecured easy to access consumer lending creating a "debt trap" and exacerbate financial distress (Baugh, 2015; Parrish and King, 2009; CFPB, 2016; Melzer, 2011). In this case, the heavily indebted households are vulnerable to income shocks and increased social and financial exclusion. The households may not undertake investments that increase their earnings to break the vicious cycle of borrowing and repaying or change to economic activities with higher returns (Haas, 2006).

The use of technology to access and administer credit reduced transaction and information costs associated with lending, thereby driving demand and expanding the supply of credit. Technological progress, from the introduction of credit cards to recent advances in digital credit, enables financial institutions to more efficiently screen for default risks, and enables household to borrow more at relatively low interest rates (Gross & Souleles, 2001; Narajabad, 2012; Livshits, MacGee, & Tertilt, 2010; Sanchez, 2012).

On the demand side, various studies have analysed factors that contribute to borrowers taking on excess, welfare-reducing debt. Empirical evidence shows borrowers who do not understand the terms and conditions of the loans, and thus are vulnerable to fees and other consequences of default tend experience difficulties in repaying their loans and have lower welfare (Lusardi & Tufano, 2015; Stango & Zinman, 2009; Johnson, Kotlikoff, & Samuelson, 1987; Gathergood, 2012). Other studies have focused on the role of behavioural biases, such as payment/interest bias preference for current consumption, and emulative consumption that influence borrowing behaviour (O'Donoghue & Rabin, 1999; O Donoghue, 2006 Stango & Zinman, 2008; Ausubel, 1991; Adkisson and Saucedo, 2012; Gathergood, 2012; Luzzetti and Neumuller, 2016; Laibson, 1997).

The existence of information asymmetries between borrowers and lenders have also been shown to exacerbate the potential adverse effects of consumer credit, as they can lead to the problems of adverse selection and moral hazard. Karlan and Zinman (2005) show that about 20 per cent of the overall default rate of a South African lender can be attributed to information asymmetry. Dobbie and Skiba (2013) find that adverse selection has a significant impact on the likelihood of default on payday loans – borrowers who choose a larger loan are more likely to default. The results suggest that higher interest rates attract riskier borrowers who care less about high rates because they are less likely to repay the loans. Ausubel (1999) found that consumers who accept worse credit card offers are more likely to default on their loans and file for bankruptcy. As the digitization of lending increases access to credit among higher-risk populations, cardholders may increasingly borrow more than they can afford raising default rates.

Bond, Musto, and Yilmaz (2009), similarly, establish that lenders are often more informed than borrowers and that this information asymmetry can lead to predatory lending. The authors, using a model developed based on the U.S. sub-prime mortgage market, show that when lenders have information to suggest that a borrower may be unable to repay their loan, these lenders have a strong incentive to withhold this knowledge and offer loan re-financing at untenable rates – a practice that is disguised as charitable and is thus known as "phantom help". Through refinancing, the lender is able to extract additional cash from the borrower before an inevitable foreclosure.

Therefore, where lenders have an informational advantage over borrowers, increased credit can lead to an increase in indebtedness, with lenders taking advantage of "insider" knowledge (e.g. of borrowers' repayment capacity, level of financial distress, or the urgency of their need for a loan) to extend harmful re-financing loans with exorbitant rates.

Thus, the literature on the digital credit uptake, financial literacy and household indebtedness is not only incoherent but also scanty. Whereas the literature on the effects of credit usage is quite robust, the impact of digital loan products has been hitherto unexplored in empirical studies. This is because it is a nascent industry that has only recently emerged, growing out of the increased use of mobile money infrastructure in emerging markets. Thus, this paper aims to analyse the uptake of digital credit and its impact on household distress. We also assess the effect of financial literacy on digital credit uptake, control for household and location-specific factors.

4.0 Methodology and data

We establish the relationship between the type of credit and consumer characteristics by estimating a multinomial model. In the model, consumers choose to use conventional credit, digital credit or not depending on a set of individual and socio-economic characteristics.

Potential determinants of uptake of digital credit, conventional credit or non-uptake of credit include the level of financial literacy, age, gender, level of income, level of education and occupation of the main income earner and access to social amenities.

The explanatory variables can be broadly categorised as individual characteristics including financial literacy x_i, household h_i and location c_i characteristics. In the context of panel data analysis, this relationship can be specified as follows:

$$y_{it} = a + \beta_1 x_{it} + \beta_2 x_{it} + \beta_3 x_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

Where y_i consists of those who use conventional credit, digital credit or do not have credit. **Equation 1** is estimated assuming that unobserved household characteristics are fixed. This allows estimation of the effect of x_{it}, h_i and c_i on the digital credit outcomes. To analyse the factors that influence, the choice between conventional and digital credit, we estimate equation except that y_i.

We also estimate the impact of digital credit on household welfare and indebtedness. We measure welfare using household expenditure. This is informed by the fact that households with a higher level of expenditure tend to hand higher welfare. This is because household hold spending on basic needs enhances their wellbeing. The contribution of digital credit is also inferred from the impact of credit on household spending. On the one hand, digital credit enables households to invest beyond current income and bequest. On the hand, digital credit enables households to spend on basic needs beyond current income. In addition, credit smoothens fluctuations in current and future consumption which increases welfare. However, the self-reported income of the household head is a good proxy for household expenditure, notwithstanding inaccuracies in self-report income by the respondents in survey studies. Hence, we use household expenditure and household heads' income as proxies of household expenditure.

The ability of households to repay their debt is indicated by income generated from household investment (Clark et al., 2006). Therefore, an increase in household income as a result of utilising credit indicates that utilisation of credit eases financial constraints and earnings from investment increases the ability to repay the loan, thereby reducing household indebtedness.

In addition, household income generated from physical and human capital investment is used to repay household debt. In this regard, a positive contribution of digital credit to household income reduces household indebted, while a negative effect of debt on household income increases household indebtedness.

$$w_{it} = \gamma_i y_{it} + л_i h_{it} + \delta_i c_{it} + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 2$$

Where w_{it} income is ε_{it} is the error term in the income equation. γ_i, $л_i$ and δ_i are parameters on credit, household characteristics and locational characteristics. Hence, we estimate **equation 2** with income and household expenditure as the dependent variable. This model can be estimated by the least square method, but endogeneity between income and access to credit may bias the coefficient. Furthermore, the coefficients may be inconsistent, which compromises inferences as well as the attribution of digital credit to household welfare changes. We correct endogeneity by estimating an exactly identified two step simultaneous equation (Greene, 2000). Households experiencing difficulties in repaying their loans tend to sale assets to settle the loans. We estimate a binary response model in which the dependent variable d_{it} takes one for a household who sold assets to repay a loan and zero otherwise. An estimable model is represented by **equation 3** below.

$$d_{it} = \gamma_i y_{it} + л_i h_{it} + \delta_i c_{it} + \beta_i w_{it} + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3$$

Data

The study utilises demand-side data from the FinAccess Household Survey 2015/16 and the Digital Credit Tracker Survey conducted by Financial Sector Deepening Kenya (FSD Kenya), the Central Bank of Kenya (CBK) and the Consultative Group to Assist the Poor (CGAP) in 2017, using the FinAccess 2015/16 Household Survey sample. **Table 1** shows the distribution of digital and conventional credit users by social economic characteristics.

Table 1: Digital Credit and Formal (Conventional) Credit Users

	Respondents	Digital Credit Users	Conventional Credit Users
Total	3130	1040	1,193
Male	41%	47%	46%
Female	59%	53%	54%
Rural	64%	52%	62%
Average Monthly Income (KSh)	10817.08	14139.46	15855.75
Average Monthly Expenditure (KSh)	8123.165	10476.84	10771.97
Farming	51%	44%	54%
Employed	20%	29%	28%
Casual worker	34%	34%	28%
Self-employed	37%	48%	45%
No education	6%	1%	3%
Primary completed	24%	20%	22%
Secondary completed	25%	33%	27%
Average Age	36.78	33.51	38.12
Married	65.47	12.29	53.48
Not married	34.23	7.21	27.02
Cognition of interest rate	77.68%	17.99%	59.69%
Total number of loans	10	3	7

Source: FinAccess Digital Credit Tracker Survey 2017

A majority of the farmers use conventional credit, while most of the respondents that are self-employed use digital credit. The self-employed prefer digital credit to conventional credit. This may be attributed to unpredictable liquidity changes that the self-employed encounter, which compels them to use digital credit. The proportion of secondary school graduates using digital and conventional credit is greater than primary school graduate. Secondary school graduates are more likely to have more financial skills and higher cognitive abilities to make informed decisions with respect to credit.

5.0 Results

5.1 Digital credit uptake and Financial Literacy

Households facing financial constraints may either utilise conventional credit and digital credit or may not seek credit at all. Hence, the decision to utilise either conventional, digital credit or not utilising credit is influenced by social economic characteristics.

Hence, table 2 analyses the credit utilisation decisions of households. In column 1, the decision to use conventional and digital credit as well as not using credit is estimated using a multinomial logit model. The coefficients are odd of using conventional and digital credit relative to not using credit. The odds indicate that household in urban areas is less likely to use conventional credit relative to not using credit compared to a rural household. However, households in urban areas are more likely to use digital credit than not using credit at all. This implies that households in rural areas are more likely to use conventional credit than digital credit. The differences in the conventional and credit utilisation compared to not utilising credit between rural and urban household is statistically significant. The implication of this results is that, despite the ease with which digital credit can be accessed in the rural areas, rural households still prefer conventional credit to digital credit, notwithstanding the significant cost of accessing financial services in rural areas. A large household size, on the one hand, is more likely to use conventional credit when faced with financial constraints. On the other hand, digital credit is less likely to be utilized by a larger household. In addition, large households prefer not to borrow at all rather than use digital credit. Gender of the household head influences the utilisation of conventional and digital credit. Whereas a male household head is less likely to utilize conventional credit, the male head is more likely to utilize digital credit compared to not using credit. The propensity to use digital credit relative to not using credit is statistically significant. This can be attributed to male households' heads being the main income earner as well as economic decision makers. Hence, male household heads make borrowing decisions to ameliorate financial constraints. Married household heads are more likely to use credit services compared to not using credit. This can be explained by the fact that households encounter emergencies or liquidity problems in the intervening periods before earning, which may be proportional to the household size. As result, married household heads borrow to meet their contingencies.

Table 2: Digital credit uptake

	Credit uptake decision+		Digital credit vs conventional	Digital credit
	Conventional credit	Digital credit		
	1		2	3
Rural	-0.128**	0.374***	-0.493***	0.341***
	(0.058)	(0.102)	(0.108)	(0.083)
house hold size	-0.003	-0.055***	0.049**	-0.072***
	(0.011)	(0.021)	(0.023)	(0.018)
Gender of house hold head	0.106*	0.440***	-0.410***	-0.162**
	(0.058)	(0.097)	(0.106)	(0.081)
Marital status	0.239***	0.423***	-0.233**	0.100
	(0.058)	(0.101)	(0.109)	(0.084)
Education	0.018	0.064*	-0.052	0.047
	(0.029)	(0.038)	(0.039)	(0.032)
Amenities	-0.038*	-0.131**	0.115**	-0.069
	(0.024)	(0.053)	(0.056)	(0.044)
Age	0.006***	-0.013***	0.022***	-0.023***
	(0.002)	(0.004)	(0.004)	(0.003)
Remittances	-0.278**	-0.577***	0.333*	-0.325**
	(0.129)	(0.178)	(0.180)	(0.158)

	Credit uptake decision+		Digital credit vs conventional	Digital credit
	Conventional credit	Digital credit		
	1		2	3
Income	0.472**	0.323***	0.158***	0.268**
	(0.028)	(0.048)	(0.050)	(0.040)
literacy_1	-0.473***	-1.602***	1.122***	-1.032***
	(0.059)	(0.157)	(0.164)	(0.113)
Employed	0.459***	0.572***	-0.243*	0.365***
	(0.094)	(0.154)	(0.157)	(0.127)
Own Business	0.018	0.366***	-0.438***	0.519***
	(0.076)	(0.132)	(0.140)	(0.109)
Dependent	-0.244***	-0.687***	0.324*	-0.321**
	(0.081)	(0.179)	(0.187)	(0.152)
Other	-0.554*	0.135	-0.641	0.546
	(0.300)	(0.495)	(0.558)	(0.497)
Casual	-0.153*	-0.017	-0.228	0.139
	(0.079)	(0.148)	(0.156)	(0.119)
Constant	-4.611**	-4.501***	-0.185	-2.962***
	(0.406)	(0.655)	(0.690)	(1.106)
N	8,475		8,475	8,475

*** $p<0.01$; ** $p<0.05$; *$p<0.1$; + not using credit is the reference category; Std. errors in brackets

Household heads who have schooled beyond secondary school have higher odds of using conventional credit and digital credit relative household heads without education or have schooled up to primary. The differences in the odds of using conventional credit relative to not using credit among secondary school graduate and beyond compared to primary school and less are not statistically significant. However, the odds of using digital credit relative to not using credit are significant. This suggests that utilisation of conventional credit is not influenced by the level of education, utilising digital credit is influenced by education. The educated have a cognitive ability not only to use digital infrastructure but also to access digital credit (Gesthuizen 2011)

Access to social amenities reduces odds of utilising conventional and digital credit relative to not borrowing (Table 2). This implies that easier access to amenities reduces demand for credit. A possible explanation is that access to social economic amenities enables households to accumulate savings and undertake investment, which can be liquidated to alleviate liquidity stress instead of borrowing. Furthermore, easier access to amenities increases human and physical capital formation, which increases factor earnings. The earnings are saved or used to accumulate assets, which can be sold to ease financial constraints.

An increase in the age of the household head by one year increases the odds of using conventional credit, while odds of using digital credit reduces. The likelihood of using conventional and digital credit relative to not using credit are statistically significant. Older household heads have accumulated assets and social networks that can be pledged or act as credible guarantors for conventional credit, respectively. Hence, it is easier for them to acquire credit compared to younger household heads. However, older household heads, may not use digital credit due to lack of awareness or enthusiasm for loans. The older household heads also have a lower propensity to accumulate risky and expensive loans due to their lower earning potential. The results on digital credit are consistent with the life-cycle hypothesis whereby the young accumulate debt to hasten the rate of accumulation of asset. However, as they age, they pay off their debt (Ando and Modigliani, 1963).

Households receiving remittances are less likely to use credit. This is because, remittances fill the financial shortfall, which would otherwise be bridged by credit (Jack and Suri, 2014). An increase in monthly income by Ksh 1, increases the odds of using conventional and digital credit relative to not using credit by 0.472 and 0.323 respectively. The increase in the likelihood of using credit as a result of an increase in monthly income is statistically significant. This suggests that access credit is utilised to ease liquidity strain in the intervening earning period. More importantly, an increase in income increase demand for credit as well as access to a wider range of financial services (Russell et. al., 2013).

Financial literacy is measured by the respondent's understanding of interest rate and collateral. Interest rate and collateral are basic financial concepts, which inform credit seeking decision and the amount of credit granted in a credit market riddled with information asymmetry, respectively. The results in table 2 show that the financially literate are less likely to use credit. Suffice to note that the financially literate, are less likely to use digital credit compared to conventional credit. The digital loans are of short maturity and bear high-interest rate and exorbitant fees, which are easily discerned by the financially literate. As a result, digital credit is less likely to be consumed by the financially literate.

The occupation of the household head not only affects the level of earnings but also fluctuation of income, which influences financial constraints a household faces and hence demand credit. In **table 2**, the odds of an employed household head using credit are higher than not using credit compared to a household head who derives a large proportion of income from agricultural activities[5]. Even though the employed are more likely to use digital credit relative to household heads engaged in agricultural activities, the higher odds are insignificant. This implies that the formally employed and farmers are equally likely to use digital credit rather than not use credit when faced with liquidity problems. Household heads who own business are likely to use credit relative to farmers, while dependants are less likely to use credit. Whereas casual workers and farmers are equally likely to use conventional credit, casual workers are less likely to use digital credit. The odds of not using digital credit relative to not using credit all are statistically significant. This implies that casual workers have lower credit utilisation compared to farmers, yet their incomes are unpredictable, and hence, access to credit would enable them to invest and stabilize their incomes.

To analyse drivers of choice between conventional and digital credit, logistic regression is estimated, whereby, the dependent variable is binary assuming 1 for household heads using conventional credit and zero for using digital credit. The regression results from the logistic model are presented in column 2. The results indicate that households in urban areas prefer digital credit to convention credit compared to rural households, but male household heads are 0.24 times more likely to use digital credit relative to female household heads. Male utilise digital credit because of their higher risk tolerance compared to female (Patel et. al, 2012). An increase in age and income by 1 year and KSh 1 increases the odds of using conventional credit by 0.022 and 0.158, respectively. This implies that older and richer household heads prefer conventional credit to digital credit. This can either be attributed to the high-interest rate on digital credit or lower risk tolerance.

The business owners and financially literate have a higher probability of using digital credit compared to conventional credit. This suggests that household heads deriving income from their businesses rely on digital credit to finance short term capital requirement for their businesses. This may be due to the convenience of obtaining digital credit. The financially literate, utilize their financial knowledge to evaluate loan characteristics with respect to the suitability and convenience of the type of credit against their financial circumstances to make credit utilisation decisions. The stringent terms and conditions on digital credit relative to conventional credit are more easily deciphered by the financially literate than the educated. Hence, the lower the probability of the financially literate using digital credit, while the educated have a higher probability of using digital credit.

5 Agricultural is the reference occupation category relative to which propensity to use credit or not to use credit is compared.

Column three presents parameter estimates for digital credit seeking decision relative to not using credit. The results show that urban households, the educated, the financially literate, the employed, business owners and households with higher income have a higher probability of using digital credit relative. However, older household heads, recipients of remittances, dependants and proximity to social economic amenities reduces the probability of using digital credit. Hence the results are consistent with choices between digital credit, conventional credit and not using credit in column one and the choice of digital credit and conventional credit in column two.

Therefore, digital credit uptake is influenced by the geographical location of the households. This is because the location of household influences access to social economic infrastructure and hence ease of access to financial services. The location also influences household head occupation and wealth. As a result, financial constraint experienced by households is occupation and location specific and the type of credit sought to ameliorate the constraints is influenced by the knowledge and cognition of credit cost and age of the household head as well as the convenience of accessing the credit services.

5.2 Digital Credit and household Indebtedness

Access to credit enables households to undertake investment beyond their current income, savings and bequest. However, household debt is sustainable if the income generated from investment financed by debt is just sufficient to repay debt. Hence, households experiencing difficulties in repaying their loans may sell their assets to repay loans. Therefore, to analyse the effect of digital credit utilisation on household indebtedness, we estimate the odds of a household selling assets to repay a loan. In table 3 columns 1 and 2, the likelihood of a household head selling the household asset to repay a loan is estimated. We control for household and occupation characteristics which may influence the likelihood of selling an asset to repay a loan. In column 1 households using digital credit are 1. 372 times more likely to sell their assets to pay the loans compared to households that do not use digital credit. This is equivalent to a higher probability of 0.219 relative to household heads that do not use digital credit. Financial literacy reduces the probability of selling the asset to repay loans. This could be due to household heads making financially aptitude decisions, which avert debt distress (Poddar, et. al., 2015, Oksanen, et. al., 2015). An increase in the age of a household head reduces the odds of selling the asset to repay the loan. The odds are not statistically significant. This implies that debt distress does not vary with age, hence there are no significant differences in debt accumulation over the life span of the household head. With respect to occupation, the employed and business owners have a lower probability of selling their asset to repay their loan compared to farmers.

The results in column 2 in which the conventional credit takes a value of one and digital credit zero is included as an explanatory variable, corroborate with results in column 1. Conventional credit users are less likely to sell their assets to repay a loan compared to digital credit users. The financially literate household heads have a lower probability of selling their asset to repay their loan of about 0.214 compared to the financially illiterate. The employed have a higher probability of experiencing debt distress. Dependants are less likely to utilise credit and hence, have a lower probability of debt distress (See section 5.1). The employed household heads take on excessive debt, oblivious of the economic shocks which reduce their ability to repay the loans (Montgomerie 2013).

Table 3: Digital Credit Utilisation and Household Indebtedness

	Sold asset	Sold asset	No. of loans	No. of loans	No. of loans
	1	2	3	4	5
Digital credit	1.372**			0.374*	0.316*
	(0.105)			(0.021)	(0.022)
Convention_digital credit		-1.482**	-0.178*		ref
		(0.121)	(0.023)		
Without credit					-0.266**
					(0.011)
Rural _urban	0.107	-0.066	-0.009	-0.009	-0.014
	(0.087)	(0.097)	(0.017)	(0.011)	(0.011)
Household size	0.015	0.017	0.002	0.002	0.000
	(0.017)	(0.019)	(0.003)	(0.002)	(0.002)
Gender of household head	1.280**	1.349**	-0.012	0.007	-0.006
	(0.086)	(0.100)	(0.02)	(0.013)	(0.013)
Marital status	0.434**	0.664**	0.002	0.022	-0.01
	(0.089)	(0.111)	(0.019)	(0.012)	(0.012)
Education	0.056	0.020	-0.003	0	-0.002
	(0.037)	(0.045)	(0.004)	(0.003)	(0.003)

	Sold asset	Sold asset	No. of loans	No. of loans	No. of loans
	1	2	3	4	5
amenities	-0.073	-0.036	-0.003	-0.002	0.001
	(0.040)	(0.050)	(0.008)	(0.004)	(0.004)
age	0.000	0.000	0	0	0
	(0.003)	(0.003)	(0.001)	(0.000)	(0.000)
Remittances	-0.425*	-0.498*	0.005	-0.004	0.023
	(0.179)	(0.211)	(0.032)	(0.027)	(0.027)
literacy_1	-0.223*	-0.292*	0.02	0.025	0.004
	(0.095)	(0.117)	(0.019)	(0.014)	(0.014)
Income	-1.051**	-0.859**			
	(0.048)	(0.056)			
Employed	0.294*	0.258*	0.051	0.071	0.033***
	(0.131)	(0.156)	(0.026)*	(0.020)**	(0.020)
Own Business	0.145	-0.055	0.001	0.011	-0.006
	(0.113)	(0.135)	(0.023)	(0.016)	(0.016)
Dependent	-1.011**	-1.088**	-0.011	-0.018	0.006
	(0.133)	(0.1649)	(0.025)	(0.015)	(0.015)
Other	-0.654	-0.297	-0.007	-0.009	0.023
	(0.614)	(0.652)	(0.093)	(0.046)	(0.046)
Casual	-0.011	0.120	-0.002	-0.013	-0.001
	(0.121)	(0.143)	(0.025)	(0.016)	(0.016)
Constant	8.636	7.787***	1.643	1.192	1.431
	(0.391)	(0.765)	(0.475)**	(0.680)	(0.655)*
alpha	-	-	-0.834	-0.088	-0.163
			(0.937)	(0.887)	(0.893)
N	4401	2646	3,128	8,475	8,475

*** p<0.01; ** p<0.05; *p<0.1; ref- reference category; Std. errors in brackets

The number of outstanding loans is also an indicator of debt distress. Suffice to note that households may refinance existing loans, thereby having more than one loan, without compromising their ability to meet their loan obligation. Nevertheless, the number of outstanding loans indicate the level of indebtedness. Table 3 column 3 to 5 present endogenous Poisson regression estimate of the number of loans outstanding in a household. The number of loans outstanding depends on utilisation of credit, hence we instrument for credit utilisation with its predicted values. In column 3 table 3, using conventional credit reduces the number of loans by 0.178 relative to digital credit. However, using digital credit increases the difference in the expected count of loans by 0.374 compared to not using digital credit. Whereas using digital credit increases the difference in the expected count of loans by 0.316 compared to conventional loans, those without credit have lower expected count of loans by 0.266 columns 4 and 5, respectively. This result implies that households utilising digital credit have more loans compared to those using conventional credit. This is consistent with estimates form the random effects model in table 2.

Access to financial services like credit enables households to hasten the rate of capital accumulation as well as switch to occupation with higher earnings and hence, higher ability to service loans. Therefore, household earnings are a good indicator of the contribution of credit to not only household welfare but also the ability to repay loans. The utilisation of credit exacerbates household indebtedness if earnings generated from investment financed by credit are insufficient to meet loan repayments. To assess the marginal contribution of credit to household indebtedness, we regress self-reported household expenditure and income on credit utilisation and a set of control variables that potentially influence income outcomes. This is based on the fact that on the one hand, the level of household income is correlated with household spending. On the other hand, self-report household expenditure tends to be a more accurate estimate of household income, than self-reported income. Therefore, we present the results of two indicators of households' indebtedness in table 4 columns 1 and 2. The results show that households using digital credit spend about 18.18 percent less compared to those who do not use digital credit. In column 2, income is use instead of expenditure. The results indicate that the monthly income of digital credit users is about 23 percent less than non-users. Hence, using digital credit does not augment incomes and therefore it has a negative contribution to income, despite being preferred by households with higher income.

In column 3 of table 4, household expenditure is regressed on credit and proximate controls, to establish marginal contribution to the income of digital credit as compared to conventional credit. Credit is binary, whereby, conventional credit takes a value of 1 and digital credit 0. The coefficient on credit indicates that households using conventional credit spend 23 per cent than households that use digital credit. The difference in expenditure is statistically significant.

This implies that households utilising conventional credit to ease their financial constraints have a higher ability to repay their loans compared to those who use digital credit. Therefore, using digital credit is likely to predispose the household to debt distress compared to using digital credit. This could be due to the amounts and terms of digital credit that does not enable households to make an investment that changes earnings significantly. Indeed, the of digital loans granted range from KSh 100-3,000,000, at an average of 252.2 annual interest rate. The loans are also short time yet, an investment with high returns require large long-term loans, which can only be obtained as conventional credit.

Nevertheless, households are better-off with digital credit compared to not having credit at all. This is indicated in column 4, in which the household is examined by regressing expenditure on utilising conventional credit, digital credit and not utilising credit (Note that conventional credit is the reference category). The estimates show that households using digital credit spend about 0.155 times less than those with conventional credit, households without credit spend about 0.444 less than those with conventional credit. This implies that whereas using digital credit reduces the ability to repay household debt relative to using conventional credit.

Table 4: Digital Credit and income outcomes

	Expenditure	income	Expenditure	Expenditure
	1	2	3	4
Digital credit	-0.167*	-0.207**	ref	-0.155**
	(0.077)	(0.036)		(0.047)
Convention digital credit	-	-	0.206**	ref
			(0.045)	
Without credit				-0.444**
				(0.025)
Cluster type	0.181**	0.283**	0.290**	0.282**
	(0.056)	(0.026)	(0.038)	(0.025)
Household size	-0.022*	0.043**	0.048**	0.038**
	(0.011)	(0.005)	(0.008)	(0.005)

	Expenditure	income	Expenditure	Expenditure
	1	2	3	4
Gender of household head	-1.003**	-0.286**	-0.442**	-0.321**
	(0.055)	(0.025)	(0.038)	(0.025)
Marital status	0.10	0.265**	0.14**	0.200**
	(0.055)	(0.026)	(0.040)	(0.025)
Education	0.003	-0.002	0.011*	0.238**
	(0.014)	(0.006)	(0.01)	(0.032)
amenities	0.017	-0.025*	-0.033***	-0.029**
	(0.022)	(0.010)	(0.017)	(0.010)
age	-0.002	0.001	0.004**	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Remittances	-0.398**	-0.383**	-0.441**	-0.381**
	(0.128)	(0.059)	(0.073)	(0.057)
literacy_1	0.225**	0.183**	0.141**	0.192**
	(0.068)	(0.031)	(0.042)	(0.030)
Farming	ref	ref	ref	ref
Employed	0.840**	0.439**	0.458**	0.433**
	(0.096)	(0.044)	(0.057)	(0.042)
Own Business	0.681**	0.301**	0.387**	0.277**
	(0.075)	(0.034)	(0.049)	(0.034)
Dependent	-0.768**	-0.245**	-0.054	-0.210**
	(0.076)	(0.035)	(0.058)	(0.035)
Other	0.144	0.025	0.005	0.038
	(0.292)	(0.116)	(0.213)	-0.115
Casual	0.02	-0.126**	-0.161**	-0.108**
	(0.076)	(0.035)	(0.055)	(0.034)

	Expenditure	income	Expenditure	Expenditure
	1	2	3	4
Constant	9.692**	8.988**	9.193**	9.685**
	(0.318)	(0.146)	(0.202)	(0.137)
N	8,364	8,102	3,058	

*** p<0.01; ** p<0.05; *p<0.1; ref- reference category; Std. errors in brackets

The implication of this results is that utilisation of digital credit depends on age, education, occupation, the gender of household head, age, marital status and social economic amenities. Households facing financial constraints in rural areas are more likely to use conventional credit even if digital credit is available. However, household heads would use digital credit if they had options of not using credit or using conventional credit. This is attributable to the convenience of accessing digital credit. Despite the fact that digital credit is easily accessed and most preferred, there is evidence that using digital credit exacerbates household debt distress and reduces earnings. The financially literate have the capability to utilise affordable credit and make aptitude financial decisions, which reduces the probability of debt distress.

6.0 Conclusion

This paper analysed digital credit uptake and its impact on household indebtedness. The analysis established that income, occupation, education, social amenities and age of the household head influences the utilisation of digital credit.

In particular, the educated, are more likely to use digital credit while the financially literate are less likely to use digital credit. Hence, there is evidence that digital credit is utilised to ameliorate short term liquidity constraint because it is easily accessed, despite the high cost and short repayment period. However, the adverse terms and conditions of digital credit are more easily discerned by the financially literate than the educated. As a result, the financially literate utilise credit with favourable terms and conditions.

The results also show that using digital credit reduces income and increases the probability of selling household assets to repay a loan. Digital credit users are more likely to have more loans than conventional credit users. Therefore, using digital credit reduces household income as it does not bridge the financing gap to enable households to undertake investments that generate sufficient income to repay household debt. This exacerbates household indebtedness and reduces welfare as a result of selling household assets to repay the loan and a reduction in income. This implies that the loan amount, interest rate and maturity of the loans need to be revised to enable households and entrepreneurs to use digital credit for capital accumulation, which augments incomes and welfare.

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Table 5: Current Digital Credit provider, loan amount and cost in Kenya

	Provider	Loan range (KSh)	Fee or nominal interest rate	Repayment period (days unless specified)	Annual Percentage Rate (APR)
1.	Branch	250–50,000	1%-14% (as monthly rates)	14-365	12%–170%
2.	Equitel Eazzy Loan	50–200,000	14.5% annual rate + 1% of loan amount as appraisal fee	30	27%
3.	Equitel Eazzy Plus Loan	1,000–3,000,000	14.5% annual rate + 2%–3% of loan amount as appraisal fee	2–6 months	21%–27%
4.	Jumo/ Kopa Cash	500–13,000	0.5% daily	7–28	183%
5.	KCB-M-Pesa	50–1,000,000	14% annual rate + 2.5% of loan amount as negotiation fee	30 90 180	73% 61% 49%
6.	Kopa Chapaa	500–10,000	8.5%–17%	10	310%–621%
7.	Micromobile	Lesser of 50% of monthly salary or 100,000	Unspecified	30–60	
8.	Mjiajiri	Varies; increases as user recruits members	200 Ksh registration fee, earn commission to recruit new members	Varies	Similar to pyramid scheme
9.	M-pawa-Sacco	100–120,000	Set by SACCO; interest deducted from loan before disbursement	Set by SACCO	Varies, as set by SACCO
10.	M-Shwari	100–20,000	7.5%	30	91%
11.	Okoa Stima	100–1,000	10%	7	521%
12.	Pesa na Pesa	500–100,000	10%	7	521%
13.	Pesa Pata	2,000–20,000	30%	30	365%
14.	Pesa Zetu	Varies	6%–10%	28	85%–130%
15.	Saida	Up to 25,000	7.5% and up	30	91% and up

	Provider	Loan range (KSh)	Fee or nominal interest rate	Repayment period (days unless specified)	Annual Percentage Rate (APR)
16.	Tala	500–50,000	5%–20%	30	61%–243%
17.	Zindisha	100–1,000,000	Initial membership fee of 5% of loan request, then 5% per loan	Varies	Varies according to repayment period

Source: CGAP

Table 6: Probability of selling asset to repay a digital loan

Variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
Digital credit*	0.214	0.013	16.600	0.000	0.189	0.240	0.258
Cluster type	-0.005	0.016	-0.320	0.746	-0.036	0.025	1.471
Household size	-0.005	0.003	-1.600	0.110	-0.011	0.001	4.395
Gender of household head	0.258	0.015	16.820	0.000	0.228	0.288	1.460
Marital status	0.038	0.016	2.340	0.019	0.006	0.070	0.650
education	0.001	0.007	0.130	0.897	-0.012	0.014	0.201
amenities	-0.011	0.007	-1.580	0.114	-0.025	0.003	-0.135
age	0.000	0.001	-0.770	0.439	-0.001	0.001	37.002
remittances	-0.013	0.032	-0.410	0.680	-0.076	0.049	1.947
income	-0.061	0.004	-15.880	0.000	-0.068	-0.053	7.865
Financial literacy*	-0.042	0.018	-2.340	0.019	-0.078	-0.007	0.240
Employed*	-0.020	0.024	-0.820	0.411	-0.067	0.027	0.142
Own Business*	-0.008	0.020	-0.400	0.693	-0.048	0.032	0.230
Dependent*	-0.234	0.030	-7.790	0.000	-0.292	-0.175	0.131
Other*	-0.177	0.140	-1.260	0.208	-0.452	0.098	0.004
Casual*	0.024	0.021	1.160	0.247	-0.017	0.065	0.171

Table 5: Mfx Probability of selling assets to pay a loan- conventional and digital credit

variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
credit*	-0.353	0.026	-13.83	0.000	-0.403	-0.303	0.771
Cluster type	-0.016	0.026	-0.63	0.529	-0.067	0.035	1.457
Household size	0.004	0.005	0.84	0.402	-0.006	0.014	4.448
Gender of household head	0.332	0.026	12.61	0.000	0.281	0.384	1.371
Marital status	0.159	0.026	6.17	0.000	0.109	0.210	0.676
education	0.005	0.011	0.43	0.664	-0.017	0.027	0.207
amenities	-0.013	0.012	-1.07	0.284	-0.037	0.011	-0.119
age	0.000	0.001	0.07	0.946	-0.002	0.002	37.151
remittances	-0.123	0.052	-2.36	0.018	-0.225	-0.021	1.944
income	-0.212	0.014	-15.27	0.000	-0.239	-0.184	9.329
Financial literacy*	-0.071	0.028	-2.55	0.011	-0.126	-0.016	0.234
Employed*	0.064	0.039	1.65	0.099	-0.012	0.140	0.158
Own Business*	-0.013	0.033	-0.41	0.684	-0.078	0.051	0.222
Dependent*	-0.241	0.031	-7.81	0.000	-0.302	-0.181	0.131
Other*	-0.071	0.152	-0.47	0.638	-0.369	0.226	0.006
Casual*	-0.029	0.035	-0.84	0.400	-0.098	0.039	0.159

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