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Can FinTech shape the dynamics of consumer credit usage among the un(der)banked?

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Davis Bundi Ntwiga

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Working Paper Series

34



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Can FinTech Shape the Dynamics of Consumer Credit Usage Among the Un(der)banked?

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Abstract

We use the 2016 FinAccess Household survey data of 2015 from 8665 households and desktop reviews to examine how perceptions, behaviour, financial literacy and socio-economic characteristics of un(der) banked consumers can shape their dynamics towards credit usage. The challenges and opportunities for the market players are examined using desktop reviews and their role towards an increase in financial inclusion and credit usage through FinTech. The disruptive innovations have provided new possibilities, challenges and opportunities to boost financial and credit usage in the market. Consumer perceptions on cost, trust, source of financial advice, financial literacy and socio-economic characteristics influences credit usage. The business models being developed by the FinTech providers are taunted to change the landscape of lending to the un(der) banked.

Keywords: *FinTech, un(der)banked, credit usage, perceptions and behaviour, challenges, opportunities, socio-economic characteristics*

JEL Classification: *G00, G41, G23*

1.0 Introduction

Financial inclusion is defined as the use of formal accounts and is critical in reducing poverty and increasing inclusive economic growth [Allen et al (2016)]. The topic has gained momentum as a global agenda with central banks in emerging and developed countries putting in place policy frameworks to promote financial inclusion in their respective countries [Amidzic et al (2014)].

When individuals participate in the financial system, they can invest in education, manage risk, start and expand businesses, absorb financial shocks, increase savings and boost productive investments [Demirguc-Kunt et al. (2015)]. Financial inclusion increases with lower account costs, stronger legal rights, more politically stable environments and the proximity to financial service providers [Allen et al (2016)].

The number of adults globally who have opened an account at a financial institution or through a mobile money provider between 2014 and 2017 was 515 million. An increase in adults with accounts has been noted with 51 percent having an account in 2011, 62 percent in 2014, and 69 percent in 2017. The developing economies contributed a big margin in these reductions by use of mobile innovations, where 63 percent of adults against the high economies 94 percent have an account [Demirguc-Kunt et al.(2017)].

Globally, around 1.7 billion are unbanked, 56 percent of the unbanked are women and 50 percent of the unbanked comes from 40 percent of the poorest households [Demirguc-Kunt et al.(2017)], while 73 percent of the 1.7 billion reside in 25 countries, mostly in Asia and Africa [IFC (2017)]. A comparison of the gender shows that 72 percent of the men have an account compared with 65 percent of the women, which has remained unchanged since 2011 [Demirguc-Kunt et al.(2017)]. The two major forms of financial exclusion are voluntary and involuntary exclusion. For voluntary exclusion, the consumer may not be in need of

the services or restrictions due to culture or religion. For the involuntary exclusion, the reasons could be due to insufficient income, high risk, discrimination, weak contract enforcement, lack of information, product features or price barriers [Amidzic et al (2014)].

Financial institutions are traditionally been in the forefront to foster financial inclusion. The efficiency of banking institutions fosters economic development, facilitate financial intermediation and contribute to optimal allocation of financial resources [Borovicka (2007)]. The Sub-Saharan Africa (SSA) has been among the fastest growing regions in the world since the 1990s with an accelerated growth, reduction in inflation to a single-digit and macroeconomic stability. The growth has led to expansion of access to financial services, upgrade in institutional and regulatory capacity and expansion of cross-border banking activities. These developments are not significant enough to sustain current and future credit needs, coupled with high cost of borrowing, limited competition, formation of bank cartels and short lending maturities hinder the competitiveness and diversification of the economic structure [Mecagni et. al (2015)]. In Kenya, the private sector credit to gross domestic production was 35 percent in 2015 compared to SSA average of 46 percent and the global average of 129 percent [Ruriga and Hussein (2017), Sengupta (2012)]. Gross loans increased from Ksh. 2.17 trillion in 2015 to Ksh. 2.29 trillion in 2016, and the non-performing loans to gross loans increased from 6.8 percent in 2015 to 9.2 percent in 2016 [CBK (2016)].

On the background of these challenges, there has been an impressive growth in financial inclusion in SSA in the recent years driven by growth in agent banking and mobile money where 43 percent of adults are financially included. The future of the financial sector in Africa is digital with the market asking for more sophisticated and relevant products on savings, digital banking and credit access [IFC (2018)]. Financial technology (FinTech) innovations and technologies like block-chain are taunted to increase credit access to the un(der)banked [PWC (2016), Demirguc-Kunt et al.(2017)]. The estimated global financial opportunity from the un(der) banked customers is USD 380 billion in annual revenues [IFC (2018)]. These are the opportunities for the financial service providers. Innovations in credit market are deliberate to employ business models that are mobile platform based, data intensive and capital light [Demirguc-Kunt et al.(2017)]. The disruptive technologies will be a continuous event to innovate and shape customer behaviour [McWaters (2015)].

In the year 2012, Safaricom Kenya (a mobile network operator (MNO)) and the Commercial Bank of Africa (CBA), started a mobile based savings account and micro-credit facility dubbed M-shwari ("Shwari" means calm in Swahili) based on the M-Pesa platform [Ntwiga (2017), Hwang and Tellez (2016), IFC (2017)]. The digital credit market has continued to expand rapidly with four regulated banks (CBA, Equity, Cooperative bank and Kenya Commercial Bank (KCB)) being among the players; and a growing number of FinTechs and non-bank institutions. The market share



of digital credit in Kenya is distributed as; Mshwari 14 percent, KCB Mpesa 5.7 percent, Equity Eazzy 1.2 percent, Tala 0.9 percent, Mcoop cash 0.4 percent and Branch 0.2 percent [Totolo (2018)]. The mobile money is growing in Kenya and in 2017, there were 37 million registered mobile accounts and US\$ 36 billion (KES 3.6 trillion) in transactions [IFC (2018)].

Credit scoring has always been a challenge among the un(der) banked due to lack of financial histories data [Ntwiga (2016)]. Digital credit providers are using different avenues of data to solve this problem. KCB Mpesa and MShwari partnership with Safaricom Kenya use telecommunication variables to score, manage and disburse loans. Equity bank utilizes the bank account data and credit reference bureau data to score and allocate credit. Tala and Branch FinTechs have smart phone based applications to collect phone usage information and Facebook data for the latter to score customers [Totolo (2018), Hwang and Tellez (2016)]. New players are coming to the market every year as their services and products continue to be popular even among the un(der) banked. The deployments are trying new features for credit scoring, use and drive uptake which is currently at around 6 million users [Hwang and Tellez (2016), Totolo (2018)]. FinTech advances has provided new possibilities, challenges and opportunities to boost financial, credit access and promote financial depth [Mecagni et. al (2015), Jagtiani and Lemieux (2017)].

1.1 Scope of Study

FinTech is a very broad subject that touches on

many and different aspects of financial technology [Jagtiani and Lemieux (2017)]. This study is limited to consumers access to mobile wallets geared towards the retail market lending among the un(der) banked. The under-banked are consumers who have a formal bank account but have poor credit history and lack funds to build it; while the unbanked consumers do not have a formal bank account [PWC (2016)]. FinTech is a combination of innovative business model and technology to change, disrupt and enhance provision of financial services or products. The terms, digital lenders and FinTech are used to refer to the same services while, consumer, customers and borrowers are used interchangeably in the study.

1.2 Problem Statement

There is growing consumer demand for digital financial services as innovations in the financial sector continue to advance. Between 2014 and 2017, adults in developing economies using digital payments increased by 12 percent to 44 percent [Demirguc-Kunt et al.(2017)]. Usage and access of financial services are influenced by the socio-economic characteristics of the customers [Allen et al (2016)]. Benefits of FinTech abounds though some are skeptical due to perceived risks, technological failure and lack of consumer protection. Financial service providers are also skeptical but need to understand that FinTech can cater for mass-market. The financial opportunity around the globe among the un(der) banked is approximately USD 380 billion in annual revenues. In SSA, 95 million adults who are un(der) banked receive cash payment and 65 million use semi formal savings [IFC (2018)] with 57 percent financially

excluded [IFC (2018)] and banks penetration being below 35 percent [IFC (2017)]. Digitization of retail payments involves challenges that must be an attractive option for the customers and the service providers. There is a huge demand for unsecured and short-term credit at the consumer level and small businesses globally [PWC (2016)] and regulators need to take up the challenge of taking disruptive innovations to the next level [IFC (2018)]. Therefore, this study delves on the perceptions and behaviour of the consumers, their socio-economic characteristics, and how they affect credit usage from the FinTech and other financial service providers to enhance credit usage. Market players too face challenges and opportunities that enhance or curtail the growth of the disruptive innovations in Kenya.

1.3 Research Objectives

The overall objective of the study is to understand the effect of perceptions, behaviour and socio-economic characteristics of the consumers, and challenges and opportunities faced by the market players in adoption of the disruptive innovations to cater for the un(der)banked.

- To identify the challenges and opportunities faced by the market players due to emergence of the disruptive innovations.
- To analyze how credit usage is shaped by the perceptions and behaviour of the consumers.
- To analyze the socio-economic characteristics and financial literacy of the consumers and how they shape the credit usage among the financial service providers.

1.4 Hypotheses

Objectives (b) and (c) forms the two hypotheses of the study.

H_{1a} : Perceptions and behaviour of the consumers affects their credit usage from the financial service providers.

H_{1b} : Socio-economic characteristics of the consumers shape credit usage from the financial service providers.

The rest of the paper is organized as follows. Section 2 presents the literature review. Section 3 has the methodology, with section 3.1 the data analysis methods for each objective and section 3.2 presents the multinomial logistic regression model. In section 4, we have the analysis, discussions and findings where section 4.1 summarizes the first objective, on challenges and opportunities faced by the market players with four subsections; consumer, FinTech providers, financial providers and financial regulators. Section 4.2 highlights the findings for the second study objective and first hypothesis, perceptions and behaviour of consumers towards credit access and has three subsections. Section 4.3 has the third objective and second hypothesis on socio-economic characteristics and how they shape credit access; and this section has three subsections. Section 5 is the conclusion and section 6 the policy recommendations.

2.0 Review

FinTech is the future of Africa's credit access as what now matters to the consumers is the ability to access the services they desire irrespective of the kind of the provider. The penetration of smartphones in Africa is growing, expected to be 720 million by 2020 from 226 million in 2015 [IFC (2018)].

The growth of social media networks and availability of big data continue to permeate our lives. Social interactions generates a trail of data, social media data (SMD) that contains our abilities and dispositions. [Ntwiga (2016)] noted that the availability of powerful data science tools for mining SMD offers a rich set of data for consumer credit scoring. This reduces information asymmetry among the un(der) banked [Jagtiani and Lemieux (2018)].

Big data can loop in consumers with no financial history and un(der) banked to gain better insights and reduce information asymmetry [Daniel and Grissen (2015)] and [Jagtiani and Lemieux (2018)] noted that soft information improves the credit scoring process for the FinTech to supplement the availability of unsecured consumer credit. [Daniel and Grissen (2015)] used mobile phone behavioral signatures data to predict loan repayment in a developing country and found that the bank can reduce defaults by 41 percent while still accepting 75 percent of the borrowers. [Masyutin (2015)] applied the SMD which showed a better prediction of fraudulent cases and [Ntwiga (2016)] noted that SMD can estimate consumer credit risk as the data is time dependent unlike the hard information used by banks for credit scoring process. The M-Shwari and KCB-M-pesa credit scoring algorithm uses a set of MNO variables from Safaricom Kenya [Ntwiga (2017), Ntwiga et. al (2018)].

The best indicators of financial access are the number of people, firms and households receiving credit and using other financial products from the

financial service providers. Credit demand is difficult to size but there is huge demand for unsecured and short-term credit at the consumer level and small business globally [PWC (2016)]. The ability to access micro credit loan promotes individual outcomes [FSD (2010)] while the perceptions about mobile banking and technology determine the rate of adoption as income alone is not a sufficient indicator [Ivatury and Pickens (2006)]. A positive change in income is observable when the poor use the digital credit facilities [Ahlin and Jiang (2008), Chavan and Ramakumar (2002)] but financial inclusion is a means to the end [IFC (2018)].

The FinAccess Household Survey of 2016 noted that the main reasons people join a group are: access to a lump sum for emergencies, daily needs, social reasons, keep money safe, acquire a lump sum for investment and commitment to save [FSD (2016)]. This compares well to the financial diaries study in which it indicates the implications of the findings to the financial services providers as: they should provide products that cater to small and inconsistent incomes; offer better tools for managing day to day transactions and risks; assist women better leverage their social networks; accessibility; and services that endure and support women to face major life transitions [FSD (2014)].

People may have access to financial services but do not use them. The relationship between access and usage is complex and there are a number of contributing factors. Such services may be un-affordable, fear of

rejection of the users by service providers, unsuitable to their needs and the likelihood of the service providers unwilling to service that market segment due to the poor credit risk profiles [Kranz (2005)]. A study by [Demirguc-Kunt et al.(2017)] noted the reasons why adults remain un(der)banked, where 20 percent cited lack of documentation and distrust of the financial service providers with 66 percent saying they have too little money to use an account. [Djankov et al (2008)] findings in Mexico indicates an overwhelming majority being unbanked at 89 percent due to lack of enough money, 25 percent cited cost and distance and another 25 percent do not have an account as a family member already has one, only 6 percent cited religious reasons. Lower barriers are reported in countries with lower account costs and greater penetration of financial service providers [Allen et al (2016)].

Financial inclusion and individual characteristics like gender, income, age, education, marital status and household size are analyzed by [Allen et al (2016)]. Household attributes like wealth and education are strongly correlated with usage of formal financial sector with less educated not saving or borrowing [Djankov et al (2008)]. Financial literacy and education levels influence awareness, access and usage of credit services. Employment (wealth or income) is also among the important indicators of credit usage and access as well as geographic region, urban versus rural areas [Kranz (2005)]. The characteristics of the borrowers differs by age, purpose of the loans, gender and trust they have toward FinTechs [Totolo (2018)]. The social characteristics of access and usage are age,



education, employment and gender of the consumer. The male and female profiles of access and usage differs with young people likely to demand less of credit, and this indicates differences based on age. Women have a higher rate of using informal financial services at 51.4 percent compared to men at 30.9 percent. In the use of mobile financial services, the difference between men (75.5 percent) and women (67.5 percent) is 8 percent [FSD (2016), FSD (2014)].

There are challenges and opportunities in operating digital financial services because it is neither easy or cheap. This means the services must be an attractive option to the customers and the providers [Demirguc-Kunt et al.(2017)]. Opportunities abound to better understand the market as only 5 percent of digital financial services are likely to succeed within the first five years of launch [IFC (2018)]. The successes, challenges and opportunities are sometimes country specific [Demirguc-Kunt et al.(2017)]. An analysis of the financial inclusion and country characteristics by [Allen et al (2016)] noted that these characteristics are unique to the economy. [IFC (2017)] observes that M-Pesa operations in Kenya took off but failed to launch in South Africa, underscoring that FinTech solution may work in one country and fail in another.

Influences of risk perceptions are unpredictable outcomes, emotional reactions, uncertainty due to lack of knowledge and seriousness of the consequences. [Agaliotis and Hadzic (2015)] noted that consumer behaviour observed over different products offers differing price sensitivity reactions

and [Beckett et.al (2000)] noted that the influence is based on the type of financial product. The subjectivity of how risk is perceived creates uncertainties due to lack of knowledge and consequences there in [Diacon and Ennew (2001)]. A robust relationship between financial behaviour and perceptions on credit access exists [Annim et al. (2012)] as trust forms the link in the relationship [Beckett et.al (2000)]. Consumers are only rational to a certain extent, as perceptions and behaviour are shaped by the environment, how it is conceptualized since no universally agreed measurement exists [Diacon and Ennew (2001)]. A borrower's experiences, costs and benefits are important to change financial behaviour and engender financial inclusion [Annim et al. (2012)].

The Technology Acceptance Model (TAM) developed by Davis (1989) has two constructs. Perceived ease of use and perceived usefulness of information technology. Perceived usefulness highlights the degree to which an individual believes that using a particular technology would enhance their life performance. Perceived ease of use indicates the degree to which a person believes that using technology would be free of effort [Chen, Li and Li (2011)]. The TAM is the most appropriate as compared to Theory of Planned Behaviour and Theory of Reasoned Action when applied in online contexts. TAM is ideal for information system usage based on concepts of ease of use and is more robust to cater for usage dynamics [Chen, Li and Li (2011)]. TAM focuses on perceptions, behaviour, convenience and usefulness of information technology to increase its adoption. The constant

changes in technology creates threats to existing and new business models [Lai (2017)]. This theory captures the study objectives through challenges and opportunities posed by technology, perceptions and behaviour of the consumers and their key socio-economic characteristics that shape credit usage.

Therefore, tapping into evolving consumer behaviour, perceptions, access and trust will drive sustainable

FinTech usage where 57 percent of adults in SSA are financially excluded [IFC (2018)] with banks penetration in SSA being below 35 percent and approximately 80 percent of Africa's one billion population lacking access to formal bank services [IFC (2017)]. Trust is crucial for the industry growth as the public has an adverse view of the financial systems.

3.0 Methodology

The study employed mixed methods to analyze the the data. The desktop reviews and the mixture of qualitative and quantitative secondary data from the 2016 FinAccess Household Survey. The two sources of data were; the desktop reviews to expound on the first objective of the study. This is through qualitative and quantitative analysis from existing literature to capture the market sentiments based on challenges and opportunities of the market players in Kenya.

The main market players are the consumers, FinTech providers, financial service providers and the regulators or government bodies mandated to oversee and regulate the market. The FinTech and financial service providers were separated into two categories since the majority of the traditional financial service providers do not use FinTech to offer credit facilities to its clients.

The other source of data is the 2016 FinAccess Household Survey data which is both qualitative and quantitative collected collaboratively by Central Bank of Kenya, Kenya National Bureau of Statistics and Financial Sector Deepening in 2015. A total of 8665 households were interviewed on access and usage of financial services in Kenya during the period of the study. The data is rich and deep on financial usage and access, covering knowledge and understanding of our financial products and services [FSD (2016)]. The analysis on this data is to understand the perceptions and behaviour, and the socio-economic characteristics and financial literacy of the consumers in credit usage among the financial service providers. In the perceptions and behaviour, the variables of study are cost of loans (interest rate), source of advice, trust of the financial provider and the main characteristics of a good financial instrument (see **table 3**). The socio-economic characteristics are, age, gender, marital status, income, education level and geographical cluster, and financial literacy (see **table 5**).

3.1 Data Analysis

The desktop reviews were done to identify and summarize the opportunities and challenges facing the market players. Market sentiments and the different benefits untapped are summarized to enlighten on FinTech dynamics in Kenya. The analysis of the 2016 FinAccess Household Survey data employed descriptive statistics to summarize the study variables using SPSS version 20 for second and third objectives of the study. For objective two, Multinomial logistic regression predicted the odds of credit usage based on the perceptions and behaviour of consumers; trust of the financial institution, source of financial advice, cost of loan in terms of interest rate and the characteristic of financial instruments. In objective three, the multinomial logistic regression predicted how credit usage is shaped by the socio-economic characteristics and financial literacy of the consumers.

3.2 Multinomial Logistic Regression Model

In each of the two objectives that utilize multinomial regression, $C = 3$ is the number of categories of the response variable (credit usage), K is the number of categories in each explanatory variable and N is the set of observations. For example, in objective two, $N = 4$, $K = 8$ and $C = 3$. The Multinomial logistic regression model for the second and third objectives can be generalized as:

$$\text{Log} \left(\frac{\pi_{i0}^j}{\pi_{i0}^0} \right) = \alpha^{(j)} + \beta_i^{(j)} X_{ii} + \dots \beta_k^{(j)} X_{ki}$$

Where $i = 1, 2, 3, \dots, C-1$ with C being the number of categories in the response variable; $k = 1, 2, 3, \dots, K-1$, with K being the number of categories in each explanatory variable. The $C-1$ and $K-1$ means that one of the categories is the reference category in the logit regression; $j = 1, 2, \dots, N$, being the number of explanatory variables in the model; and $\alpha^j + \beta_i^j, \dots, \beta_k^j$ are unknown population parameters to be estimated in the logit regression model. The observations Y_i have a multinomial distribution with probability parameters: $\pi_i^0, \pi_i^1, \pi_i^{C-1}$ where $i = 1, 2, \dots, N$ and $C = 3$. There are X_1, X_2, \dots, X_{K-1} explanatory variables for each of the N set of observations.

3.2.1 Multicollinearity test

The variables in objective two and three were tested for multicollinearity. **Table 2** shows that the four variables: source of financial advice, characteristics of financial instrument, trust and cost of credit had $1 < VIF < 1.1$, thus no multicollinearity among the four variables. **Table 4** shows that the eight variables: household head, financial literacy, geographic cluster, education level, marital status, age groups and income groups, had $1 < VIF < 2$, thus no multicollinearity is evident among the variables. Thus, the Multinomial logistic regression model can be used to analyze objective two and three of the study.



3.2.2 Classification of response categories

The correct classification of the three categories in the response variable are tabulated in **table 1** based on the FinAccess Household Survey. **Table 1** shows the predicted classification on the three categories of credit usage. The categories, $C = 3$ are: currently have credit, used to have credit and never had credit, with the later as the reference category. The model correctly classify of the subjects in currently have credit with of used to have credit and of the never had credit being correctly classified. Overall, the success rate is for the model to correctly classify the three categorical variables.

Table 1: Classification of the response variable categories

Observed	Predicted			Percent Correct (%)
	Currently have	Used to have	Never had	
Currently have	4693516	440455	2215715	63.9
Used to have	2881364	435624	2291733	7.8
Never had	2464030	354886	3771507	57.2
Overall percentage (%)	51.4	6.3	42.4	45.5

4.0 Analysis, Discussions and Findings

We present the qualitative analysis and quantitative data analysis, discussions and findings that capture the three objectives of the study.

4.1 Challenges and Opportunities Faced by Market Players from Disruptive Innovations

The four main market players are the consumers, FinTech lenders, financial providers and financial regulators or government policies geared toward increasing credit access among the un(der) banked [IFC (2018), Hwang and Tellez (2016), Demirguc-Kunt et al.(2017), Mazer and Mckee (2017), Jagtiani and Lemieux (2018), Hwang and Tellez (2016), Ivatury and Pickens (2006), Jagtiani and Lemieux (2017)].

4.1.1 Challenges and opportunities faced by the consumers

4.1.1.1 Opportunities

- Ability to access instant loans as technology is used to register, score, allocate and disburse funds to the customer. This makes it attractive due to availability in short notices/emergencies.
- Continuous disruptions and innovations means an increased customer experience through services and products.
- Products and services can be tailored to meet the consumer perceptions and behaviour as innovations can capture the changing trends and shifting demographics using big data.
- Loan eligibility is assessed from the existing digital access of the consumer, thus not discriminated due to lack of financial histories.
- As competition and innovations shift, consumers can be offered debt restructuring through an automated flexible payment mode.



- Customers can make choices of alternative financial services online by comparison and this increases the expectations as shaped by experiences outside of the banking hall.
- Customers can source for financial advice from independent influences, peer conversations and “word of mouth” through use of technology.
- A new range of choices as technological features are richer with more engaging and rewarding experience for the consumer.

4.1.1.2 Challenges

- Lack of trust towards financial service providers force consumers to rely on peers for financial advice through the social media.
- Small loans disbursed, short repayment period and high cost of borrowing.
- FinTech is unregulated and this may offer an opportunity not to observe prudent lending practices thus consumers not protected. Consumer privacy may also be compromised.
- FinTech exposes the consumers due to irregular cash flows compounded by lack of self-discipline in usage of digital loans.
- Perceived risk and technological failure.
- Taking a loan without understanding the consequences of non-payment and possibly use the money to engage in social ills. For example [Totolo (2018)] observed that 3 percent borrowed for sports betting.

4.1.2 Challenges and opportunities faced by the FinTech providers

4.1.2.1 Opportunities

- Peer-to-peer (P2P) lending is still in its infancy and partnership between traditional firms and FinTech can increase the penetration of this form of lending.
- Build the trust and confidence of the consumers by investing in customer care services and offer customized reward programs to increase customer retention and experience.
- Innovative use of big data and artificial intelligence (AI) for marketing, risk management based on the customer's risk profile and to model the changing trends and shifting demographics of the consumers.
- High mobile penetration and technological evolution reduces barriers to entry of new customers.
- Customer relations, disbursement, repayments, and collections are managed remotely, which reduces operational costs.
- Improve the design of the purchase process to increase consumer attention to the terms and conditions.
- Currently they are 6 million digital loan borrowers and increasing daily [Totolo (2018)].
- Generation Y has a high propensity to use mobile channels and they expect a rich digital experience that integrates their banking needs and their digital lives.

4.1.2.2 Challenges

- Continuous disruptions and innovations means changes in strategic, compliance, operational and cyber-risk (cybercrime and cybersecurity).
- Borrowers denied credit by banks can access digital credit.
- Technological failure and consumer perceived risks.
- Poor disclosure of terms, conditions and prices; coupled with weak client communication once the loan is disbursed.
- A voice of a single customer is amplified by the social media. Bad customer experiences spread through the media and often cause damage to associated brands.

4.1.3 Challenges and opportunities faced by the financial providers

4.1.3.1 Opportunities

- Clustering consumers in different credit risk profiles due to increase in the availability of big data and technological advancements.
- Adopt FinTech innovations to improve their digital service delivery and lower transaction costs for faster banking services and products.
- P2P lending is still in its infancy and partnership between financial providers/FinTech can increase the penetration of this form of lending. For example, in South Africa, Rainfin, a P2P is backed by Barclays Bank and has over USD 80,000 transactional value per day [IFC (2017)].

- Build the trust and confidence of the consumers by investing in customer care services and offer customized reward programs to increase customer retention.
- Banks can leverage on FinTech data to lower non performing loans and offer more efficient and improved banking processes.
- Innovative use of big data and artificial intelligence for marketing and risk management based on the customer's risk profile.
- Can lower operating costs, reduce queues in the banking hall, need for fewer bank branches and reduce manual paperwork and documentation.

4.1.3.2 Challenges

- Traditional banking revenues being sucked up by new competitors with credit card usage being eroded as competition intensifies. Liquidity risk and volatility of deposits as customers loyalty changes in searching for better returns.
- Cyber-risk rise as new technologies and business models are developed and this can increase cyber-risk if controls do not keep pace with change.
- Increase in systemic risk due to information technology inter-dependencies between market players (FinTech, banks and others) as there are variances in expertise and experience in managing information technology risks. This compounds the compliance requirements among the parties.
- Strategic risk as new FinTech entrants capture new market share and deliver more efficient



and less expensive services that meet customer expectations.

- Consumers trust peers for financial advice and this has led to less reliance upon traditional sources of financial advice.

4.1.4 Challenges and opportunities faced by the financial regulators

4.1.4.1 Opportunities

- Develop mechanisms to make digital loan data publicly available to assist the industry to draw broad conclusions.
- Implement the regulatory framework to enhance prudent lending practices as FinTech is taunted to increase financial inclusion.
- Level the playing ground through common market standards to enhance competition and business conduct for the regulated and unregulated digital lenders.

4.1.4.2 Challenges

- Lack of FinTech regulation means consumer privacy may be compromised when information such as utility bills, social networks, insurance

claims and bank account transactions are used without the borrower's consent.

- Cyber-risk rise as new technologies and business models are developed and this can increase cyber-risk if controls do not keep pace with change.
- Lack of coordination among regulators in the market and conflict of jurisdiction in regulating FinTech in Kenya.
- FinTech outlook for Africa in general is unclear and financial regulators can steer the sector to enhance credit access.
- Customers can have multiple digital loans which translate to higher default risk from serial defaults. For example, [Totolo (2018)] noted that 35 percent of consumers had loans from more than one digital lender.

Therefore, the consumers, FinTech providers, regulators and traditional financial service providers face different degrees of disruptions of their business models from technology innovations and increased acceptance in the society as postulated by the Technology Acceptance Model [Davis (1989)].

4.2 Credit Usage and Consumer Perceptions and Behaviour

The second study objective is to analyze how credit usage is shaped by the perceptions and behaviour of the consumer based on source of financial advice, characteristics of the financial instrument, trust of the service provider and cost (interest rate) of credit. The multinomial logistic regression predicted the odds of the credit usage to the perceptions and behaviour of the consumers. The data for discussion is based on **figure 1, table 2 and table 3.**

Table 2: Summary of the categories of credit usage, perceptions and behaviour variables

Variable	Categories	Code	percent	VIF
Credit Usage	Currently have credit	C-1	37.60	
	Used to have credit	C-2	28.70	
	Never had credit	C-3	33.70	
Source of financial advice	Self	A-1	42.00	1.011
	Friends/Family	A-2	41.50	
	Bank	A-3	6.70	
	ROSCA/Chama	A-4	2.50	
	SACCO	A-5	1.30	
	Don't Know	A-6	1.30	
	Radio	A-7	1.50	
	Others	A-8	3.10	
Characteristics of financial instrument	Keep most money	FI-1	10.90	1.00
	Easily accessed	FI-2	33.80	
	Helps in Emergencies	FI-3	18.00	
	Most trusted	FI-4	12.00	
	Use most often	FI-5	6.00	
	Money to invest	FI-6	0.80	
	Safest	FI-7	8.70	
	Others	FI-8	9.90	
Most trusted	Bank	T-1	40.50	1.088
	Mobile Money	T-2	25.40	
	SACCO	T-3	8.20	
	ASCA/Chama	T-4	5.00	
	FinTech (Mshwari/KCB Mpesa)	T-5	3.20	



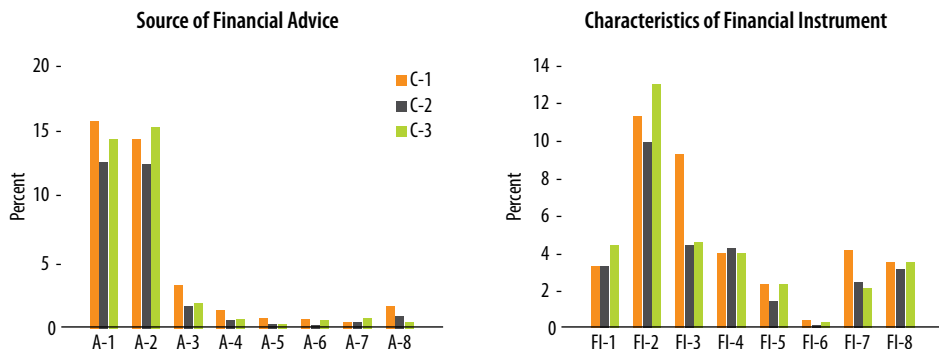
Variable	Categories	Code	percent	VIF
	Microfinance	T-6	1.80	
	None	T-7	13.50	
	Others	T-8	2.60	
Provider with highest interest rate	Bank	IR-1	39.00	1.099
	SACCO	IR-2	7.50	
	Microfinance	IR-3	7.30	
	Informal moneylender	IR-4	2.40	
	Shylock	IR-5	3.00	
	ASCA/ROSCA/chama	IR-6	3.00	
	FinTech (Mshwari/KCB MPesa)	IR-7	3.90	
	Don't know	IR-8	33.70	

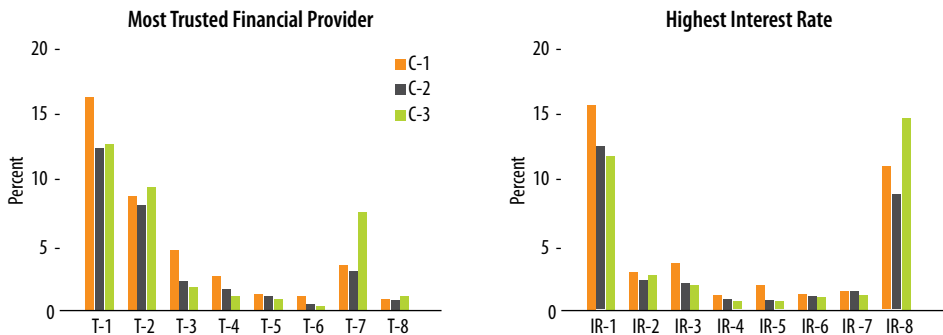
Pseudo R-squared, Nagelkerke

VIF - Variance Inflation Factor (test for multicollinearity)

Table 2 shows the categories of the response variable (three categories) and explanatory variables each with eight categories. The reference category is the last category for each variable. **Table 2** highlights the codes used in **figure 1** and **table 3**.

Figure 1: Credit usage against consumer perceptions and behaviour





In **figure 1**, the first plot (source of financial advice) shows that customers who seek for financial advice from self or family/friends were the majority in the sample had an almost equal proportion of credit usage. In the second plot (characteristics of financial instruments), those customers who felt a financial instrument is easy to access had almost equal proportions among those who currently have, used to have and never had credit. An instrument that helps in emergencies was more favored by

those who currently have credit. The third plot (most trusted financial provider) shows that those who currently have credit felt that banks were the most trusted, followed by mobile money with almost equal proportions in the three credit usage categories. In the fourth plot (highest interest rate), those who currently have credit felt that banks had the highest interest rates, while those who never had credit did not know which institution charged high interest rates.

Table 3: Parameter estimates for perceptions and behaviour

Credit Usage	Code	B	Std Error	Wald	df	Sig.	Exp(B)	95 CI for Exp(B)	
								Low Bound	Upper Bound
C-1	Intercept	-.049	.005	88.763	1	.000			
	A-1	-.519	.004	21397.579	1	.000	.595	.591	.599
	A-2	-.733	.004	42765.622	1	.000	.481	.477	.484
	A-3	-.255	.004	3964.079	1	.000	.775	.768	.781



Credit Usage	Code	B	Std Error	Wald	df	Sig.	Exp(B)	95 CI for Exp(B)	
								Low Bound	Upper Bound
C-1	A-4	-.406	.005	6894.407	1	.000	.666	.660	.673
	A-5	.322	.007	2273.151	1	.000	1.380	1.362	1.399
	A-6	-.264	.006	2133.168	1	.000	.768	.759	.776
	A-7	-1.099	.006	38440.638	1	.000	.333	.329	.337
	A-8	0			0				
	FI-1	-.233	.002	8856.628	1	.000	.792	.788	.796
	FI-2	-.088	.002	1862.271	1	.000	.916	.912	.920
	FI-3	.776	.002	119415.028	1	.000	2.173	2.164	2.183
	FI-4	-.046	.002	349.657	1	.000	.955	.951	.960
	FI-5	.069	.003	600.072	1	.000	1.072	1.066	1.078
	FI-6	.307	.006	2670.406	1	.000	1.359	1.343	1.375
	FI-7	.650	.003	59173.472	1	.000	1.916	1.906	1.926
	FI-8	0			0				
	T-1	.471	.004	17504.794	1	.000	1.602	1.590	1.613
	T-2	.238	.004	4298.045	1	.000	1.268	1.259	1.277
	T-3	1.120	.004	75697.401	1	.000	3.065	3.041	3.090
	T-4	1.071	.004	59569.100	1	.000	2.917	2.892	2.942
	T-5	.663	.005	19440.892	1	.000	1.940	1.922	1.959
	T-6	1.433	.006	57140.616	1	.000	4.189	4.140	4.239
	T-7	-.419	.004	12046.329	1	.000	.658	.653	.663
	T-8	0			0				
	IR-1	.290	.001	42090.651	1	.000	1.337	1.333	1.340
	IR-2	-.002	.002	.679	1	.410	.998	.994	1.003

Credit Usage	Code	B	Std Error	Wald	df	Sig.	Exp(B)	95 CI for Exp(B)	
								Low Bound	Upper Bound
C-1	IR-3	.544	.002	51720.404	1	.000	1.723	1.715	1.731
	IR-4	.363	.004	8658.865	1	.000	1.438	1.427	1.449
	IR-5	1.102	.004	87384.162	1	.000	3.009	2.987	3.031
	IR-6	.368	.003	11236.580	1	.000	1.445	1.435	1.455
	IR-7	.147	.003	2234.262	1	.000	1.158	1.151	1.166
	IR-8	0			0				
C-2	Intercept	-.211	.005	1521.768	1	.000			
	A-1	-.222	.004	3346.568	1	.000	.801	.795	.807
	A-2	-.370	.004	9313.803	1	.000	.691	.685	.696
	A-3	-.351	.004	6212.264	1	.000	.704	.698	.710
	A-4	-.571	.006	10648.635	1	.000	.565	.559	.571
	A-5	-.048	.008	39.275	1	.000	.953	.939	.967
	A-6	-.663	.007	9488.174	1	.000	.515	.509	.522
	A-7	-.780	.006	17165.182	1	.000	.458	.453	.464
	A-8	0			0				
	FI-1	-.144	.002	3375.551	1	.000	.866	.862	.870
	FI-2	-.135	.002	4285.556	1	.000	.874	.870	.877
	FI-3	.136	.002	3254.513	1	.000	1.145	1.140	1.151
	FI-4	.125	.002	2642.415	1	.000	1.133	1.127	1.138
	FI-5	-.349	.003	13077.329	1	.000	.705	.701	.709
	FI-6	-1.608	.011	21990.288	1	.000	.200	.196	.205
	FI-7	.243	.003	7396.016	1	.000	1.275	1.268	1.282
	FI-8	0			0				



Credit Usage	Code	B	Std Error	Wald	df	Sig.	Exp(B)	95 CI for Exp(B)	
								Low Bound	Upper Bound
C-2	T-1	.272	.004	5623.861	1	.000	1.312	1.303	1.321
	T-2	.198	.004	2907.096	1	.000	1.219	1.210	1.228
	T-3	.529	.004	15444.879	1	.000	1.697	1.683	1.711
	T-4	.680	.005	22101.973	1	.000	1.973	1.956	1.991
	T-5	.609	.005	16076.011	1	.000	1.838	1.821	1.855
	T-6	.747	.007	13108.097	1	.000	2.111	2.084	2.138
	T-7	-.452	.004	13438.499	1	.000	.636	.632	.641
	T-8	0			0				
	IR-1	.369	.001	62997.894	1	.000	1.447	1.443	1.451
	IR-2	.046	.002	356.299	1	.000	1.047	1.042	1.052
	IR-3	.288	.003	12249.371	1	.000	1.334	1.327	1.340
	IR-4	.468	.004	13529.699	1	.000	1.596	1.584	1.609
	IR-5	.521	.004	15213.678	1	.000	1.684	1.670	1.698
	IR-6	.469	.004	17717.543	1	.000	1.598	1.587	1.609
	IR-7	.417	.003	18264.884	1	.000	1.517	1.508	1.526
	IR-8	0			0				
The reference category is: Never had credit or code C-3									

The output in **table 3** shows the parameter estimates of the Multinomial logistic regression of the perceptions and behaviour of the consumers against the credit usage. The perceptions and behaviour are measured using source of advice, characteristics of the most important financial instruments, most trusted financial provider and the financial institutions with the highest interest rates. The credit usage is categorized as: currently have credit, used to have credit and never had credit.

4.2.1 Credit usage: Odds of currently have to never had credit

Table 3 shows the logit output from the data analysis. The multinomial logit for self advice, advice from friends/family, bank, chama and radio relative to other sources is 0.519, 0.733, 0.255, 0.406 and 1.099 unit lower for currently have to never had credit, respectively. The logit for SACCO relative to other sources is 0.322 unit higher for currently have to never had credit. Therefore, SACCOs are the only source of advice that are likely to increase credit usage while other sources of advice mentioned reduces the likelihood of credit usage. The findings are statistically significant ($p<0.001$).

The multinomial logit of the characteristics of the financial instruments shows that if it helps in emergencies, use it most often, can get money to invest and safe relative to other characteristics is 0.776, 0.069, 0.307 and 0.650 unit higher for currently have to never had credit, respectively. These characteristics increases the likelihood of the respondent having credit. The logit of the characteristics of the financial instruments shows that if the instrument can keep most of the money, easy to access and most trusted relative to other characteristics is 0.233, 0.088 and 0.046 unit lower for currently have to never had credit, respectively. These characteristics reduces the likelihood of the respondent having credit, and the

findings were statistically significant ($p<0.001$).

The multinomial logit for trust of banks, mobile money, SACCO, chama, FinTech and microfinance relative to trusting other institutions is 0.471, 0.238, 1.120, 1.071, 0.663 and 1.433 unit higher for currently have to never had credit, respectively. Therefore, trust of mobile money, bank, microfinance, chama, FinTech and SACCO increases the chance of a customer having credit now. Only those who responded none as the financial service provider they trust, negatively affected credit usage, with all the findings being statistically significant ($p<0.001$).

The multinomial logit for that banks, microfinance, informal lender, shylock, chama and Fintech having the highest interest rates relative to do not know response is 0.290, 0.544, 0.363, 1.102, 0.368 and 0.147 unit higher for currently have to never had credit, respectively. SACCO have the highest interest rates relative to do not know is 0.002 unit lower for currently have to never had credit. Therefore, using FinTech, bank services, microfinance account, chama member, shylock and informal lenders increases your chance of currently having a loan, with the findings being statistically significant ($p<0.001$). For those with SACCO accounts, this reduces their chance of currently having a loan but the results are not statistically significant ($p=0.410$).



4.2.2 Credit usage: Odds of used to have to never had credit

The multinomial logit for self advice, advice from friends/family, bank, chama, SACCO, radio and do not know relative to other sources is 0.211, 0.222, 0.370, 0.351, 0.048, 0.780 and 0.663 unit lower for used to have to never had credit, respectively. Therefore, those who used to have credit are more likely not to take credit irrespective of the source of financial advice. The findings are statistically significant ($p < 0.001$).

The multinomial logit of the characteristics of the financial instruments shows that if it helps in emergencies, most trusted and safe safe relative to other characteristics is 0.136, 0.125, and 0.243 unit higher for used to have credit to never had credit, respectively. These characteristics increases the likelihood of the respondent having had credit. The logit of the characteristics of the financial instruments shows that if the instrument can keep most of the money, easy to access, use it more often and can access money to invest relative to other characteristics is 0.144, 0.135, 0.349 and 1.608 unit lower for used to have credit to never had credit, respectively. These characteristics reduces the chances of the respondent to ever had credit (increases the likelihood of never have had credit), with the findings being statistically significant ($p < 0.001$).

The multinomial logit for trust of banks, mobile money, SACCO, chama, Fintech and microfinance

relative to trusting other institutions is 0.272, 0.198, 0.529, 0.680, 0.609 and 0.747 unit higher for used to have to never had credit, respectively. Therefore, trust of banks, mobile money, SACCO, chama, FinTech and microfinance increases the chance of a customer having had credit previously. Only those who responded none as the financial service provider they trust, negatively affected credit usage (-0.452); and the findings were statistically significant ($p < 0.001$).

The multinomial logit for that banks, SACCO, microfinance, informal lender, shylock, chama and Fintech having the highest interest rates relative to do not know response is 0.369, 0.046, 0.288, 0.468, 0.521, 0.469 and 0.147 unit higher for used to have to never had credit, respectively. Therefore, using FinTech, bank services, a SACCO, microfinance account, chama, shylock and informal lenders increases your chance of having had credit, with the findings being statistically significant ($p < 0.001$).

4.2.3 Hypothesis - perceptions and behaviour of the consumers affects their credit usage

The perceptions and behaviour of the respondents shows that irrespective of the source of advice, there is likely to be reduced credit usage. Interest rates (cost of credit) and trust of the financial provider increases the likelihood of either currently having or having had credit previously. The characteristics of the financial instruments had varying influence on credit usage

among the respondents. The findings of the perceptions and behaviour of the consumer were statistically significant ($p < 0.001$)

Perceptions and behaviour are unpredictable outcomes [Agaliotis and Hadzic (2015)] and are subjective since customers are rational to a certain extent [Diacon and Ennew (2001)], and echoed by the Technology Acceptance Model constructs [Davis (1989)]. Consumers needs, aspirations and perceived risk are shaped by uncertainties, lack of knowledge, consequences and environmental influences. Therefore, accept the hypothesis that perceptions and behaviour of the consumers influences their credit usage.

4.3 Credit usage and socio-economic characteristics

The third study objective is to analyze how financial literacy and socio-economic characteristics influence credit usage from the financial service providers. The socio-economic characteristics are age, education level, gender of the household head, marital status, income and geographic cluster. The multinomial logistic regression predicted the odds of the credit usage to the socio-economic characteristics and financial literacy among the consumers.

Table 4: Summary of credit usage and socio-economic characteristics of the consumer

Variable	Categories	Code	percent	VIF
Credit Usage	Currently have credit	C-1	37.6	
	Used to have credit	C-2	28.7	
	Never had credit	C-3	33.7	
Household head	Male	G-1	77.5	1.181
	Female	G-2	22.5	
Financial literacy	Low	FL-1	27.6	1.513
	Medium	FL-2	36.9	
	High	FL-3	35.5	
Geographic cluster: Rural/ Urban	Rural	GC-1	61.4	1.149
	Urban	GC-2	38.6	
Education level of Respondent	None	E-1	9.8	



Variable	Categories	Code	percent	VIF
Education level of Respondent	Primary	E-2	46.1	1.644
	Secondary	E-3	32.5	
	Tertiary	E-4	11.6	
Marital status	Single	MS-1	24.5	1.324
	Divorced/Separated	MS-2	4.9	
	Widowed	MS-3	8.5	
	Married/Living with partner	MS-4	61.9	
	Don't know	MS-5	0.2	
Age Groups (in years)	16-30	AG-1	43.5	1.222
	31-45	AG-2	31.6	
	46-60	AG-3	14.5	
	61-75	AG-4	7.6	
	> 75	AG-5	2.8	
Income groups (KES)		IG-1	1.8	1.266
	101-1,500	IG-2	12	
	1,501-3,000	IG-3	14.3	
	3,001-7,500	IG-4	24.0	
	7,501-15,000	IG-5	22.3	
	15,001-30,000	IG-6	15.3	
	30,001-100,000	IG-7	8.8	
	100,001-200,000	IG-8	0.9	
	> 200,000	IG-9	0.6	

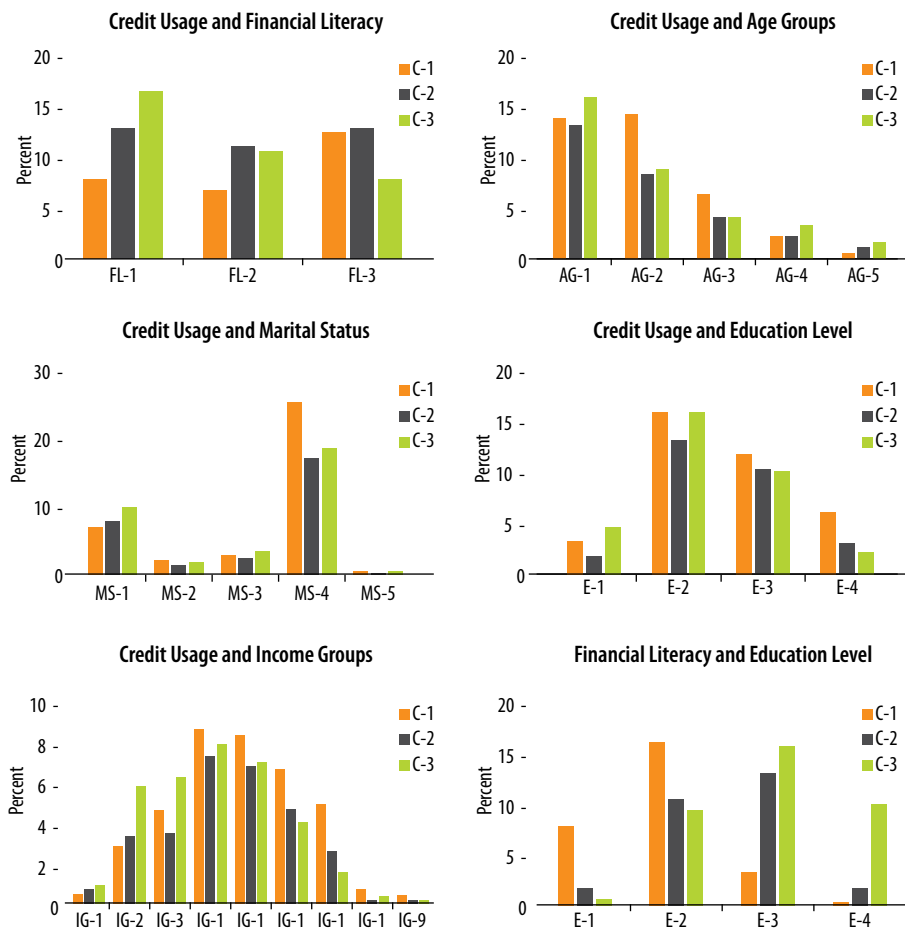
Pseudo squared, Nagelkerke

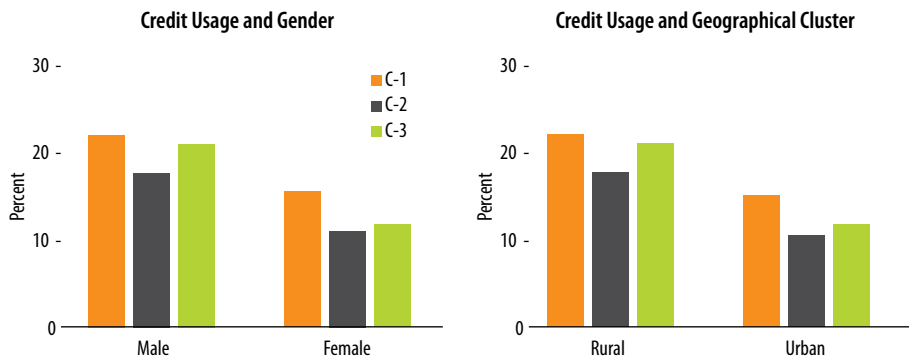
VIF - Variance Inflation Factor (test for multicollinearity)

Table 4 shows the categories of the response variable (three categories) and explanatory variable each has between two and nine categories. The reference

category is the last category for each variable. **Table 4** highlights the codes used in **figure 2** and **table 5**.

Figure 2: Credit usage against financial literacy and socio-economic characteristics of the consumer





In **figure 2**, the first plot (financial literacy) shows that customers with low literacy level have high proportions of those who never used credit but those with high financial literacy have high proportions of those who are currently using or have used credit. In the second plot (age groups in years), the group of 16-30 years had the highest number of those who have never used credit, while the group 31-45 had the highest number of those currently using credit. In plot three (gender), the male and female proportions of those who currently have, used to have and never had credit is almost the same. Plot four (marital status) shows that those married or living with a partner currently have credit, while in plot five (education level), those

who have completed primary or secondary education had an equal number of credit usage while tertiary educated had a high number of those currently have credit. In plot six (geographic cluster), the proportions are almost the same in credit usage and in plot seven (income levels), those earning KES 3,000 or less had a high proportion that has never used credit while those earning between KES 3,001 and KES 100,000 were high users of credit. Plot eight compares the financial literacy level and education level, where those with no formal schooling had the lowest financial literacy and those with tertiary level with highest proportion of those who had the highest financial literacy levels.

Table 5: Parameter estimates for socioeconomic characteristics and financial literacy

Credit Usage	Code	B	Std Error	Wald	df	Sig.	Exp(B)	95 CI for Exp(B)	
								Low Bound	Upper Bound
C-1	Intercept	.234	.016	219.692	1	.000			
	G-1	-.089	.002	3105.469	1	0.000	.915	.912	.917
	G-2	0			0				
	FL-1	-.998	.002	316191.239	1	0.000	.369	.367	.370
	FL-2	-.557	.001	141777.975	1	0.000	.573	.571	.574
	FL-3	0			0				
	GC-1	.147	.001	13931.852	1	0.000	1.159	1.156	1.161
	GC-2	0			0				
	E-1	-.402	.003	17967.080	1	0.000	.669	.665	.673
	E-2	-.456	.002	39724.801	1	0.000	.634	.631	.637
	E-3	-.435	.002	40288.070	1	0.000	.648	.645	.650
	E-4	0			0				
	MS-1	.037	.013	8.128	1	.004	1.038	1.012	1.065
	MS-2	.584	.013	1966.493	1	0.000	1.794	1.748	1.841
	MS-3	.707	.013	2898.336	1	0.000	2.028	1.976	2.080
	MS-4	.675	.013	2694.167	1	0.000	1.964	1.915	2.015
	MS-5	0			0				
	AG-1	.559	.004	19932.082	1	0.000	1.749	1.736	1.763
	AG-2	.869	.004	48939.390	1	0.000	2.385	2.367	2.404
	AG-3	.857	.004	45844.293	1	0.000	2.357	2.339	2.376
	AG-4	.276	.004	4422.147	1	0.000	1.317	1.307	1.328
	AG-5	0			0				



Credit Usage	Code	B	Std Error	Wald	df	Sig.	Exp(B)	95 CI for Exp(B)	
								Low Bound	Upper Bound
	IG-1	-1.068	.009	12992.459	1	0.000	.344	.337	.350
	IG-2	-.955	.008	12917.490	1	0.000	.385	.379	.391
	IG-3	-.695	.008	6940.175	1	0.000	.499	.491	.507
	IG-4	-.403	.008	2362.194	1	0.000	.669	.658	.680
	IG-5	-.391	.008	2236.998	1	0.000	.676	.665	.687
	IG-6	-.258	.008	965.192	1	.000	.773	.760	.786
	IG-7	.239	.008	805.242	1	.000	1.270	1.249	1.291
	IG-8	.478	.010	2075.942	1	0.000	1.613	1.580	1.647
	IG-9	0			0				
C-2	Intercept	-.455	.018	641.231	1	.000			
	G-1	.066	.002	1610.997	1	0.000	1.069	1.065	1.072
	G-2	0			0				
	FL-1	-.695	.002	144618.962	1	0.000	.499	.497	.501
	FL-2	-.407	.002	69524.773	1	0.000	.665	.663	.667
	FL-3	0			0				
	GC-1	.194	.001	22441.507	1	0.000	1.215	1.212	1.218
	GC-2	0			0				
	E-1	-.756	.003	50326.043	1	0.000	.470	.467	.473
	E-2	-.131	.002	2781.136	1	0.000	.878	.873	.882
	E-3	-.022	.002	90.609	1	.000	.978	.973	.982
	E-4	0			0				
	MS-1	.346	.015	545.163	1	.000	1.414	1.373	1.456
	MS-2	.542	.015	1304.283	1	.000	1.719	1.669	1.770

Credit Usage	Code	B	Std Error	Wald	df	Sig.	Exp(B)	95 CI for Exp(B)	
								Low Bound	Upper Bound
	MS-3	.930	.015	3886.350	1	0.000	2.535	2.462	2.610
	MS-4	.634	.015	1833.366	1	0.000	1.885	1.831	1.941
	MS-5	0			0				
	AG-1	.012	.004	10.110	1	.001	1.012	1.005	1.019
	AG-2	-.001	.004	.031	1	.861	.999	.992	1.007
	AG-3	.059	.004	242.298	1	.000	1.061	1.053	1.069
	AG-4	-.139	.004	1289.611	1	.000	.870	.863	.876
	AG-5	0			0				
	IG-1	-.011	.010	1.042	1	.307	.989	.969	1.010
	IG-2	-.191	.010	383.850	1	.000	.826	.810	.842
	IG-3	-.307	.010	991.973	1	.000	.736	.722	.750
	IG-4	.158	.010	264.819	1	.000	1.171	1.149	1.193
	IG-5	.161	.010	278.711	1	.000	1.175	1.153	1.198
	IG-6	.209	.010	463.179	1	.000	1.232	1.209	1.256
	IG-7	.489	.010	2475.556	1	0.000	1.631	1.600	1.663
	IG-8	-.219	.013	286.252	1	.000	.804	.784	.824
	IG-9	0			0				
The reference category is: Never had credit or code C-3									

The output in **table 5** shows the parameter estimates of the Multinomial logistic regression of the financial literacy and the socio-economic characteristics of the consumers against the credit usage. The socio-economic characteristics are the gender of household head, geographic cluster, education level, marital status, age and income. The credit usage is, currently have credit, used to have credit and never had credit.

4.3.1 Credit usage: Odds of currently have to never had credit

The multinomial logit for low and medium financial literacy relative to high financial literacy is 0.998 and 0.557 unit lower for currently have to never had credit, respectively. That is, increase in financial literacy increases the likelihood of having credit, and the findings are statistically significant ($p < 0.001$).

The logit for male relative to female is 0.089 unit lower for currently have to never had credit. That is, female headed households were more likely to currently have credit as compared to the male counterparts. For the geographical cluster, the logit for rural relative to urban is 0.147 unit higher for currently have to never had credit. The logit for no schooling, primary education and secondary education relative to tertiary education is 0.402, 0.456 and 0.435 unit lower for currently have to never had credit. As education level increases, the likelihood of currently having credit increases. The findings are statistically significant ($p < 0.001$).

The logit for being single, divorced/separated, widowed and married relative to those who did not disclose their marital status is 0.037, 0.584, 0.707 and 0.675 unit higher for currently have to never had credit, respectively. The logit for age based on age groups, 16-30, 31-45, 46-60, and 61-75 relative to those aged over 75 years is 0.559, 0.869, 0.857 and 0.276 unit higher for currently have to never had credit, respectively. Marital status and age have a

strong influence on currently having credit with the findings being statistically significant ($p < 0.001$).

The logit for earning KES 30,001-100,000 and KES 100,001-200,000 relative to earning over KES 200,000 is 0.239 and 0.478 unit higher for currently having credit to never had credit. The logit for earning less than KES 100, between KES 101-1,500, KES 1,501-3,000, KES 3,001-7,500, KES 7,501-15,000, and KES 15,001-30,000 relative to earning over KES 200,000 is 1.068, 0.955, 0.695, 0.403, 0.391 and 0.258 unit lower for currently have to never had credit, respectively. The likelihood of currently having credit increases with increase in income, with the findings being statistically significant ($p < 0.001$).

4.3.2 Credit usage: Odds of used to have to never had credit

The multinomial logit for low and medium financial literacy relative to high financial literacy is 0.695 and 0.407 unit lower for used to have to never had credit, respectively. That is, increase in financial literacy increases the likelihood of having previously used credit, and the findings are statistically significant ($p < 0.001$).

The logit for male relative to female is 0.066 unit lower for used to have to never had credit. That is, female headed households were more likely to have used credit as compared to the male counterparts. For the geographical cluster, the logit for rural relative to urban

is 0.194 unit higher for used to have to never had credit. The logit for no schooling, primary education and secondary education relative to tertiary education is 0.756, 0.131 and 0.022 unit lower for used to have to never had credit. As education level increases, the likelihood of having had credit increases. The findings are statistically significant ($p < 0.001$).

The logit for being single, divorced/separated, widowed and married relative to those who did not disclose their marital status is 0.346, 0.542, 0.930 and 0.634 unit higher for used to have to never had credit, respectively. The logit for age based on age groups, 16–30, and 46–60 relative to those aged over 75 years is 0.012 and 0.059 unit higher for used to have to never had credit, respectively. The logit for age based on age groups, 31–45 ($p = 0.861$) and 61–75 relative to those aged over 75 years is 0.001 and 0.139 unit lower for used to have to never had credit, respectively. Marital status had a strong influence on likelihood of having had credit with the findings being statistically significant ($p < 0.001$).

The logit for earning KES 3,001–7,500, KES 7,501–15,000, KES 15,001–30,000 and KES 30,001–100,000 relative to earning over KES 200,000 is 0.239 and 0.478 unit higher for used to have credit to never had credit, respectively. The logit for earning less than KES 100, between KES 101–1,500, KES 1,501–3,000 and KES 100,001–200,000 relative to earning over KES 200,000 is 0.011, 0.191, 0.307 and 0.219 unit lower for used to have to never had credit, respectively.

Incomes of between KES 3,000–100,000 increased the likelihood of having had credit, with the findings being statistically significant ($p < 0.001$).

4.3.3 Hypothesis - socio-economic characteristics and financial literacy shape credit usage

Financial literacy increases with increase in education level with high financial literacy levels increasing current credit usage and chances of a respondent having has used credit. High education level and your marital status increased credit usage, with those married or widowed having a higher chance of using credit. Those respondents in the age groups of 31–45 and 46–60 had credit currently but changes in income had a mixed influence on credit usage. Gender had little influence on credit usage. The findings of the financial literacy and socio-economic characteristics were statistically significant ($p < 0.001$).

The socio-economic characteristics influence on credit usage are similar to the sentiments of various research work [Totolo (2018), Kranz (2005), Allen et al (2016), Demircuc-Kunt et al. (2017), Djankov et al (2008)] and within the Technology Acceptance Model framework [Davis (1989)]. Therefore, accept the hypothesis that socio-economic characteristics and financial literacy shape credit usage.

5.0 Conclusion

The market players face challenges from risks emerging from new technologies, disruption of their business models, products and competition while opportunities range from ease of access, automated scoring, lending and repayment process. Financial institutions can leverage FinTech to lower non-performing loans, reduce bank queues and enhance customer service experience. Regulators task is to regulate the market to be more competitive, protect the consumer, increase public confidence in FinTech and offer market leadership.

The perceptions and behaviour towards credit usage observed that consumers who seek advice from family and friends tend not to use credit. Financial instruments characteristics that cater for emergencies and safe net are more preferred by those who use credit. Cost of credit and trust of the service providers increases credit use. FinTech had positive influence on credit usage, thus the disruptive innovations will continue to shape the dynamics of credit usage. Financial literacy increase increases credit usage with marital status having a positive influence on usage particularly among the widowed and the married. An increase in education level increased credit usage and the financial literacy levels. Age and income influence on credit usage had mixed outcomes. Socio-economic characteristics and financial literacy influences credit usage among the low income earners.

Further research can analyze the relationship between credit usage and credit access from the FinAccess Household survey data as this data set is rich and deep on financial usage and access, covering knowledge, perceptions, behaviour and understanding of financial services and products.

6.0 Policy Recommendations

Firstly, A legal regulatory framework is required with an oversight body to regulate FinTech and make FinTech data publicly available to analyze the impact of the services in the economy. A regulated environment will ensure consumer privacy is not compromised, monitor FinTech lending rates, and track consumers with multiple loans and serial defaults.

Secondly, Opportunities abound in the FinTech market and P2P lending which is unexploited market in Kenya to access more lending finance and lower lending costs. Around of billion unbanked reside in countries, mostly in Asia and Africa; with of Africa's billion population lacking access to formal bank services [IFC (2017)].

Lastly, Disruptive technologies are taunted to reduce intermediation, reduce marginal costs, automate high-value activities, empower customer with control over choices and offer niche and specialized products and services.

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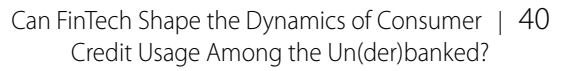
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