Report on the Competition Authority of Kenya Digital Credit Market Inquiry

Innovations for Poverty Action, presented to the

Competition Authority of Kenya

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Executive Summary

On February 21, 2020, the Competition Authority of Kenya (CAK) announced a Market Inquiry into Kenya's Digital Credit Sector. The Inquiry was conducted with research support from Innovations for Poverty Action (IPA). The inquiry's objectives are as follows:

a) Provide evidence regarding the size and nature of the digital credit market
b) Identify potential consumer protection risks and consumer outcomes within Kenya's digital credit sector
c) Increase transparency and comprehensiveness of product information and terms and conditions
d) Address probable fraud in digital financial services
e) Improve consumer redress for digital credit products
f) Increase consumer control over personal information to expand choice and competition
g) Inform the development of policies to ensure adequate consumer protection across regulated and unregulated lenders and equal protection of all Kenya consumers

Digital credit emerged in Kenya in 2012 with the introduction of M-Shwari from Commercial Bank of Africa (now NCBA) and Safaricom. In the 9 years since, the digital credit sector has grown such that at different points there have been as many as several hundred lenders estimated to be operating in the Kenyan market,[1] although the number of lenders has reduced during the COVID-19 pandemic as lending has contracted.[2] While the majority of digital lenders are unregulated, the vast majority of lending volume and value are provided by a small number of regulated banks, most noticeably the three products listed on Safaricom's M-PESA mobile money menu, M-Shwari, Fuliza, and KCB M-PESA. The market is therefore at once diverse in terms of number of providers, but with most the value and volume concentrated with products delivered by several large commercial banks.

To support the objectives of the Market Inquiry, CAK and IPA conducted two complementary research activities:

1. A phone survey of 793 users of digital financial services (DFS) from across Kenya.
2. An audit and analysis of transaction and account-level data of regulated and unregulated digital credit providers.

These two research activities were selected to provide both demand and supply-side data on what the primary consumer risks are with digital credit, and where opportunities may lie for policy reforms to minimize these risks. The phone survey also considered two other related DFS products—mobile money and mobile banking—to understand how experiences with issues such as fraud and complaints redress varied between digital credit and other DFS markets. The consideration of mobile money is particularly important given the high uptake in Kenya and mobile money's key role as the payments channel for most digital credit products. In this respect, mobile money is an enabler of the digital credit market, and the two markets are often closely tied, with digital credit products being offered by mobile money

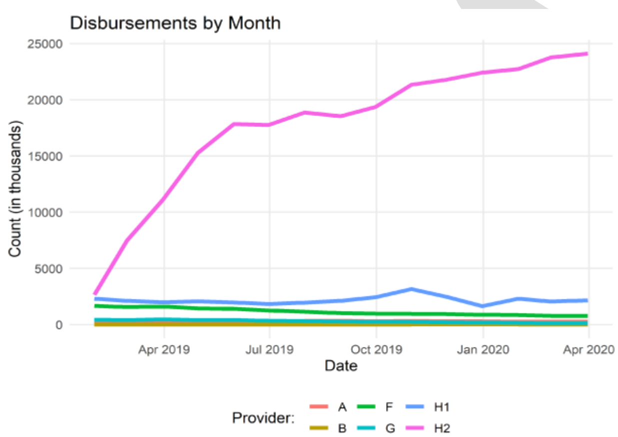
[1] Francis Gwer, with Jack Odero and Edoardo Totolo. November 2019. Digital Credit Audit Report. FSD Kenya: Nairobi. https://s3-eu-central-1.amazonaws.com/fsd-circle/wp-content/uploads/2019/11/13160713/Digital-Credit-audit-report.pdf
[2] https://www.businessdailyafrica.com/bd/corporate/companies/digital-mobile-defaulters-out-of-platforms-3282988

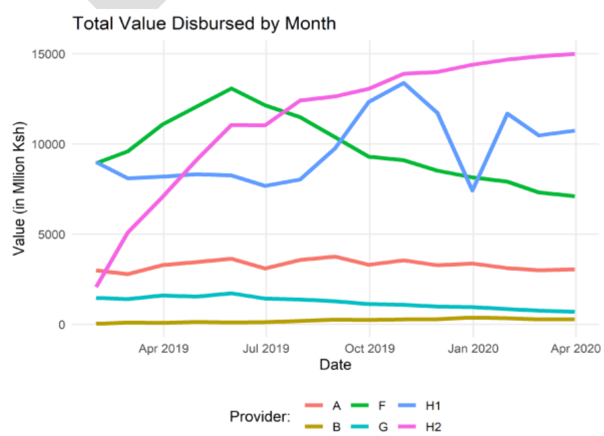
providers, lenders offering loans directly on mobile money menus, and most loans settled through mobile money payment channels.

i. Size and nature of digital credit market

54% of survey respondents in our sample had used digital credit before. Of these **91% of mobile loan users have used the three products affiliated with M-PESA, M-Shwari, Fuliza, and KCB M-Pesa, while *only 38% of mobile loan users have ever used any product besides these three*, showing the dominance of loans placed on the M-PESA platform amongst consumers.** While M-Shwari is the loan product most commonly ever used, Fuliza recorded the most active users, showing it's rapid expansion since being launched in January 2019.

Using administrative data to size the digital credit market and chart its growth, **we see a large increase in number and total value of disbursements of digital credit products in the period between January 2019 and March 2020.** This was largely due to a single entrant to the market, Provider H2, whose disbursements grew 232% from Quarter 1 (Q1) 2019 to Q1 2020, while total value of disbursements grew 213%. During this period, every other providers' loans grew in size, suggesting a degree of market segmentation took place. (See Figure below)





The administrative data was used to develop a measurement of "effective tenure"—which is the number of days before a loan is repaid. This differs from the initial loan tenure as it accounts for early and late repayment. This analysis finds that **some loans are repaid in very short periods of time, and 37.5% of accounts have an average effective tenure of less than four weeks and 5.1% have an average effective tenure of one week or less.** If borrowers are paying a month of interest for loans they only need for a week—as most loans are 30 days or longer in tenure—this represents a costly approach to credit, and may call for requiring providers to give discounts on interest fees for early repayment, as some providers have already put in practice.

As the lending volumes above show, the majority of users of digital credit and majority of volumes in our sample are for loans linked to M-PESA. **To assess market concentration in more detail we applied the Herfindahl-Hirschman Index (HHI) to the consumer survey responses on which digital lenders consumers have ever used.** Of the 430 consumers who have taken at least one digital loan, the three loan products on the M-PESA menu are the three most commonly ever used products, ranging from 34%

for M-Shwari, 25% for Fuliza, and 15% for KCB M-PESA, while only two other lenders register any significant market share—Tala at 13% and Branch at 9%. Using the HHI on the survey data we assess concentration in digital credit, **and observe an HHI of 1,946 for products ever used, placing this in the middle of the moderately concentrated market window.** This figure is likely an underestimation for two reasons: 1. The survey respondents were of higher than average socio-economic status, so more likely to use a diverse range of DFS and have phones capable of accessing FinTech lenders' apps; 2. HHI typically uses active users, not those who have ever used a product. In our survey we asked which products had been used in the past 90, days, and see higher levels of concentration than for the "ever used" question, signaling that active use of digital credit may be more concentrated than we found when applying the HHI to the products consumers had ever used. In the future CAK may wish to request all digital credit providers submit data on the number of active users and overall loan value and volumes to allow for a full calculation of HHI.

ii. Potential consumer protection risks within Kenya's digital credit sector

Late or non-payment of debt. In the consumer survey conducted as part of this Market Inquiry, **77% of mobile loan users reported having not been able to repay a loan at least once, indicating many borrowers will incur such penalty fees at some point in their use of digital credit.** While the administrative data submitted by providers for this Market Inquiry did not always include clear demarcations of the loan tenure as requested, we have been able to reconstruct repayment estimates in several cases. **Our estimates, which are intentionally conservative, still show that there is a high incurrence of penalty fees for digital borrowers, which aligns with the survey finding that 77% of borrowers have been late at some point**. These penalty fees have a median and mean cost of 12% and 52%, respectively, using our effective APR calculation. While Annual Percentage Rate, or APR, takes the total cost paid on the loan and coverts it to an annual interest rate using the contracted tenure of the loan, effective APR uses the actual time until the loan was repaid as the tenure of the loan.[3] This may call for a review of policies regarding assessment of penalty fees to ensure they are fair and proportional, given the high incidence of penalties in digital credit. Particular focus could be made on those repeat borrowers who habitually pay penalty fees, to determine why they habitually pay late fees and if any interventions can be done to inform them of the cost of this behavior to reduce such occurrences.

Multiple borrowing. **In the consumer survey 33% of mobile loan users reported they had multiple mobile loans active at the same time before March 16th, when much of Kenya shut down due to the pandemic.** The most common reasons given for taking multiple loans were emergencies (52%) and loan limits too small being the dominant reasons (35%), while 12% took a second loan when they did not pay back a first loan, and 7% and 4% to pay back another mobile or non-mobile loan, respectively.

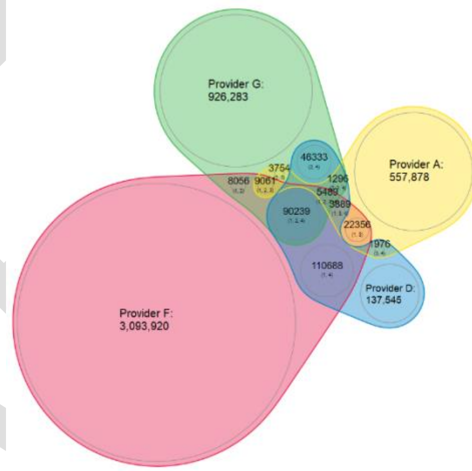
Using the administrative data submitted by providers, the research team developed several methods to gain further insights into multiple borrowing behavior. Four providers had sufficient data to check for multiple accounts. The data from these four providers was linked using the ID as an identifier. **Overall, 6% of borrowers with these four providers have multiple accounts, with wide variation in overlap**

[3] APR is computed $\text{APR} = \left(\frac{\text{Cost}}{\text{Principal}} \times \frac{\text{365 days}}{\text{Tenure}}\right) \times 100\%$.

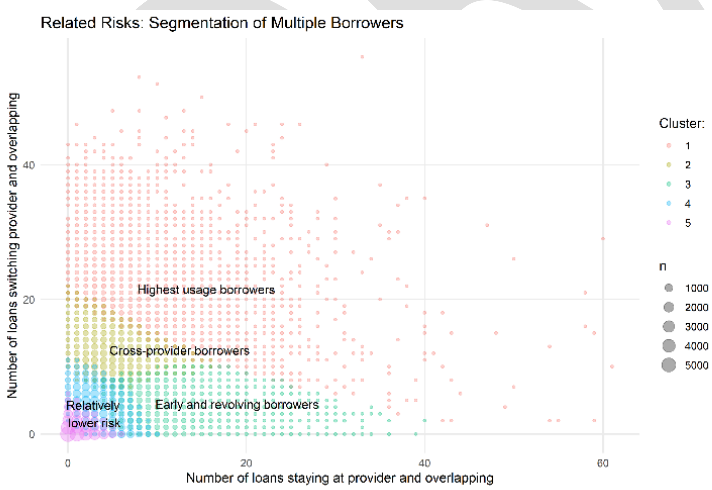
across providers. Male borrowers are more likely to have multiple accounts than female borrowers: 9.71% of men have more than one account as compared to 7.74% of women. We also see a higher degree of multiple account holding among adults aged 25-44 as compared to older and younger cohorts, with 11.08% holding multiple accounts. This is followed closely by adults aged 45-64, of whom 8.01% hold multiple accounts. In contrast, young adults and the elderly do not hold multiple accounts at a high rate.

Multiple borrowers tend to borrow from different lenders in relatively short periods—indicating some level of loan stacking. **Of the multiple borrowers identified in the administrative data, 95.8% of these took a new loan within 30 days of a prior loan**—with 86.8% taking additional loans from their previous lender, and 81.8% taking additional loans from a new lender.

The probability of multiple borrowing with any provider is of course dependent on the number of accounts that provider has overall—the more accounts, the more that can potentially have loans elsewhere**. At the upper extreme, 65% of Provider D's borrowers have also borrowed from at least one other lenders (see figure on right).** Provider D is one of two FinTechs, while the other two providers are banks, and their high overlap shows the relative market share of FinTechs vis-à-vis banks in digital credit, as well as their dependence on borrowers which also engage with bank-based digital lenders.



Multiple borrowing can be an indicator of higher probability of debt stress. To better understand which users may have higher risk of debt stress, a data-driven segmentation of multiple account holders was conducted.[4] This gives a useful breakdown of the types of multiple borrowers and how they differ.



The figure on the left plots this segmentation over the total number of loans a borrower multiple borrows on, disaggregated to those at the same provider on the x-axis, and cross-provider multiple borrowing on the y-axis. As the figure shows, there are different segments of borrowers with higher or lower potential risk, and in particular "Highest usage borrowers" and "Cross-provider borrowers" seem to be at-risk clusters worth monitoring more closely.

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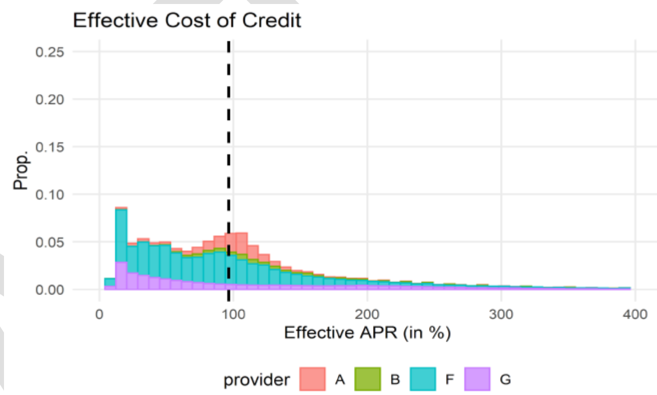
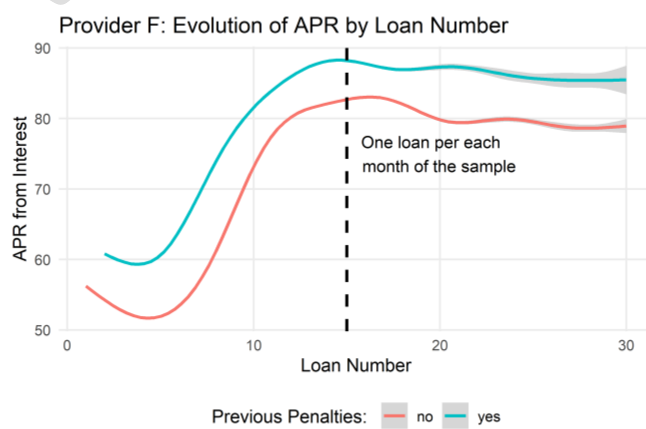
[4] In particular we perform k-means clustering with information including total loans taken, total number of times multiple borrowing (and across which providers), if borrowers switched often. We set $k = 5$ for this analysis.

iii. Transparency and comprehensiveness of product terms and conditions

Consumer Price Awareness. The consumer survey found that recall of digital credit fees is lower than mobile money at 40% (within plus or minus 5%), although this is still fairly high for recall on a survey. Fee knowledge does not appear to vary dramatically by demographic segment, though younger and better educated consumers in our survey were more likely to report the correct mobile money fee than their older or less educated counterparts. Most users report learning about the fees only when they receive a receipt after the transaction has been completed, though a sizable minority learn of the fee from a notification on their phone before the transaction is finalized. The lack of consumer recall of seeing fees pre-transaction could be due to their focus pre-transaction on executing the transaction or taking the loan, and not reviewing product terms.

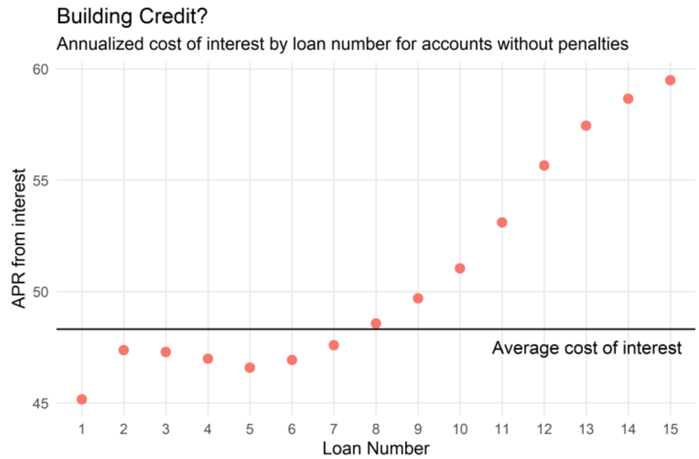


The cost of digital credit in Kenya. To measure the effective cost of credit we calculate the true cost of a loan to a consumer based on usage, not the stated product terms. This measurement can be done using a statistic similar APR which we call Effective APR, which accounts for early repayment and late payment behavior. Those interested can find our definition of effective APR in Appendix A. We find that the cost of digital credit in our dataset is relatively expensive, with a mean Effective APR of 280.5% and median Effective APR of 96.5%. As implied by the difference between the mean and median, the distribution of cost of credit is highly right skewed, meaning we observe a long right tail of high cost credit (see figure above). One reason for highly skewed distribution is the presence of early repayment. The shorter the amount of time credit is taken out for, the higher the APR is in effect.



Risk-Based Pricing. Risk-based pricing refers to a provider offering different pricing for loans based on their perception of the borrower's probability to not pay back the loan. In recent years in Kenya there have been calls for increased use of risk-based pricing by lenders to reward borrowers who have positive loan repayment history. Given the high prevalence of repeat borrowing and short tenure of most digital credit, risk-based pricing could be particularly beneficial for digital credit customers.

Risk-based pricing has the potential to improve credit markets for both the established and marginal borrower. Borrowers who have established a good credit history will ideally see a reduction in their cost of credit. On the other hand, more risky marginal borrowers will be able to receive higher priced credit, allowing them to enter the market and access credit.



Fortunately, some providers are already utilizing risk-based pricing strategies, although evidence about the benefits of this is not consistent within our sample. Using data from Provider F as a case study, we find mixed evidence for risk-based pricing, with both loan size and pricing seeming to respond to borrowers' late repayments, as shown in the graph above, "Provider F: Evolution of APR by Loan Number." However, the price of loans tends to rise with loan number for borrowers who have clean credit histories, not just for those who have repaid late in the past. Since Provider F increased their interest rates in the midst of our sample, it is likely that the increase around this 10th loan is at least partially due this increase, which happens to coincide with when these loans were taken. Other explanations might include a more subtle form of risk-based pricing: late repayment rises on these later loans, and so the loan number or frequency with which borrowers take on loans might be factored into the credit decision. Alternatively, the patterns of later repayment may reflect riskier borrowers at these numbers of loans, which would be reflected in pricing.

To get a cleaner estimate of how loan sizes and price change after late loans, we use regression analysis to control for number of loans taken, the total disbursed in those loans, individual effects, and whether or not there had been a general increase in the price of credit yet. After controlling for these factors, we find that a one Ksh increase in the value of cumulative penalties accrued is associated with a 0.65-basis point increase in annualized interest (not counting interest related to penalties or excise tax). Likewise, a one Ksh increase in the value of cumulative penalties accrued is associated with a 1.16 Ksh decrease in the size of loan disbursed. However, despite controlling for a variety of factors, we still see an increase in the average cost of loans to clean accounts. In fact, these accounts pay an above average cost of credit for loans after their seventh loan, as can be seen in the graph above, "Building Credit?" which plots the cost of credit over the first fifteen loans for an average borrower who is never penalized over these loans. This is not consistent with a model of "building credit," where repeated successful repayments tend to drive down the price of credit over the long run.

iv. Address probable fraud in digital financial services

The consumer survey conducted for the Digital Credit Market Inquiry confirms the high prevalence of attempted fraud, in particular third-party fraud. **82% of respondents report receiving a call or SMS from an unknown person asking for money or sensitive personal information, or offering a product or service.** 77% of scammers asked consumers for them to send money for a variety of reasons (for example, to reverse what appeared to be money sent to the consumer in error but was in fact fake).

Other common requests included asking for a password or PIN (21%), personal information (19%), or account details (13%).

While phishing scams are quite common, consumers seem to be good at identifying these as scam attempts. 16% of consumers responded to scammers messages, but of these only 13% followed the scammers instructions. The vast majority of consumers simply ignore these phishing attempts (76%). Consumers identify scams using a variety of methods. Noticing that the call or SMS comes from a regular number rather than a business line or short code is the most-reported method. Others report hearing about the scam from others, or from their own prior experience. Finding holes in the scammer's story is also common if the scammer asks about a service the consumer does not use or greets the respondent with the wrong name. However, while many consumers know to ignore these scams, just 8% reported the scams to anyone. CAK and others in government and industry could consider utilizing the fraud detection tips of survey respondents to increase awareness amongst all DFS users of how to detect fraud, and encourage more sharing of cases of fraud—even when the consumer does not fall victim—to keep ahead of new types of fraud and to flag phone numbers or accounts perpetrating fraud attempts.

v. Improve consumer redress for digital credit

The survey asked consumers about a set of common DFS challenges, to understand how many consumers may experience these issues across two periods: 1. Any challenges experienced since January 2020; 2. The most significant challenge ever experienced—to not miss any issues which may have caused substantial difficulty or harm in the past. Phishing scams were the most common issue experienced, followed by incorrectly sending money to the wrong recipient. There is also a substantial portion of consumers who raised issues related to customer care, or challenges understanding the DFS product's interface or it's terms and conditions, which point to the need for potential policy reforms related to complaints handling and transparency of content on DFS platforms and communications channels. When analyzed by service type the majority of issues are related to mobile money, (excluding being denied a loan or having someone take a loan in your name, which of course is only possible with mobile loans), which points to this issue being less of a priority for immediate policy action in digital credit than other issues highlighted in this Market Inquiry.

vi. Increase consumer control over personal information to expand choice and competition

<u>Consumer choice in providers.</u> Survey respondents were asked to share the reasons they chose their primary DFS provider for mobile money, mobile banking, and mobile loans. Surprisingly, **only 12% of users of mobile loans cited price as a factor in their choice of digital credit provider. Speed of loan disbursement and ease of repayment terms were the most common reasons**. It is interesting to note that "Only provider I am allowed to borrow from" was a greater factor than price in consumers' decisions. These responses reflect the fact that consumers who do not use a device able to download apps are restricted to the lender or lenders which their mobile money provider allows access to their SIM Toolkit or USSD menu and mobile money channels. This may help explain why only 27% of mobile loan users in the survey reported they know the fees charged by other mobile loan providers, meaning that awareness of price differences is relatively low in digital credit.

Competition in digital credit. The consumer survey found some evidence of consumers borrowing from multiple lenders, with 33% of borrowers having had multiple mobile loans active at least once prior to the pandemic. The administrative data analysis in the Inquiry found at least 6% of borrowers had taken loans from multiple lenders across a four-lender sample from January 1, 2019 through March 31, 2020. The absence of the two largest digital credit products as well as smaller but significant FinTech lenders in the data means that the level of multiple account holding is a “lower bound” on the true degree of multiple account holding, which is likely much higher.

We recommend that further analysis be done with a larger sample so as to ascertain the true level of multiple borrowing. This audit would include a larger sample of lenders, submitting standardized data including identifiers such as MSISDN or, ideally, National ID number. The analysis would likely focus on the following research questions:

1. How many borrowers who did not repay a loan at one provider were able to borrow with another provider later, and did they default again?
2. What is the state of switching behavior in the digital credit market?
3. How prevalent is loan stacking—when multiple loans are taken out at the same time?
4. To what extent do lenders compete for well-qualified borrowers based on price?

vii. Key policy recommendations

1. Develop policies which will contribute to a more competitive digital credit ecosystem

The research identified two trends—Increasing concentration of loans linked to mobile money providers, and multiple borrowing in an environment with high information asymmetry on positive repayment between banks and non-banks—which raise potential risks for competition and consumer choice in the long-run. To address these, we propose four policy measures:

- Develop standards for channel access, product placement and revenue-sharing for digital credit services on mobile money menus to ensure fair competition and consumer awareness of a diverse set of product options—in particular for those without the ability to download apps due to device or network limitations.
- Establish rules regarding the use of competitors’ data by mobile money providers and their partner lenders. Mobile money providers hold significant data on their competing digital lenders which could provide them a competitive advantage by leveraging this data for their competing credit products and to target good paying borrowers from other providers. To avoid this risk of unfair advantages for lenders linked to mobile money providers, rules on utilization of competitors’ data that is accessible due to being a mobile money provider or other facilitator of digital lending transactions.
- Expand sharing of consumer information for bank and non-bank digital lenders through both credit information systems and other information-sharing schemes. This would include real-time or same-day sharing of positive and negative credit history, mobile money data, and KYC information.

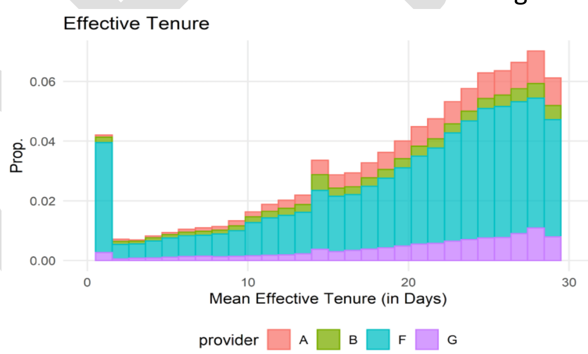
- Once information-sharing systems are developed, facilitate the creation of third-party services which allow consumers to receive competing offers from digital credit providers based off common borrower information, to increase switching and risk-based pricing competition.

2. Develop standards on structure and timing of fees in digital credit to ensure comprehension for consumers across bank and non-bank products.

While many lenders have relatively simple fee structures, analysis of administrative data identified some fee structures and fee dynamics which could make product comparison difficult and obfuscate charges. This includes applying multiple fees at once, applying fees late in the loan cycle, administrative charges, and penalty fees. The frequent payment of penalty fees for some products in our data also indicates that consumers may not be sufficiently attentive to penalty fees and their costs. Improvements in presentation of information and consumer education could help reduce complexity and improve consumers' usage of digital loans, reducing late repayment.

3.

Digital borrower data analysis showed many borrowers repay their loans in less than 30 days, including more than 4% who repay in less than one day. The analysis also found frequent repeat borrowing is common—in the case of one provider more than 50% of borrowers took 5 or more loans during the 15 month sample period. (see graph on right) Some providers already reduce interest and other charges for early repayment, and reduce interest rates on subsequent loans after prior positive repayment. There are potential consumer benefits if all providers are required to do risk-based pricing that offers discounts to repeat borrowers in good standing. These practices should be standardized across the industry by refunding a portion of finance charges for the many borrowers who repay digital loans well before their due date; and reducing the proportion of fees to loan value charged to repeat borrowers who consistently repaid prior loans. These schemes should further be supported by information sharing schemes which allow providers to manage multiple borrowing risks where customers present a false representation of being in good standing with one lender while defaulting on obligations to another lender, have multiple loans active at the same time, or borrow from one lender to service an outstanding debt with another lender.



4. Require digital lenders to provide periodic reports on the actual total charges paid by borrowers

Early repayment, late payment, and loan roll-overs can shift actual costs far from advertised costs. Loan repayment varied significantly. To better monitor pricing trends in the market, data on actual amounts charged and duration of loan cycles should be reported quarterly to assess the effective costs incurred by borrowers and monitor trends in pricing over time.

5. Expand use of administrative data analysis as a digital credit market monitoring tool

Transaction and account level data has proven useful to identify competition and consumer protection indicators, and should be utilized for future market supervision. While there were inconsistencies and incomplete submissions, the administrative data analysis was still able to produce new and important insights regarding true cost of credit products; behavior of different borrower segments; and competition in digital credit. A second round of analysis with more complete data submissions and full participation of leading digital lenders should be done to build a new data-driven market monitoring tool. This tool could be developed by CAK and CBK—which currently oversees bank-based digital lenders and may soon take on supervision of non-bank digital lenders—in partnership with IPA's data science team, and designed in a way that the analysis could be transitioned to CAK and/or CBK staff once a common template for data submissions is established and enforced across DFS providers.

6. Require providers to submit aggregated complaints information to monitor consumer risks in DFS

The Market Inquiry identified several variations in the experiences of different demographic segments with key DFS challenges. More research is needed to understand why traditionally vulnerable population segments report lower levels of consumer protection challenges with DFS, and monitor new risks like fraud going forward to address new types of fraud as they emerge. A starting point for this analysis should be requiring that all providers—not just banks—submit monthly complaints reports detailing the types and volumes of issues raised by customers, demographic breakdown of these complaints, and the actions taken to remedy these complaints. This will allow for proactive monitoring and addressing of consumer protection risks early on across providers within the DFS industry.

I. Market Inquiry Objectives and Research Methodologies

On February 21, 2020, the Competition Authority of Kenya (CAK) announced a market inquiry into Kenya's Digital Credit Sector. The Inquiry was conducted with research support from Innovations for Poverty Action (IPA). The inquiry's objectives are as follows:

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1. The digital credit market in Kenya

Digital credit refers to loans which are delivered via mobile phone, web browser, and app, where the enrollment, origination and repayment are managed through digital channels. Mazer and Chen (2016) identify three primary attributes of digital credit products—"Instant, automated, and remote."[5] In this report we use the terms digital credit and mobile loans interchangeably, as they are both used commonly in the industry. Our definition of the market for digital credit focuses on loans which are lent through digital channels such as SIM toolkit, USSD, app, and web browser, versus loans where there is an in-person aspect of the lending process.

Digital credit emerged in Kenya in 2012 with the introduction of M-Shwari from Commercial Bank of Africa (now NCBA) and Safaricom. In the 9 years since, the digital credit sector has grown such that at different points there have been as many as several hundred lenders estimated to be operating in the Kenyan market,[6] although the number of lenders has reduced during the COVID-19 pandemic as lending has contracted.[7] While the mix of regulated and unregulated lenders has made assessing the number and market share of lenders in the market, bank and MNO-facilitated products accounted for 97% of the total supply of digital loans in 2018,[8] a figure that has likely only increased with the closure of smaller FinTechs during COVID-19 and the rapid takeoff of the Fuliza product in 2019.

This reflects an interesting paradox in the Kenyan digital credit market: While the majority of digital lenders are unregulated, the vast majority of lending volume and value are provided by a small number

[5] Greg Chen and Rafe Mazer. February 8, 2016. "Instant, Automated, Remote: The Key Attributes of Digital Credit." CGAP: Washington, D.C. https://www.cgap.org/blog/instant-automated-remote-key-attributes-digital-credit
[6] Francis Gwer, with Jack Odero and Edoardo Totolo. November 2019. Digital Credit Audit Report. FSD Kenya: Nairobi. https://s3-eu-central-1.amazonaws.com/fsd-circle/wp-content/uploads/2019/11/13160713/Digital-Credit-audit-report.pdf
[7] https://www.businessdailyafrica.com/bd/corporate/companies/digital-mobile-defaulters-out-of-platforms-3282988
[8] https://www.microsave.net/wp-content/uploads/2019/09/Digital-Credit-Kenya-Final-report.pdf

of regulated banks, most noticeably the three products listed on Safaricom's M-PESA mobile money menu, M-Shwari, Fuliza, and KCB M-PESA. (For a more complete discussion of this, see Section 1. Size and nature of the DFS and digital credit markets.)

2. Policy responses to digital credit

As with any consumer lending, digital credit raises significant consumer protection risks and concerns. There have been several policy measures taken in recent years to address these risks, including:

1. Guidelines on pre- and post-transaction disclosure of costs for all DFS providers by CAK in 2016, which resulted in improvements in pricing transparency for both regulated and unregulated digital credit providers.
2. Circular No. 6 of 2016 from CBK, which requires that all changes in the terms or features of a product issued by a commercial or microfinance bank regulated by CBK must be approved in advance by CBK.
3. The Kenya Banking Sector Charter of 2018, which includes requirements related to risk-based credit scoring, product key facts statements, and complaints handling.
4. Enforcement actions taken against non-bank digital lenders by CAK regarding breaches of transparency and conscionable conduct provisions of the Competition Act, including consumer protection trainings and sensitization for the lenders' staff.
5. CBK Gazette Notice 55 of April 8, 2020 which removed all negative listings less than Ksh 1,000 from the Credit Reference Bureaus, and prohibited non-bank digital lenders from being allowed to participate in the credit information system.

In addition to these policy measures in place, there are active discussions to place non-bank lenders under the supervision of CBK, although those are only proposed legislation at this moment.

3. Research methods

To support these objectives, CAK and IPA conducted two complementary research activities:

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4. An audit and analysis of transaction and account-level data of regulated and unregulated digital credit providers.

These two research activities were selected to provide both demand and supply-side data on what the primary consumer risks are with digital credit, and where opportunities may lie for policy reforms to minimize these risks. The phone survey also considered two other related DFS products: Mobile money and mobile banking, so as to understand how experiences with issues such as fraud and complaints redress varied between digital credit and other DFS markets. The consideration of mobile money is particularly important given the high uptake in Kenya and mobile money's key role as the payments channel for most digital credit products. In this respect, mobile money is a key enabler of the digital credit market, and the two markets are often closely tied, with digital credit products being offered by mobile money providers, lenders offering loans directly on mobile money menus, and most loans settled through mobile money payment channels.

Phone survey of DFS consumers. 793 DFS users were surveyed from September 14 – October 18, 2020. The survey used random digit dial (RDD) method, where numbers were randomly selected to dial using a list of all possible mobile numbers following the Kenyan mobile phone number allocation system that were active within Kenya when the RDD samples was generated on September 10, 2020. We began the survey by asking respondents their age and experience using digital financial products. Only adults (age 18 and above) and those that had used mobile money, mobile banking, or digital credit products in the last 90 days were eligible to participate.

We collected respondents age, gender, education, and income, among other demographic characteristics. We were not able to directly collect information about respondent's urban versus rural status over the phone. However, we estimated respondents' urban vs rural status based on constituency. A cutoff of 600 individuals/km2 was selected so that the urban population approximately matched the World Bank urban population estimate for 2009, the latest year where constituency-level population statistics are available. Because of changes in constituencies between 2009 and today, we were able to generate an urban indicator for 71% of respondents. Approximately 36% of respondents were categorized as residing in urban areas using this method (compared with 23% of the population according to the World Bank 2009 estimate).

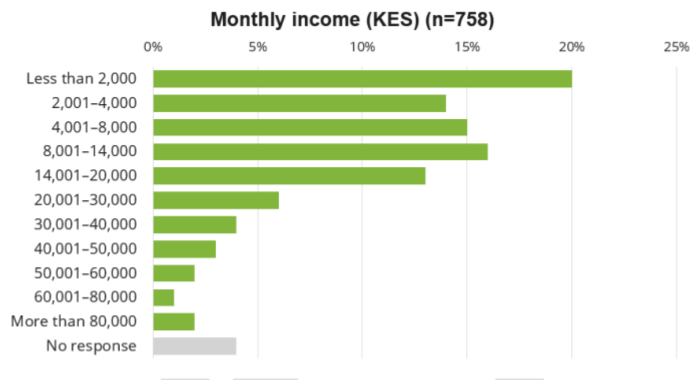
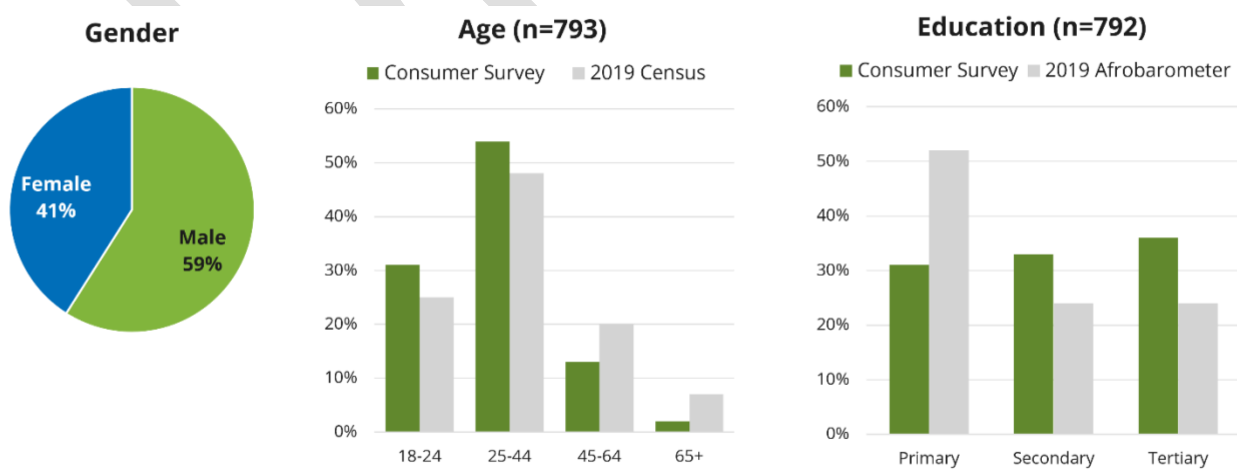


Figure 1: Monthly income of survey respondents

As shown in Figure 1, most respondents earn less than KES 20,000 per month, with 20% of the sample earning less than KES 2,000 per month. As is common with RDD surveys, and DFS users overall, the sample was more urban, male, younger, wealthier and better educated than Kenya's overall adult population (Figure 2). However, geographic dispersion was relatively balanced in lines with Kenya census data. As Table 1 shows, survey responses per province align fairly closely with census population data. As might be expected, Nairobi is overrepresented while North Eastern is under-represented. This is likely



Afrobarometer is non-partisan, pan-African research institution conducting public attitude surveys on democracy, governance, the economy and society in 30+ countries repeated on a regular cycle.

Figure 2: Demographics of survey respondents

partially due to differences in phone access (so response to phone surveys) and partially due to differential DFS usage.

Table 1. Geographic distribution of survey respondents versus census data

Province	**Survey**	**Census**	**Province**	**Survey**	**Census**
Rift Valley	23%	25%	Nyanza	11%	12%
Nairobi	19%	11%	Western	9%	10%
Eastern	14%	15%	Coast	9%	9%
Central	14%	13%	North Eastern	1%	4%

<u>Digital credit administrative data analysis methodology.</u> Measuring the size and nature of the digital credit market is complicated by the lack of regulatory coverage and definitions. To address this challenge, past studies in Kenya have utilized sources such as demand-side survey data[9], and credit reference bureau data.[10]

Both of these sources are important for understanding digital credit, and this study similarly employs a demand-side survey as part of its methodology. To enhance the coverage of lenders to include those not reporting to credit bureaus, and to gain greater insights into borrower demographics, the ways in which fees are charged during the loan cycle, and the true cost of credit based on usage patterns, this research sought transaction-level data on digital credit as part of its sources of information.

In April, 2020, CAK requested transaction-level data from both regulated and unregulated digital credit providers for all digital loan accounts from January 1, 2019 – March 31, 2020. This information request was made to remedy the lack of any publicly available data covering the entire scope of the digital credit market. Lack of comprehensive data covering bank and non-bank digital lenders poses a risk to effective consumer protection and competition policy development and supervision, so this information request sought to shed light on these issues through new methods of data collection and analysis.

This information request included data related to the amount of loans disbursed, amount, type and date of all transactions, gender and age of borrower, and the MSISDN associated with that account—which was anonymized through a hashing process before being used. See Table 2 for a sample of the data that was requested.

Table 2. Data fields requested of digital credit providers

MSISDN	Account number	Product	Sex	Date of Birth	Location of mobile transaction or agent
Transaction type (disbursement, repayment,	Transaction date and time	Transaction value	Fees assessed by mobile money provider charged to customer	Account balance prior to transaction	Account balance after transaction

[9] https://www.cgap.org/sites/default/files/publications/Working-Paper-A-Digital-Credit-Revolution-Oct-2018.pdf
[10] https://www.microsave.net/wp-content/uploads/2019/09/Digital-Credit-Kenya-Final-report.pdf

penalty, fee or charge)					

While most of the loan products documented by the data were relatively homogeneous, we found some notable differences in these products. The most prominent difference between Providers and Products is whether or not a provider is a deposit-taking institution and thus under the purview of the Central Bank of Kenya or a FinTech. We also found subtle differences in loan products. For example, Provider B's digital loan product was a salary loan and Provider H's data featured an overdraft product (H2). Finally, access channels differed between providers. Essentially, those providers whose credit products are available through USSD/SIM Toolkit tend to be more mass market than those available through mobile applications since these can be accessed through feature phones.

Table 3. Providers submitting loan data for Digital Credit Market Inquiry

Provider/ Product	Type	Product Details	Access Channel(s)	Data Submitted	Identifier
A	Deposit-taking	Mobile loan	Mobile Application	Transaction	MSISDN
B	Deposit-taking	Salary loan	Mobile Application	Transaction	Account ID
D	FinTech	Mobile loan	USSD/SIM Toolkit, Mobile Application	Transaction	MSISDN
F	Deposit-taking	Mobile loan	USSD/SIM Toolkit	Transaction	MSISDN
G	FinTech	Mobile loan	Mobile Application	Transaction	MSISDN
H1	Deposit-taking	Mobile loan	USSD/SIM Toolkit	Aggregate	-
H2	Deposit-taking	Overdraft	USSD/SIM Toolkit	Aggregate	-

Overall, we received submission from nine providers, and completed in-depth analysis of six of the providers (Table 3). For providers excluded from the analysis, two small providers (C and E) submitted account level statistics on current loans only. These statistics were not comparable to those from other providers and would not change the results of the inquiry. Provider D's transaction data was not used in most analysis on account of what appeared to be missing transactions.[11]

After receiving the data from the Providers, the data was de-identified by the CAK with help from Innovations from IPA. Importantly, IPA did not have access to the personally identifiable information as it was received. The tool made two changes to the dataset. First, birthdates were stripped from the datasets and replaced instead with year of birth, except for those born in 1930 or earlier, in which case the year of birth was left as 1930. Second, MSISDNs were hashed in a consistent manner, so that accounts could be matched across datasets.[12] However, due to this process individuals in the sample cannot be reverse identified from this data.

[11] For example, an unusual number of loans feature neither repayments nor penalties, despite loans being of relatively short tenure in the dataset. The notable exception is that this data was used in the analysis of multiple account holders.

[12] Individual numbers are anonymized by use of a hash algorithm and "salt." When CAK receives the first complaints dataset, unique MSISDNs are extracted from the dataset and a random string of numbers and letters (salt) is stored with these MSISDNs. MSISDN and the salt are concatenated, and the resulting string is hashed. When new data is received by CAK, this data is checked against the numbers already existing in their dataset. For

II. Findings from the Digital Credit Market Inquiry

The survey and administrative data analysis conducted under the Digital Credit Market Inquiry were designed to produce findings relevant to the stated objectives of the inquiry. As such, we have organized our discussion of these findings around each of these seven objectives. In each sub-section below we present the most relevant findings for each of the Inquiry objectives, which form the basis of evidence for the policy recommendations made in this report.

1. Size and nature of the DFS and digital credit markets

A. Consumer uptake and usage patterns

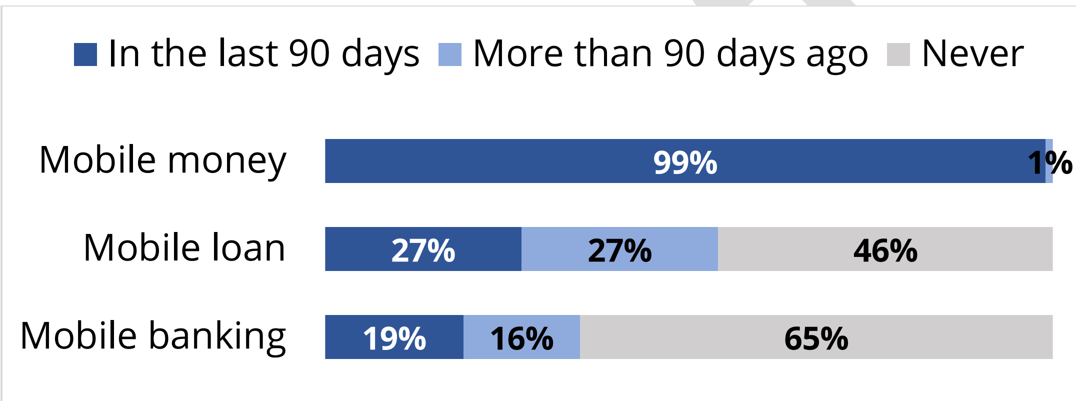


Figure 3: Rates of usage of different DFS product types by survey respondents

Figure 3 presents the DFS product usage of survey respondents. The consumer survey captured DFS usage across three product markets: mobile money, mobile banking, and mobile loans. Of these consumers, 24% reported having ever used all three product types of DFS, 42% two types, and 34% just one type of service before.

As to be expected, this survey affirms Kenya's world-leading mobile money usage, with 99.5% of DFS users being mobile money users. Amongst these users, 99.8% report having ever used M-Pesa. The only other providers with more than 3% of consumers reporting ever using their networks are Equitel with 17% and Airtel with 15%. M-PESA' was even more dominant in terms of active users: M-PESA's active rate was 97% in our survey, while no other provider had an active rate above 4%. This aligns with the Q3 2020 market shares reported by the Communications Authority, with M-PESA accounting for 99% of active registered mobile money subscriptions.[13]

In digital credit, 91% of mobile loan users have used the three products affiliated with M-PESA, M-Shwari, Fuliza, and KCB M-Pesa, while *only 38% of mobile loan users have ever used any product besides these three*, showing the dominance of loans placed on the M-PESA platform amongst

those which already exist, the already generated salt is used. For those MSISDN numbers that have not been merged, new salt is generated for those unique MSISDN numbers and appended to the end of the dataset. Then, the numbers are hashed as before.

[13] Communications Authority of Kenya. 2020. https://ca.go.ke/document/sector-statistics-report-q1-2020-2021/

conumers. While M-Shwari is the loan product most commonly ever used, Fuliza recorded the most active users. (Figure 4) The rapid expansion of Fuliza customers since January, 2019 is detailed later on in this report, along with its implications for other digital credit providers.

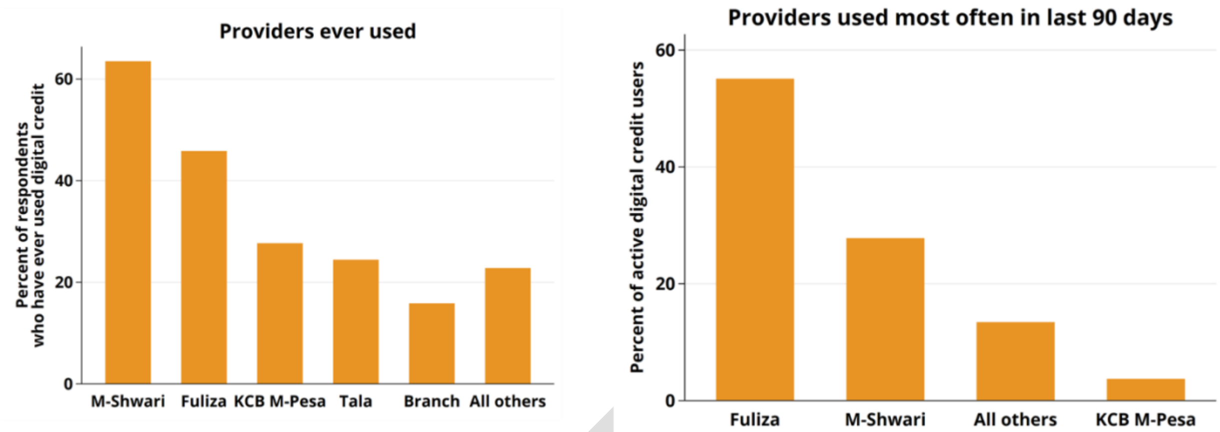


Figure 4: Use of digital credit providers by survey respondents

B. <u>Loan size and tenure</u>

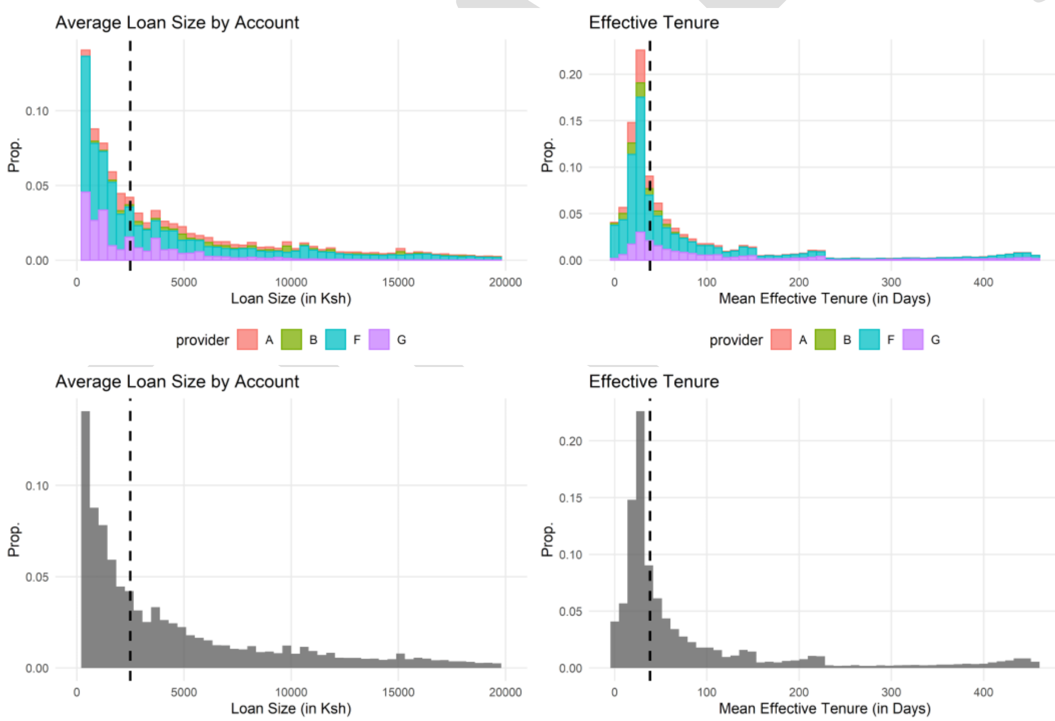
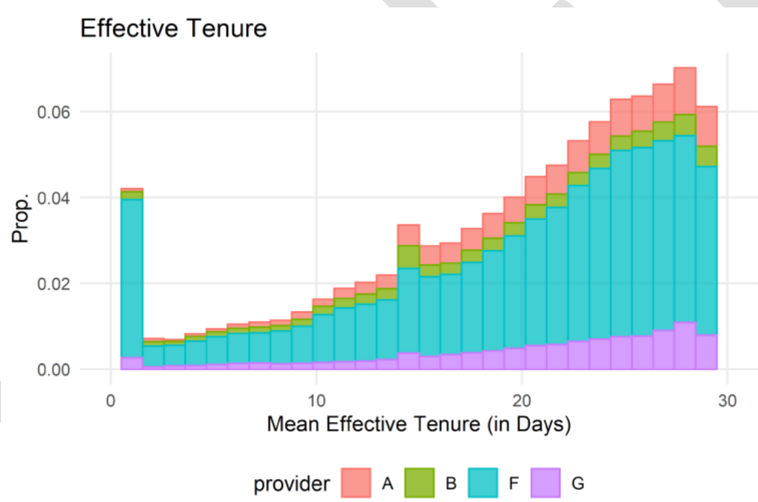


Figure 5: Size and effective tenure of loans from all providers in administrative data

The administrative data submitted by digital lenders gives a window into the size and tenure of digital loans, presented in Figure 5. As to be expected, these loans tend to be small and short in nature. **In our sample of providers, the average account has an average loan size of Ksh 6,593.** Provider G has the smallest average loan size at 4,034 Ksh, while Provider A averages loans of Ksh 9,815, representing the highest average of the traditional digital credit products. As expected, the one salary loan portfolio in our sample, Provider B, has a significantly higher average loan amount of Ksh 12,128.

Since some borrowers took multiple loans in the same year and providers did not always put the date they closed a repaid loan in their data submitted,, we built a loan tenure measurement focused on the number of days a borrower ended with a non-zero balance (i.e., owing the provider no money) and divided this by the number of loans they were disbursed over the timeframe of January 1st, 2019 to March 31, 2020. Our method for measuring tenure is perhaps more useful than official loan tenures, as it sheds light on how many borrowers repay loans early, which is lost when only looking at repayment due date. In fact, many borrowers do repay loans in less than 30 days, which is generally the shortest tenure most providers offer, although some digital lenders in Kenya have offered tenures as short as 7 days (See Figure 6.) **As to be expected, we see relatively short median effective tenures in the market of 35 days.** Comparing between Providers, Provider B has the lowest mean effective tenure of 31 days. Providers A and F have relatively similar mean effective tenures, of 64 and 76 days, respectively. On the other hand, Provider G tends to have a higher effective tenure, of 118 days.

Figure 6: Effective tenure by provider



Despite no provider offering loans less than 30 days in length, **Figure 5 shows that some loans are repaid in very short periods of time, even within the same day (same day repayments are counted as one day loans). In particular, 37.5% of accounts have an average effective tenure of less than four weeks and 5.1% have an average effective tenure of one week or less.** If borrowers are paying a month of interest for loans they only need for a week, this represents a costly approach to credit, may call for requiring providers to give discounts on interest fees for early repayment, as some providers have put in practice.

C. Demographics of digital credit users

Table 4. Portion of age groups who have taken digital loans

Age bracket	Portion of respondents in this age group
18-24 years	46%
25-44 years old	59%
45-64 years old	53%
65+ years	58%
Total	54%

Utilizing the survey data, as well as the portion of administrative data which included gender and age data, we are able to break down demographics of digital borrowers in some detail. From the survey, we see that **male consumers are more likely to use digital credit than female consumers (58% of male respondents versus 48% of female respondents) and 25-44 year old consumers are more likely to use digital credit than younger or older consumers.** (Table 4) Western and Nyanza had the highest rates of usage (63% and 55% respectively, while North Eastern had the lowest usage at 43%. There was however no noticeable urban/rural difference in usage in our sample, although the results are more suggestive than definitive on this point due to the challenges of properly assessing this via phone survey. **Those with primary or secondary education both had 51% usage rates, while those with tertiary education had a usage rate of 60%. There was also a difference in usage by type of device owned, with 56% of owners of a phone that can access the internet having taken digital loans versus 48% of those with feature phones.**

The administrative data features gender information for 52.4% of accounts. **Of the accounts we have information on, 36.5% belong to women and 63.5% belong to men.** Likewise, we have ages for 60.7% of accounts. **Of those accounts we have data on, 13.8% are aged 18-24, 66.5% are age 25-44, 18.0% are age 45-64 and 1.6% are 65 or older.** The administrative data also allowed for analysis of age and gender as they compare to loan characteristics. Considering gender, we note that men tend to have longer average effective tenure of loans, as well as larger loan sizes as compared to women.

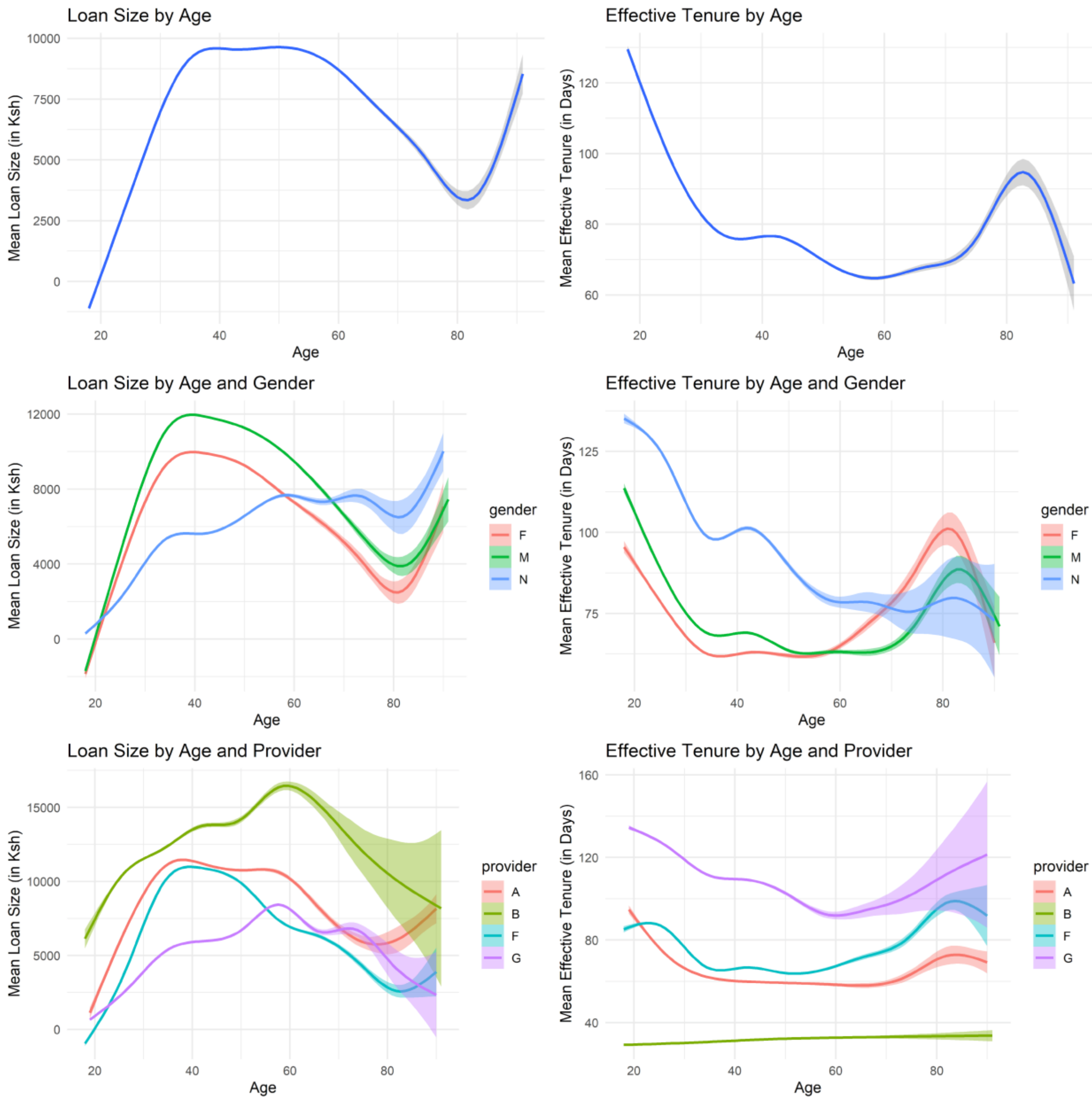


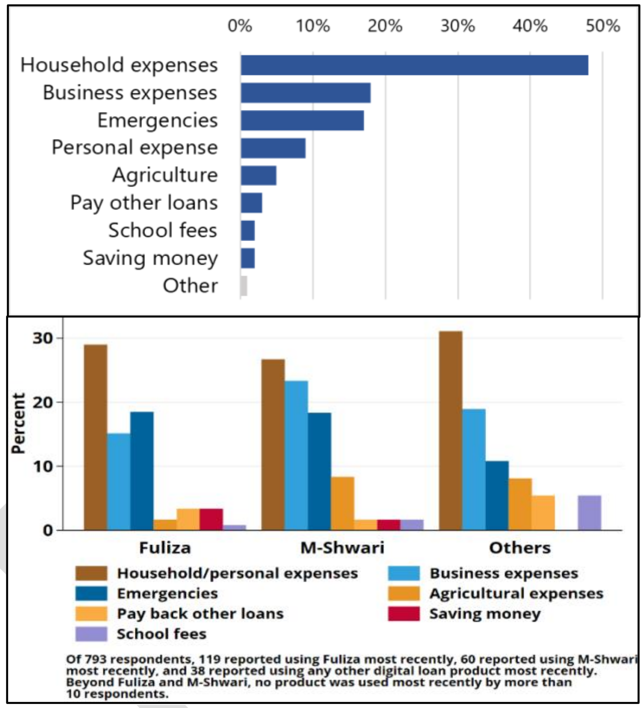
Figure 7: Loan size and effective tenure by age disaggregated by gender and provider, administrative data

As one might expect, we see in Figure 7 that loan size tends to have a “inverse-U” shaped relationship with age. That is, as one gets older, we see average loan sizes for that account grow until the late 30’s when loan size begins to level off. Loan sizes again begin falling in one’s early 50’s and falls until old age, when we see a slight increase, which may be driven by selection.[14] The length of loans in these markets falls dramatically for older cohorts of borrowers. This pattern suggests that effective tenure is driven more by repayment behavior than loan length. Again, we see some anomalous behavior for older borrowers, with a subset of older borrowers with long effective tenure.

[14] In particular, if wealthier people both borrow more and live longer, this “selection effect” could overtake the lifecycle effect.

D. Usage of mobile loans

In the consumer survey, respondents were asked what they had used their loans for in the past. **Figure 8 shows household expenses are by far the most common use of a mobile loan.** This raises concerns regarding the use of mobile loans for what may be discretionary household expenses, which do not address an emergency need nor a revenue-generating activity.



We were curious if this would differ at all by the most recently used provider, in particular to see if the recent introduction of Fuliza represented a different type of use case since the product's features are unique and it has grown rapidly. As the bottom graph in Figure 8 shows, household expenses remain the most common use for all products, although emergencies were the second most common use for those who most recently used Fuliza, while it was third for all others.

E. Evolution of digital credit market

Using administrative data to size the digital credit market and chart its growth, **we see a large increase in number and total value of disbursements of digital credit products in the period between January 2019 and March 2020. Notably, this was largely due to a single entrant to the market, which we have marked as Provider H2.** The entrant, an overdraft product, grew considerably over the period to become the largest digital credit product in the market and appeared to crowd out a number of competitors over this period. In particular, **for Provider H2, disbursements grew 232% from Quarter 1 (Q1) 2019 to Q1 2020, while total value of disbursements grew 213%.** (Table 5) **Competitors F and H1 both shrunk in terms of their number and total value of disbursements. Finally, every other providers' loans grew in size, suggesting a degree of market segmentation took place.**

Table 5. Loan disbursement by provider, January 2019 – March 2020

	Disbursements: Monthly Averages			Growth from Q1 2019 to Q1 2020 (in %)		
Provider	Count (in thousands)	Total Value (in Million Ksh)	Average Size (in Ksh)	Count	Total Value	Average Size
A	385.9	4105.5	10639.8	-15.99	1.10	20.35
B	23.4	260.5	11109.8	133.90	305.02	73.16
F	1447.4	12179.7	8414.6	-50.11	-24.56	51.21
G	367.3	1524.5	4150.2	-69.38	-48.55	68.03
H1	2722.1	12088.2	4440.8	1.67	30.15	28.00
H2	22091.5	14191.5	642.4	232.07	213.18	-5.69

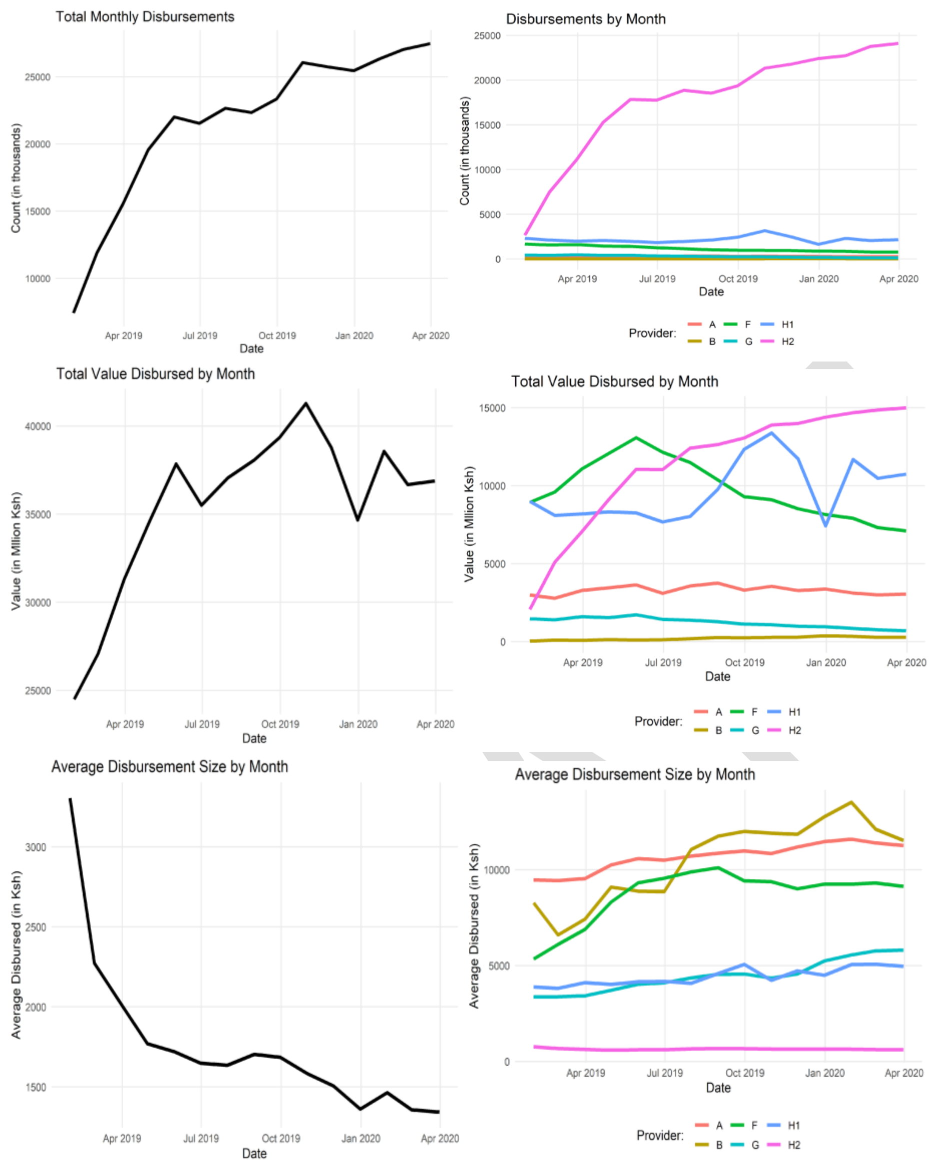


Figure 9: Evolution in loan disbursements from January 2019 to March 2020 at market level (left) and provider level (right)

F. Market concentration analysis

As the lending volumes above show, the majority of users of digital credit and majority of volumes in our sample are for loans linked to M-PESA. To assess market concentration in more detail we applied the Herfindahl-Hirschman Index (HHI) to the consumer survey responses on which digital lenders consumers have ever used. While survey responses are not a perfect data source for the HHI, it still is a national level sample of digital credit users which provides a good estimate of usage since there is no single available source for supply-side data on digital credit for bank and non-bank lenders combined. The survey data in all likelihood underestimates concentration due to over-representation of better off Kenyans, who are more likely to have smartphones—81% of our survey respondents—and so be able to access the digital lenders who do not function via USSD or SIM Toolkit, which is disproportionately composed on smaller, non-bank lenders.

HHI identifies three categories of market concentration:

1. Less than 1,500 signifies a competitive market.
2. 1,500-2,500 signifies a moderately concentrated market.
3. More than 2,500 signifies a highly concentrated market.

As would be expected, the mobile money market in Kenya registers a very high concentration level. Using our survey responses of active users yields an HHI of 8,588, while using active user data from the Communications Authority yields an HHI of 9,790. We share this to both set the context of the channel which digital credit relies upon for disbursement and repayment, and to show that the survey data likely underestimates market concentration, as our sample skews slightly higher in socio-economic status, so are more likely to have multiple accounts.

In the survey consumers were asked if they had ever used a digital credit product and if they had used one in the past 90 days. As mentioned previously, of the 430 consumers who have taken at least one digital loan, the three loan products on the M-PESA menu are the three most commonly ever used products, ranging from 34% for M-Shwari, 25% for Fuliza, and 15% for KCB M-PESA, while only two other lenders register any significant market share—Tala at 13% and Branch at 9%. Using the HHI on the survey data we assess concentration in digital credit by separating each individual product we see that there is an HHI of 1,946 for products ever used, placing this in the middle of the moderately concentrated market window.

One final note on the measurement of HHI: HHI typically uses active users, not those who have ever used a product. In our survey we asked which products had been used in the past 90, days, and see higher levels of concentration than for the "ever used" question, signaling that active use of digital credit may be more concentrated than we found when applying the HHI to the products consumers had ever used. In the future CAK may wish to request all digital credit providers submit data on the number of active users and overall loan volumes to allow for a full calculation of HHI.

2. Potential consumer protection risks and consumer outcomes within Kenya's digital credit sector

Digital credit can be a tool for productive investment, liquidity management and other household credit needs. A recent impact evaluation of M-Shwari borrowers found positive, if relatively small, impacts on school enrollment and managing negative financial shocks.[15] At the same time, consumer surveys and qualitative research have raised concerns of the possible downside of digital credit for borrowers in Kenya.[16] For this research, we focused on the following risks in digital credit:

A. Late or non-payment of debt
B. Multiple borrowing
C. Sacrifices made to pay back a debt
D. Fraudulent loan offers

A. Late or non-payment of debt

Late payment of mobile loans can trigger expensive penalties, with some providers charging a penalty fee equivalent to the initial interest fees, meaning late payment can double the costs of a mobile loan. In the consumer survey conducted as part of this Market Inquiry, **77% of mobile loan users reported having not been able to repay a loan at least once, indicating many borrowers will incur such penalty fees at some point in their use of digital credit.**

While the administrative data submitted by providers for this Market Inquiry did not always include clear demarcations of the loan tenure as requested, we can still gain useful insights by analyzing repayment and default individually at different providers. Since the providers did not include loan tenure in many cases, we have constructed a conservative definition for late and non-performing loans.

- **Late repayment**: Loan is not repaid in full on the date it is due, but is repaid in full within 90 days after the due date.
- **Non-performing/in default**: Loans where at least some portion of repayments are overdue by 90 days.

Where available, we have also used the terms and conditions of the providers to help inform our definitions by factoring in their stated minimum and maximum loan tenors. An example of this approach is Provider F, whose Terms & Conditions on their website inform us that the maximum loan length is 30 days. Despite not having information about the tenure of specific loans for Provider F, our ability to track repayment behavior and penalty fees allows us to paint a clear picture of late repayment. Interestingly, 4.5% of loans which are not paid back after 30 days are not penalized. However, all but 0.3% of these delinquent loans are repaid by day 60, indicating that these borrowers may have been able to "work out" their late repayment with the Provider (alternatively, they may have been overlooked). On the other hand, virtually no borrower that is charged a penalty fee has repaid their loan within 30 days.

[15] Tavneet Suri, Prashant Bharadwaj, and William Jack. February, 2019. FinTech and Household Resilience to Shocks: Evidence from Digital Loans in Kenya. NBER Working 25604. National Bureau of Economic Research: Cambridge, MA. https://www.poverty-action.org/study/impact-digital-credit-kenyan-households-resilience-financial-shocks
[16] https://www.microsave.net/wp-content/uploads/2019/09/Digital-Credit-Kenya-Final-report.pdf

From this perspective, our measure of late repayment is conservative as we are more likely to under-report late repayment than over-report it.

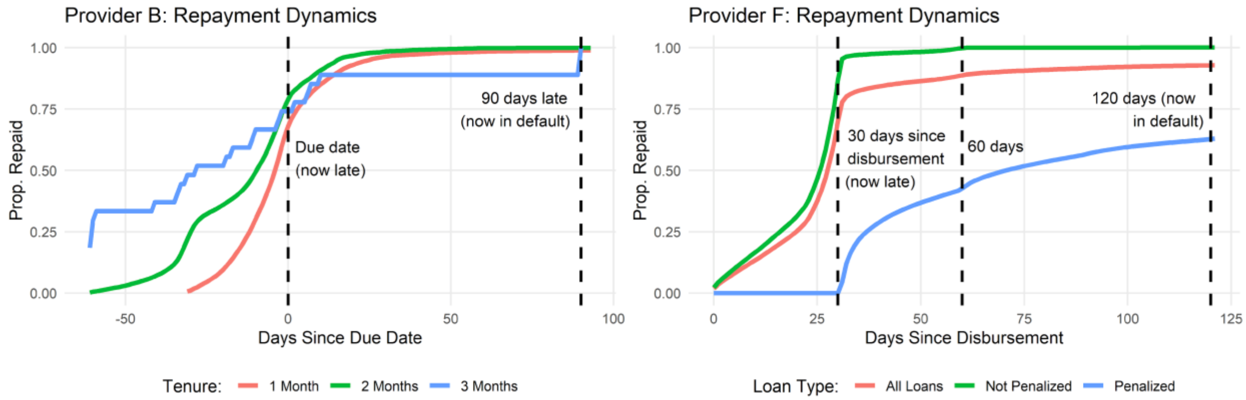


Figure 10: Repayment dynamics from Provider B and Provider F's administrative data

Similarly, we define defaults as loans that have not been repaid for 90 days after their initial due date. To operationalize this measure, we take loans that are not fully repaid after 120 days that are also penalized and mark these loans as in default. As in the case of late repayment, the number of borrowers who have not repaid by 120 days and are not penalized is quite small (less than 1 in 5,000 loans), meaning we are not likely to overstate the amount of loans that go into default.

We present the results of this analysis for Provider F in Table 6. **Using the penalty definition, we see that 19.3% of borrowers from Provider F repay their loans late and 7.2% of borrowers at this provider enter into default.** Considering loans that are already late, these statistics mean that 37.3% of these late loans go into default. From this default rate, we see that 95.6% of the value of disbursements and fees is repaid. For those loans that go into default, the average unrepaid balance on these loans is Ksh5,272.

Table 6: Repayment by gender and age from Provider F's administrative data

Gender	Prop. Late	Prop. Defaulted	Prop. Repaid (Value)	Average Defaulted
Female	19.58	6.50	96.28	4098.13
Male	19.97	7.90	95.36	5403.10
No Data	18.95	7.11	95.59	5583.02

Age Group	Prop. Late	Prop. Defaulted	Prop. Repaid (Value)	Average Defaulted
18-24	26.96	10.88	91.07	1753.31
25-44	19.58	6.83	95.39	7239.36
45-64	16.58	5.55	96.86	6874.54
65+	18.87	7.15	97.28	3138.82
No Data	19.17	7.36	95.55	4784.12

	Prop. Late	Prop. Defaulted	Prop. Repaid (Value)	Average Defaulted
All Demo.	19.36	7.22	95.63	5272.42

Provider B did not include loan tenure information in their data, but did indicate the length of the loan in months. Thus, we operationalize our measures of late repayment and default by assuming each loan is due on the same day of the month, the month after the loan is given (for one-month loans), two months after (for two month loans), etc. Likewise, we record loans in default when we observe a non-zero balance 90 days after the loan has come due. Figure 10 plots the repayment behavior of these borrowers over the number of days since the loan was due, where the loan is due on day zero. We present the results of this analysis for Provider B in Table 7. Using the penalty definition, we see that **30.7% of borrowers from Provider B repay their loans late but only 1.5% of borrowers at this provider enter into default**. Considering loans that are already late, these statistics mean that 5.0% of these late loans go into default. Despite the low default rates, defaults are large. Only 92.7% of the value of disbursements and fees is repaid. For those loans that go into default, the average unrepaid on these loans is around KSh55,452.

Table 7: Repayment by gender and age from Provider B's administrative data

Gender	Prop. Late	Prop. Defaulted	Prop. Repaid (Value)	Average Defaulted
F	32.22	1.53	92.67	53141.28
M	30.30	1.53	92.68	56925.76
N	30.15	1.62	92.69	50694.24

Age Group	Prop. Late	Prop. Defaulted	Prop. Repaid (Value)	Average Defaulted
18-24	32.74	1.79	92.75	36499.12
25-44	30.15	1.61	92.67	51820.51
45-64	33.09	1.06	92.69	95837.42
65+	33.33	0.74	92.69	129046.73
No Data	34.97	0.78	93.01	87807.21

	Prop. Late	Prop. Defaulted	Prop. Repaid (Value)	Average Defaulted
All Demo.	30.7	1.54	92.68	55451.84

Finally, we are also able to present some aggregated repayment statistics for the products submitted by Provider H. We work to construct a valid comparison statistic to the proportion of value repaid. Thus, we take total value defaulted on these products when loans would go to default and divide this by the total value disbursed by these products. We conservatively take the maximum tenure for each product (30 days) and add 90 days until that loan goes into default. For example, January's proportion defaulted is May's total amount defaulted divided by January's disbursements. [17] Then to compute proportion of value repaid, we subtract this number from one. The default rate is visualized over the first eleven months of 2019 in Figure 11. While the proportion of value repaid declines slightly over the year for Provider F and Product H2, we see large dips in value repaid for product H1. In particular, June (defaults from October) and September (defaults from January) see a particularly large amount of value not

[17] Notably, this construction is reflected in the first defaults we see for Product H2, which is introduced in January of 2019 and does not see defaults until May of 2019.

repaid. While it's unclear what is causing this, we cannot rule out that the provider has chosen to write-off loans that were defaulted upon earlier than these months.[18]

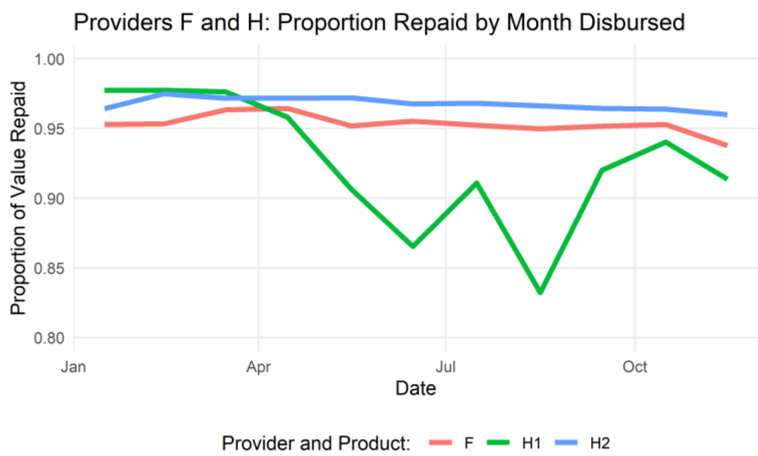


Figure 11: Variation in repayment rates by month

Statistics for proportion of value repaid for Provider H are also presented in Table 8. As might be expected from these resutls, the overall proportion of value repaid for Product H1 is lower than for Product H2, but in line with the proportion repaid for Provider B and a bit below that for Provider F. We see roughly equal repayment by gender of borrowers for both of these providers. However, when considering age, consistent with expectations, we note that younger borrowers are more likely to not repay their loans. For both products proportion of value repaid increases in each age cohort until the 55+ cohort in which in declines.

Table 8: Provider H repayment by gender and age		
Gender	H1	H2
Female	92%	96%
Male	93%	97%
Age Group		
18-24	74%	89%
25-34	91%	96%
35-44	93%	98%
45-54	94%	97%
55+	94%	96%
All borrowers	92%	97%

While the data submitted by providers raised challenges regarding assessing repayment rates due to inconsistencies in listing the loan term, we have been able to reconstruct repayment estimates in several cases. **Our estimates, which are intentionally conservative, still show that there is a high incurrence of penalty fees for digital borrowers, which aligns with the survey finding that 77% of borrowers have been late at some point**. These penalty fees have a median and mean cost of 12% and

[18] In particular, this could be explained by write-offs on December 31st or January 1st, reflected in the August and September numbers.

52%, respectively, using our effective APR calculation. This may call for a review of policies regarding assessment of penalty fees to ensure they are fair and proportional, given the high incidence of penalties in digital credit. Particular focus could be made on those repeat borrowers who habitually pay penalty fees, to determine why they habitually pay late fees and if any interventions can be done to inform them of the cost of this behavior to reduce such occurrences.

B. Multiple borrowing

Multiple borrowing is when a borrower obtains overlapping loans from multiple providers. While multiple borrowing is not synonymous with over-indebtedness or debt stress, it is often closely related.[19] For example, theoretical models of credit predict that more impatient borrowers will take on loans from multiple providers in the microfinance sector.[20] Thus, from the perspective of consumer protection, it is an important outcome to monitor to understand consumer welfare in credit markets. Similarly, we are interested in refinancing or rollover of loans across providers even when these loans just fail to overlap (Karlan et al., 2019), as that can indicate a recurring reliance on credit to meet personal or business expenses.[21]

In the consumer survey 33% of mobile loan users reported they had multiple mobile loans active at the same time before March 16th, when much of Kenya shut down due to the pandemic. These borrowers were then asked if they had multiple active loans at any point after March 16th, and 44% of these borrowers reported also having multiple active loans at some point during the pandemic. Figure 12 shows the reasons given for taking multiple loans, with emergencies and loan limits too small being the dominant reasons, while 12% took a second loan when they did not pay back a first loan, and 7% and 4% to pay back another mobile or non-mobile loan, respectively.

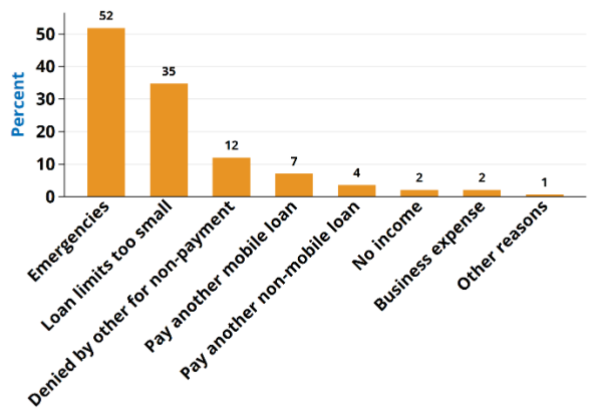


Figure 12: Reasons for having multiple active mobile loans

Using the administrative data submitted by providers, the research team developed several methods to gain further insights into multiple borrowing behavior. Our analysis starts by measuring multiple account holding, i.e., obtaining loans at multiple providers that may not overlap – a prerequisite to multiple borrowing. This is achieved by looking for all unique combinations of ID (a hashed version of the original MSISDN), age, gender, and prefix available in the dataset. Some providers have missing data in gender, age and phone prefixes, and there are inconsistencies in gender and age observed for the same borrower across providers. However, these inconsistencies are relatively small compared to the number of accounts at each provider.

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[19] Bezawit Beyene Chichaibelu, and Hermann Waibel. October, 2017. Borrowing from "Pui" to Pay "Pom": Multiple Borrowing and Over-Indebtedness in Rural Thailand. World Development, vol. 98, pp. 338-350.
[20] Craig McIntosh, and Bruce Wydick. December, 2005. Competition in Microfinance. Journal of Development Economics, vol. 78, no. 2, pp. 271-298
[21] Dean Karlan, Sendhil Mullainathan, and Benjamin N. Roth. June, 2018. Debt Traps? Market Vendors and Moneylender Debt in India and the Philippines. National Bureau of Economic Research, NBER Working Paper 24272.

Four providers had sufficient data to check for multiple accounts. The data from these four providers was linked using the ID as an identifier. This produces a single dataset with the gender, age, and prefixes from each provider.[22] **Overall, 6% of borrowers with these four providers have multiple accounts, with wide variation in overlap across providers.** As Table 10 shows, male borrowers are more likely than to have multiple accounts than female borrowers: 9.71% of men have more than one account as compared to 7.74% of women. We also see a higher degree of multiple account holding among adults aged 25-44 as compared to older and younger cohorts, with 11.08% holding multiple accounts. This is followed closely by adults aged 45-64, of whom 8.01% hold multiple accounts. In contrast, young adults and the elderly do not hold multiple accounts at a high rate.

Table 9: Age of consumers who hold accounts at multiple providers

N Providers	18-24	25-44	45-64	65+	Inconsistent	Rectified	No Data	Total
1	8.95	35.13	11.79	1.06	-	-	43.08	100.00
2	3.50	63.21	15.79	0.20	2.36	1.33	16.26	100.00
3	2.99	76.28	16.59	0.06	9.26	5.17	0.00	100.00
4	2.53	82.96	10.66	0.02	9.17	5.34	0.00	100.00

Note: Inconsistent data exists when consumer is listed as different ages at different providers, rectified data exists when maximum and minimum age differ by less than five years, and no data occurs when age is not listed at any provider.

Table 10: Gender of consumers who hold accounts at multiple providers

N Providers	Female	Male	Inconsistent	No Data	Total
1	18.79	30.71	-	50.51	100.00
2	22.43	47.51	0.60	29.46	100.00
3	28.21	57.60	1.75	12.43	100.00
4	27.37	70.26	2.35	0.02	100.00

Note: Inconsistent data exists when consumer is listed as Male and Female at different providers, and no data occurs when gender is not listed at any provider.

[22] Where we find inconsistencies in age and gender variables across datasets, we start by marking consistent entries as their respective gender or age. That is, if all non-missing variable entries related to a consumer are male, we mark that consumer male. Otherwise, we mark the data as inconsistent, or missing in the case that there are no non-missing entries. In the case of age we work to rectify some of these inconsistencies. In particular, we compute the maximum and minimum age, and rectify all data where these ages are within five years of each other, since this might have occurred in error, even when the consumer is the same. This roughly accounts for half of the inconsistencies in ages. When we do see this type of inconsistency we mark age as the mean age in the non-missing entries. For prefixes, only the first prefix recorded is kept, these are converted to operators via the telecommunications numbering plan for Kenya (Communications Authority of Kenya, 2019). An important note is that our data fidelity is directly related to the number of providers a phone number is associated with—the greater the number of accounts held by a consumer, the greater the likelihood of observing data about this consumer, whether this be age or gender. On the other hand, when a consumer id is associated with more accounts, we are more likely to see inconsistent information about that consumer.

The probability of multiple borrowing with any provider is of course dependent on the number of accounts that provider has overall—the more accounts, the more that can potentially have loans elsewhere**. At the upper extreme, 65% of Provider D's borrowers have also borrowed from at least one other lenders.**[23] Provider D is one of two FinTechs, while the other two providers are banks, and their high overlap shows the relative market share of FinTechs vis-à-vis banks in digital credit, as well as their dependence on borrowers which also engage with bank-based digital lenders. While D stands out within our sample it is difficult to say whether this type of overlap is specific to this provider or common with smaller FinTechs in Kenya, as no other FinTechs submitted data with identifiers allowing for multiple borrowing analysis. Additionally, the overlap may be aided by the fact that Provider D loan product is accessible on feature phones, whereas other FinTechs often use app-based lending.

One limitation for this analysis is if those who borrow from Equity using an Equitel line also have a line with another MNO they use for their day-to-day activities outside of Equitel transactions, then their multiple accounts would evade our measurement.[24] In addition, borrowers who do not have a known operator are also likely to be associated with multiple accounts.[25] We can be relatively confident in the quality of match to the operator because numbers are rarely ported between operators in Kenya, with only 254 numbers ported in Kenya in the fourth quarter of 2020.

To understand the behavior of multiple borrowers in more detail, we reviewed how borrowers across Providers A, F, and G sequence their borrowing, and conducted cluster analysis to see if there are higher or lower risk segments of multiple borrowers.

First, we see that multiple borrowers tend to borrow again quickly. Defining multiple borrowing as those who borrow within 30 days of their previous loan, we see that 95.8% of multiple borrowers take a new loan within this time period after the first loan. 86.8% of these borrowers multiple borrow from the same lender at some point during the 30 day window, and 81.8% from other providers. (Figure 13) As we might expect, borrowers wait longer to take another loan when taking a loan from the same borrower as opposed to other borrowers, which raises concerns about the role of information asymmetries such as lack of credit information sharing in allowing for high-frequency multiple borrowing across providers. (Figure 14) The difference is much more pronounced for Providers F and G than for Provider A, which may be due to how Provider A disburses loans, allowing multiple loans to be disbursed at once up to a credit limit.

[23] This analysis comes with a few necessary caveats. First, if we consider the extent of multiple account holding in digital credit in Kenya, we note that this number will necessarily be a lower bound. That is, if members of this sample also hold accounts with other providers we would document those given the data of those providers, hence increasing the estimate of the extent of multiple account holding. .

[24] This is quite possible, as September, 2020 data from the Communications Authority found that while Equitel accounted for 2.8% of mobile subscriptions, they only accounted for 0.1% of SMS volume, indicating these SIMs are likely purchases for other reasons. It is not unlikely that use of related financial products would be one of these uses. Getting around this issue would require use of National ID number, which was not considered for this research due to data privacy concerns.

[25] In particular, these are consumers for whom the three-digit prefix of the MSISDN did not match our list of prefixes granted to various Telephone Companies, including numbers where the prefix was not included in the original data. It is difficult to say what drives this issue.

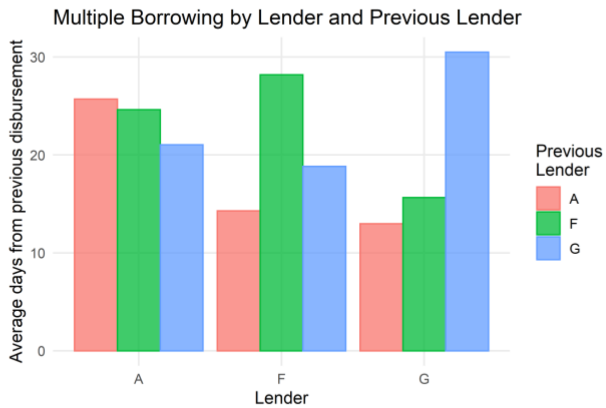

Figure 3: Repeat borrowing within 30 days of initial loan

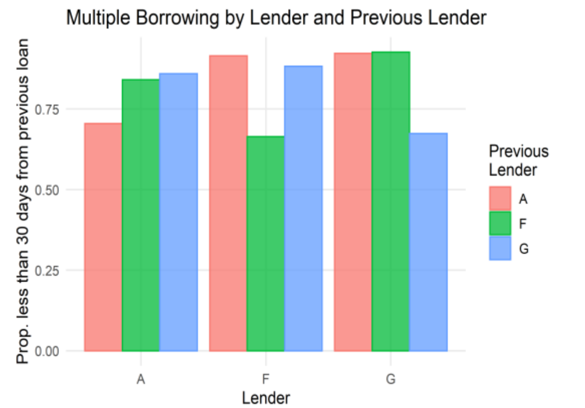

Figure 14: Repeat borrowing within 30 days as portion of loans

We also perform a data-driven segmentation of multiple account holders based on their behavior.[26] This gives a useful breakdown of the types of multiple borrowers and how they differ. Figure 15 plots this segmentation over the total number of multiple borrower loans, with those multiple loans taken at the same provider on the x-axis, and cross-provider multiple borrowing on the y-axis.

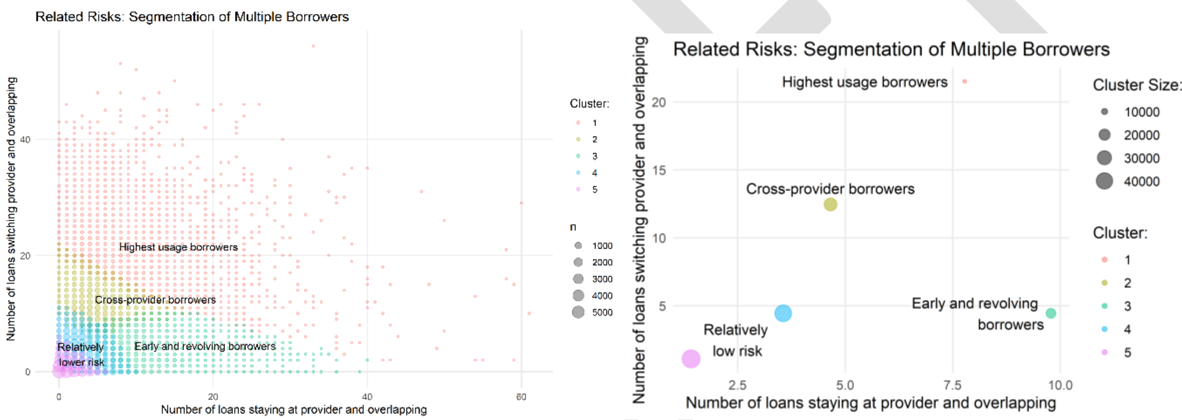

Figure 15: Multiple borrower clusters by lender and number of loans, at individual level [left] and collapsed [right]

Collapsing these clusters to their central point gives a clearer view, as shown in the right hand graph of Figure 18. In particular, cluster 3 (marked "early and revolving borrowers") tends to lie out of line with the other clusters, showing how that type of multiple borrowing is likely quite different in nature than the other types of multiple borrowing. In this way cluster analysis can offer an effective way to sort different borrower segments by their behaviors to identify more at-risk sub-populations.

In general, we tend to think that the more multiple borrowing a borrower does, the riskier they are as a borrower. While we do not have conclusive data on this due to the limited sample of submissions, data from provider F suggests this hypothesis may hold. Table 11 presents account level repayment data from this provider for all those who held multiple accounts. We see that those accounts with cross-provider borrowing tend to repay loans later and default on loans more frequently than those who only

[26] In particular we perform k-means clustering with information including total loans taken, total number of times multiple borrowing (and across which providers), if borrowers switched often. We set $k = 5$ for this analysis.

engaged in repeated borrowing. Finally, we note a reasonably strong positive relationship between multiple borrowing at same provider v. cross-provider ($\rho = 0.24$). While multiple borrowing from one provider may not be associated with high risk of default, it is associated with multiple borrowing across-providers. This is important when we cannot observe many other providers.

Table 11: Account-level multiple borrowing, Provider F

	Proportion		
Multiple Borrowing Status	Ever Late	Ever Defaulted	Accounts
Multiple accounts, no multiple borrowing	67.32	31.48	5.11
Multiple accounts, with multiple borrowing:	Ever Late	Ever Defaulted	Accounts
Repeated or cross-provider borrowing	69.85	28.74	94.89
Only repeated borrowing	64.41	27.42	12.08
Only cross-provider borrower	73.36	39.56	20.28
Repeated and cross-provider borrowing	69.77	25.49	62.53

C. Sacrifices made to pay back a debt

Defining what is too much debt can be a challenging matter. The right amount of debt for one consumer may be too little or too much for other consumers, due to personal factors like income, as well as the intended use of the loan—i.e. does the loan use provide reasonable possibility of an economic return which will cover the debt obligation? For this reason, some researchers have developed "sacrifice-based" models for measuring the effects of borrowing on individuals and households.[27] This method was first popularized by researchers like Jessica Schicks in traditional microfinance, but can be used to a similar end with digital credit. The consumer survey included several questions related to stress and sacrifice experienced by mobile loan users. Figure 16 shows the portion of mobile loan users who have made sacrifices to repay mobile loans. **The fact that the majority of those mobile loan users report reducing food and non-food expenditures to repay mobile loans is particularly concerning, as is the almost half of borrowers who have not paid another debt due to a mobile loan debt.**

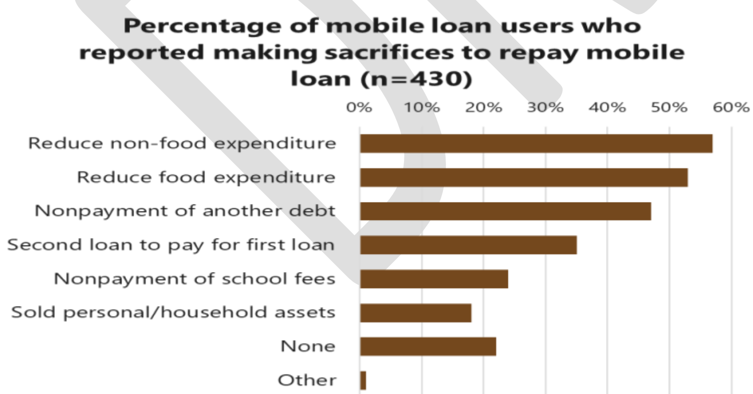

Figure 16: Sacrifices made by survey respondents, mobile loans

[27] https://content.centerforfinancialinclusion.org/wp-content/uploads/sites/2/2018/08/111108_cfi_over-indebtedness-in-ghana_jessica-schicks_en_final.pdf

64% of respondents reported they have less income since the start of the pandemic, and more than half of consumers surveyed indicated that they have borrowed money during the pandemic regardless of their ability to repay. It is clear many Kenyans are experiencing financial stress, as 58% of respondents either somewhat or strongly disagreed with the statement that they have enough money for living expenses.

This reduced income appears to be impacting loan repayment, with 75% of those with loans reporting they anticipate not being able to make debt payments on time due to the pandemic. Breaking this down further, Figure 17 shows that only 18% of those with loans currently report no anticipated difficulty in repaying their loan while most respondents plan to pay in full, but at a later date.

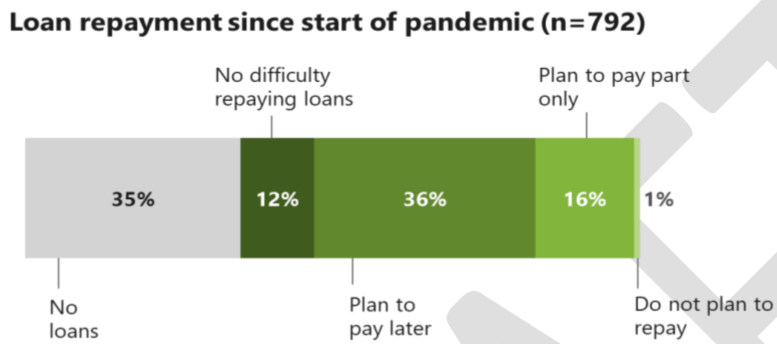

Figure 17: Loan repayment during the pandemic

D. Fraudulent loan offers

The survey asked consumers several questions regarding experiences with fraud in DFS—both attempted and realized. As discussed in a later section, the majority of consumers have been contacted by a third-party scams in DFS. However, there is little evidence that consumers were falling victim to fraudulent loans at a significant number. Of the 297 survey respondents who reported having lost money via DFS at any point, only 2% of these cases were related to mobile loans.

3. Increase transparency and comprehensiveness of product information and terms and conditions

For the past five years, substantial efforts have been made to improve transparency and comprehensiveness of product information and terms and conditions. This includes CAK efforts to ensure pre-product and post-transaction disclosure of costs for all DFS providers.

A. <u>Consumer Price Awareness</u>

The consumer survey explored questions related to price awareness in mobile money and mobile loans. Because mobile loan fees at many providers are variable, we were only able to compare official fees with recalled fees for M-Shwari loans. **We found that recall of digital credit fees is lower than mobile money at 40% (within plus or minus 5%), although this is still fairly high for recall on a survey.** (Figure 18). Fee knowledge does not appear to vary dramatically by demographic segment, though younger and better educated consumers in our survey were more likely to report the correct mobile money fee than their older or less educated counterparts.

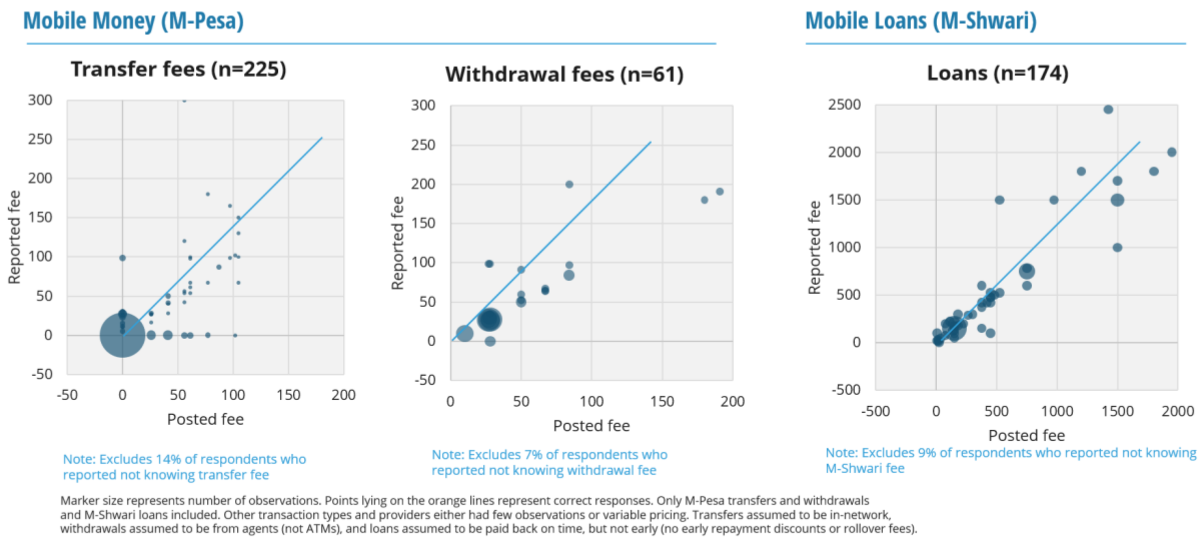

Figure 18: Knowledge of fee charged on DFS product

While the pricing transparency rules set by CAK covered pre and post-transaction price disclosure, **most users report learning about the fees only when they receive a receipt after the transaction has been completed, though a sizable minority learn of the fee from a notification on their phone before the transaction is finalized.** (See Figure 19) The lack of consumer recall of seeing fees pre-transaction could be due to their focus pre-transaction on executing the transaction or taking the loan, and not reviewing product terms.

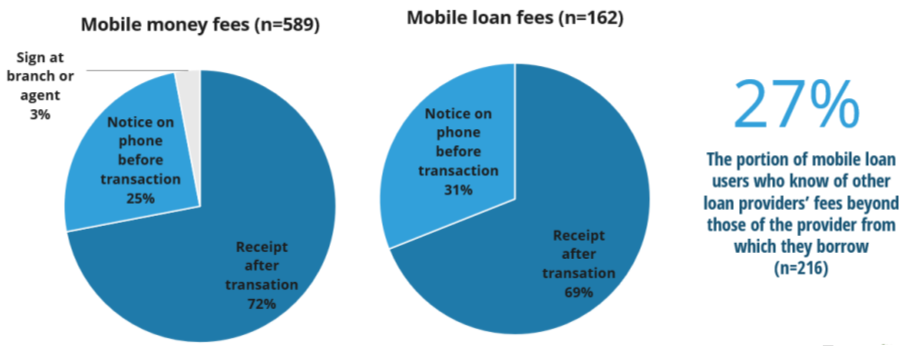

Figure 19: How consumers become aware of costs of mobile money and mobile loans

B. <u>The cost of digital credit in Kenya</u>

A headline issue in digital credit around the world, like in microfinance before it, is the cost of credit. While both digital credit and microfinance have been heralded as valuable tools for increasing financial inclusion in the developing world, a frequent concern is high interest rates on these credit products. In this section we use the administrative data submitted to CAK to measure the effective cost of credit at four digital credit providers in Kenya and take a deeper dive into the cost of constituent fees at two providers, and finally consider the dynamics of when fees are charged at one provider we have disaggregated data for.

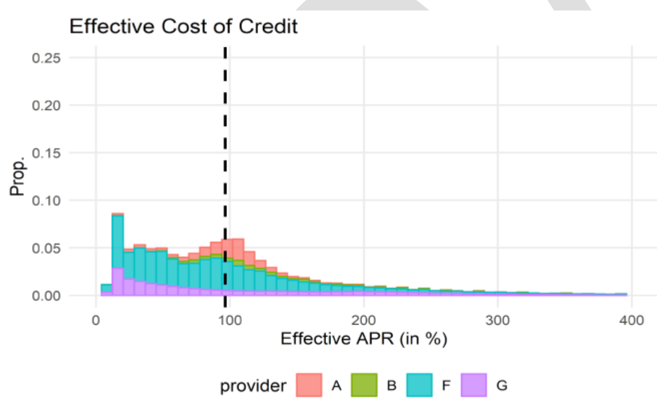

Figure 20: Effective APR of digital credit providers

To measure the effective cost of credit we process each of the providers for which we have complete data into summaries of the user accounts.[28] We want to find a way to capture not only all of the fees each consumer pays at a provider but also how quickly they repay the loan. This allows us to calculate the true cost of a loan to a consumer based on usage, not the stated product terms. To measure the

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[28] To limit the influence of outliers in the data, we do minor cleaning on the data after computation. In particular, in the case that a loan is paid back the same day, we enforce a minimum effective tenure of one day and a minimum effective balance of the loan disbursed plus fees. We enforce that a given loan can only be paid back to zero to avoid negative APRs. Finally, after computing effective APR we trim the maximum value above the 99th percentile from each dataset to reduce the impact of outliers on our results.

effective cost of credit we include any and all observable fees that are paid to access credit. This measurement can be done using a statistic similar to APR, which we call Effective APR. While Annual Percentage Rate, or APR, takes the total cost paid on the loan and coverts it to an annual interest rate using the contracted tenure of the loan, effective APR uses the actual time until the loan was repaid as the tenure. Those interested can find our definition, including calculations of effective APR, in Appendix A.

We find that the cost of digital credit in our dataset is relatively expensive, with a mean effective APR of 280.5% and median effective APR of 96.5%. (Figure 20) As implied by the difference between the mean and median, the distribution of cost of credit is highly right skewed, meaning we observe a long right tail of high cost credit.[29] We can see also see this skew in the histograms of cost of credit, presented in Figure 19 with the individual providers highlighted by color. Here we note not only the skew of the distribution but also the incredible heterogeneity in cost, both between providers, and within individual providers. We present these provider level distributions in Figure 21. In particular, this long right tail is most pronounced in providers F and G.

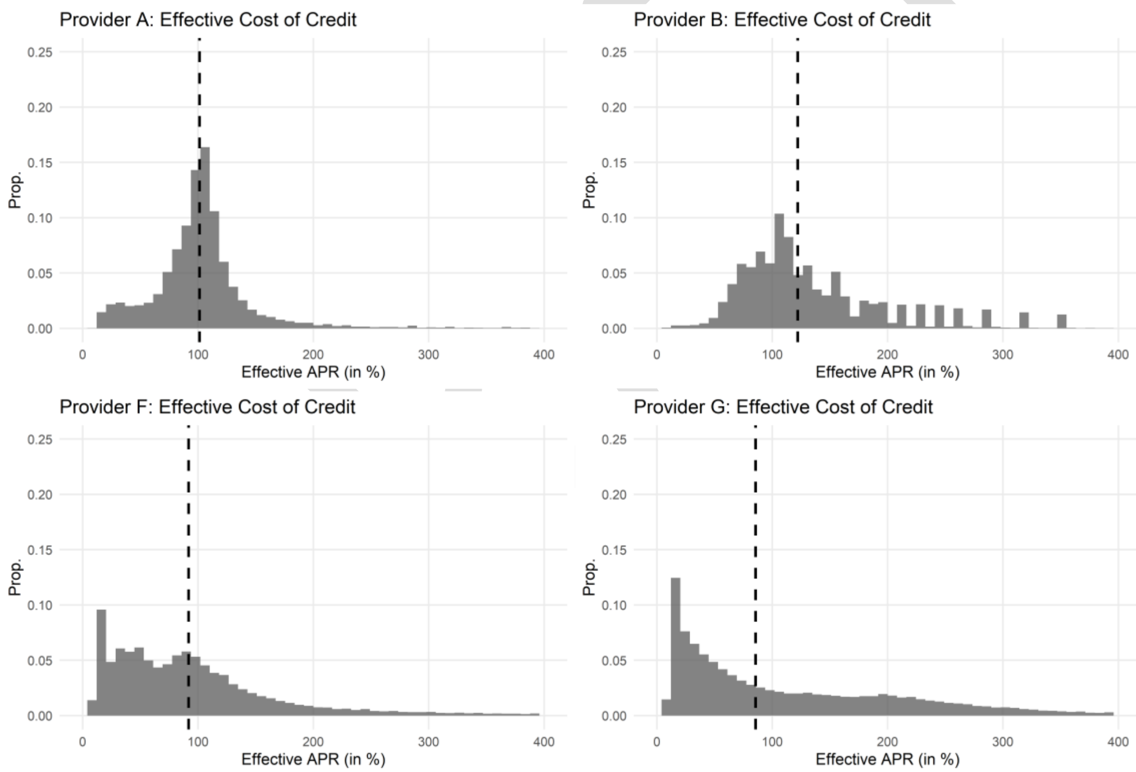

Figure 21: Effective APR distributions of digital credit providers

[29] The greater the mean is relative to the median, the more right skewed the distribution, since the mean is sensitive to the presence of outliers.

One reason for highly skewed distribution is the presence of early repayment. The shorter the amount of time credit is taken out for, the higher the APR is in effect. For this reason, we visualize effective APR only up to 400%, which is roughly the 95th percentile of the distribution of effective APR in the market. Considering Effective APR by provider, we find different results by how we measure the average experience of consumers. Considering the median consumer for each firm, we find that provider G is cheapest (at 85.5%), followed by provider F, A, and B as the most expensive. However, when we look at the mean cost of credit, which is sensitive to those who pay the highest rates of Effective APR, these results flip dramatically. In particular, Provider A offers the cheapest credit on average, followed by provider G. Provider B is the second most expensive at 192.1% but is dwarfed by Provider F, with a mean effective APR of 376.0%. For Providers like Provider F, with a low median cost of credit but high mean cost of credit, this implies that while most of their borrowers pay low rates, a small few pay very high rates, and might prompt further investigation into these outcomes. These results are presented in Table 12.

Table 12. Effective APRs of digital lenders			
Provider	**Median**	**Mean**	**Standard Deviation**
A	101%	104%	48%
B	122%	192%	281%
F	92%	376%	1078%
G	86%	133%	144%

C. Gender, age and the cost of digital credit

In addition to heterogeneity across and between providers, we see heterogeneity in the cost of credit by both gender and age. Table 13 presents costs disaggregated by gender and age in the market as a whole while Table 14 presents cost of credit disaggregated by gender and age at the provider level.

We find that women pay more for credit in effective terms than men in the market as a whole. In particular, we find that women pay 269.0% on average in effective APR as compared to 252.1% for men. This pattern holds for three of the four providers we are assessing: Provider A, B, and G. Interestingly, women pay less than men at the largest provider in our sample, though this is not enough to drive the market as a whole. The largest difference in effective cost of credit comes from Provider G, where women pay 13.9 percentage points more in effective APR as compared to men.

Table 13. Effective APR by gender and age				
Gender	**Median**	**Mean**	**Standard Deviation**	**Proportion of Sample**
Female	100%	269%	842	19%
Male	98%	252%	789	33%
No data	91%	306%	903	48%
Age group	**Median**	**Mean**	**Standard Deviation**	**Proportion of Sample**
18-24	76%	193%	638	8%
25-44	102%	223%	655	40%
45-64	101%	248%	768	11%
65+	96%	249%	831	1%
No data	91%	374%	1077	39%

Table 14. Effective APR at the provider level by gender and age								
	Provider A		**Provider B**		**Provider F**		**Provider G**	
Gender	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
Female	106%	48	194%	280	348%	1041	141%	135
Male	102%	49	191%	280	356%	1051	127%	132
No data	102%	41	196%	291	400%	1108	134%	147
	Provider A		**Provider B**		**Provider F**		**Provider G**	

Gender	Mean	Standard Deviation	Mean	Standard Deviation	Gender	Mean	Standard Deviation	Mean
18-24	102%	61	207%	308	323%	1010	110%	132
25-44	105%	50	196%	288	388%	1078	137%	146
45-64	101%	41	167%	225	394%	1126	156%	144
65+	100%	38	158%	208	350%	1084	173%	153

Considering cost of credit by age, we again find different results depending on our measure of cost of credit. **When we consider the average effective cost of credit we see that the most expensive credit in the market is taken on by older adults and the elderly, with those 45-64 paying 247.9% and those 65 and over paying 249.0% in effective APR.[30] However, when we consider the experience of the median borrower, the cost of credit follows a kind of ``inverted-U'' shape with regards to age. Those people aged 25-44 and 45-64 pay a median of 101.5% and 101.2% in effective APR, respectively.** When we visualize effective APR over the age of borrowers in the market in Figure 22 the true story seems to be somewhere in between. We note that the inverted-U pattern seems to be driven by Provider F, the largest provider in our sample. By contrast, while provider A features the same U-shaped pattern it is considerably less pronounced, Provider B features cost of credit that falls with age, and provider G sees cost of credit that rises with age.

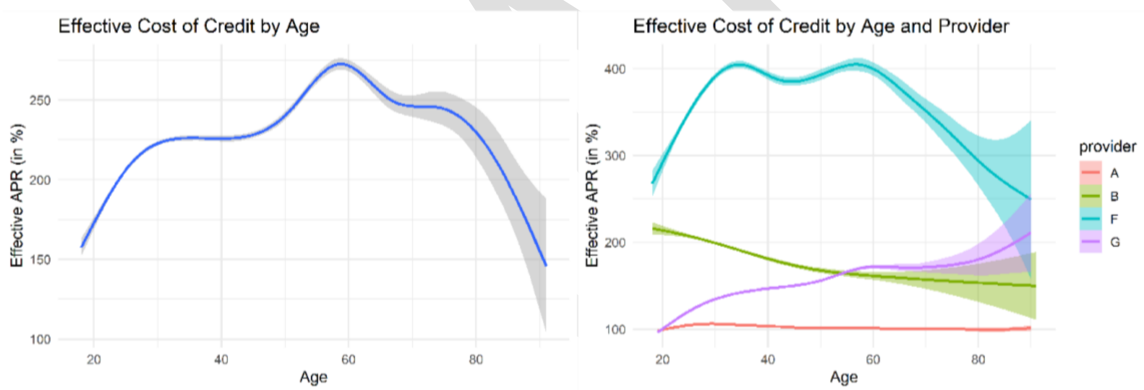

Figure 22: Cost of credit by age for Providers A, B, F, G

While we can't say precisely what drives these divergent patterns it is interesting that Provider B offers Salary Loans and Provider G is a FinTech using mobile phone metadata to assess creditworthiness. These factors could drive differences through a number of mechanisms. First, selection into providers, i.e., that those who are credit rationed by salary lenders (e.g., lacking the formal salary to qualify for these loans) are less creditworthy than others of a similar age. Second, there may be some degree of difference in early repayment across consumers at the firms (more likely at Provider G). Finally, mobile phone usage

[30] Age groups are chosen to be directly comparable to those in the Consumer Protection Survey undertaken by IPA. To flesh out more subtle differences in behavior as it relates to age we will visualize cost (and other outcomes) as a function of age.

likely differs considerably between the two groups, with younger consumers being more active on their mobile devices relative to their older peers.[31]

D. <u>What types of fees are used in digital credit?</u>

Table 15. Fee types and formats observed in data from digital credit providers

	Products						
Fee type	**A**	**B**	**D***	**F**	**G**	**H1****	**H2****
Interest	X		X	X			X
Non-interest normal	X					X	
Penalty	X		X	X			
Rollover	X					X	
Excise tax	X			X			
Other				X			X
Aggregated only		X			X		
	Products						
Fee format	**A**	**B**	**D**	**F**	**G**	**H1****	**H2****
Recorded with disbursement		X		X	X		
Recorded in own transaction	X		X				
Not tied to a transaction						X	X

* Indicates data was otherwise incomplete and therefore not analyzed
** Indicates that the provider only submitted aggregated data to CAK for this product

There is a great deal of heterogeneity in the data we received from digital credit providers regarding fee types, including the actual fee types recorded, whether or not fee types are disaggregated, and the types of fees charged. Table 15 summarizes the data received and how it can be used to understand fees in the market. Overall, only three of the five providers—providers A, D, and F—who submitted transaction level data disaggregate types of fees and charges in their data. Likewise, only the data submitted by providers A and D list fees as separate transactions (as opposed to only including the total value of fees charged on a given loan). Finally, despite these advantages, Provider D's data seems to be incomplete in other areas and so we refrain from analyzing data until we have addressed this with the provider themselves to understand the nature of what is missing.

For these reasons analysis of fees centers around providers A and F for the analysis of fee types, and provider A for when these fees are assessed. This is done with the caveat that these providers are not

[31] The kind of credit algorithms used by Provider G likely mirror those in the poverty prediction and credit algorithms literature. If so, network statistics (calculated from SMS and contact data) should be highly correlated with repayment. Likewise, mobility (as measured by GPS/radius of gyration) has been shown to be highly predictive of repayment.

necessarily representative of the rest of the market. However, this approach to analysis of fees can provide a template for future market-wide analysis of fees when more providers are required to submit disaggregated data on fees assessed. For those providers who have data disaggregated by fee type, the data processing mirrors that for effective APR, using the same method but swapping out cost from that fee type for overall cost in the formula. The same checks and adjustments are made to factors entering the calculation as well.

E. Interest fees and the interest rate cap

Due to the existence of an interest rate cap over the majority of the period for which we have administrative data, we do not expect interest fees to contribute much to the cost of credit for bank-based digital credit. This cap tied the allowed nominal interest rate to 4% above the Central Bank Rate, which was 9% over the relevant period, resulting in a cap of 13% per annum over the course of 2019. Since only the nominal interest rate was controlled, the cap only applied to fees that were explicitly named interest fees. Banks exploited this loophole to exceed the interest rate cap with what would normally be considered interest, but was labeled “facilitation fees” to avoid having to comply with the cap for digital loans.[32] The cap was repealed on November 7th, 2019.

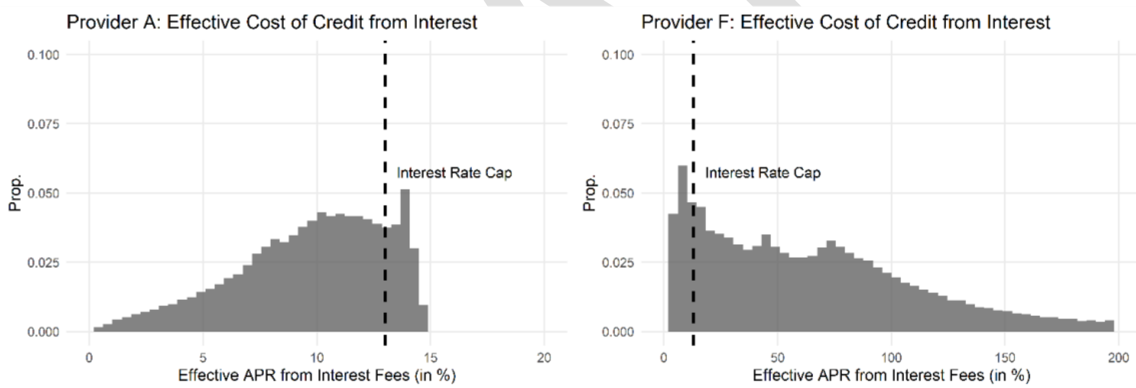

Figure 23: Distribution of interest fees for Providers A and F around interest rate cap

Consistent with this, looking at data from Provider A we see that the interest rate cap tends to control these fees under 15% Effective APR (even allowing for the effective tenure of loans to become short).[33] Additionally, visually inspecting the distributions reveals “bunching” near the interest rate as can be seen in the left panel of Figure 23. This leads to a median Effective APR that is below the cap, around 9.56%. For all Provider A fee type statistics, see Table 16 below. Considering Provider F, we do not see the same type of bunching near the cap. In fact, it's not clear that the fees marked as interest clearly separate what is (lawfully) interest from Normal Non-Interest Fees: we observe a median effective APR of 72.9% and a mean effective APR of 294.8%. For all Provider F fee type statistics, see Table 17.

[32] https://www.businessdailyafrica.com/corporate/companies/M-Shwari-fees-are-legal--court-rules-in-Cofek-case/4003102-4351822-h15a13z/index.html

[33] More specifically, more than 99% of these loans have an effective APR from interest under 15%.

Table 16. Effective APR from different fee types for Provider A				
Fee Type	Median	Mean	Standard deviation	Proportion charged
Interest	10%	9%	4.36	100%
Normal non-interest	86%	89%	49.32	100%
Penalty	0%	2%	4.78	7%
Penalty (non-zero)	5%	7%	5.36	100%
Rollover	0%	1%	3.07	17%
Rollover (non-zero)	4%	6%	5.25	100%

Table 17. Effective APR from different fee types for Provider F				
Fee Type	Median	Mean	Standard deviation	Proportion charged
Interest	73%	295%	843.8	100%
Tax	6%%	33%	102.16	100%
Penalty	8%	38%	134.11	67%
Penalty (non-zero)	12%	52%	153.75	100%

F. Normal non-interest fees

In addition to interest fees, we often see what we refer to as non-interest normal fees as loans are originated. Considering Provider A's Terms & Conditions (T&Cs), these fees include a variety of different charges including bundled insurance, excise taxes, and appraisal fees. From these T&Cs we can compute the maximum effective APR for a one-month loan as 91%.[34] There are two notable takeaways here: First, the cost falls when loans are longer (due simply to the APR formula); Second, **for one month loans, normal non-interest fees account for a large majority of the cost for this maximum size loan contract, equal to an APR of 78%, providing further evidence of costs in digital credit being frequently shifted away from interest fees during the rate cap**.

[34] $\text{APR}=\text{Central Bank Rate}+4\%+12\times(5\%\times1.1+1\%)=91\%$.

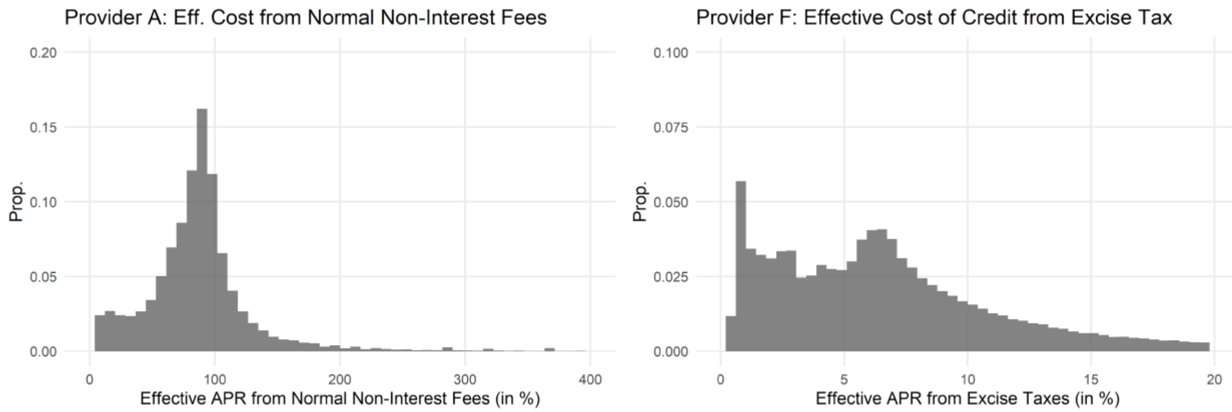

Figure 24: Effective APR of non-interest fees, Provider A

The effective cost of credit due to these normal non-interest fees tends to exceed the rate computed using information from the T&Cs for Provider A. For example, this can be seen in Figure 24. In particular, **Normal Non-Interest Fees account for a median effective APR of 86.4%, higher than the 78% discussed above. This difference might be due to early repayment, but inspecting the data suggests it is some part due to costs that exceed the 6.5% of the disbursement that is detailed in the T&Cs from Provider A.** We do not observe regular non-interest fees for Provider F, which furthers our belief that some fees are miscategorized for our purposes, though we do see excise taxes disaggregated, which tend to be on the order of less than 10% in terms of APR.

G. <u>Conditional fees: Penalties and rollovers</u>

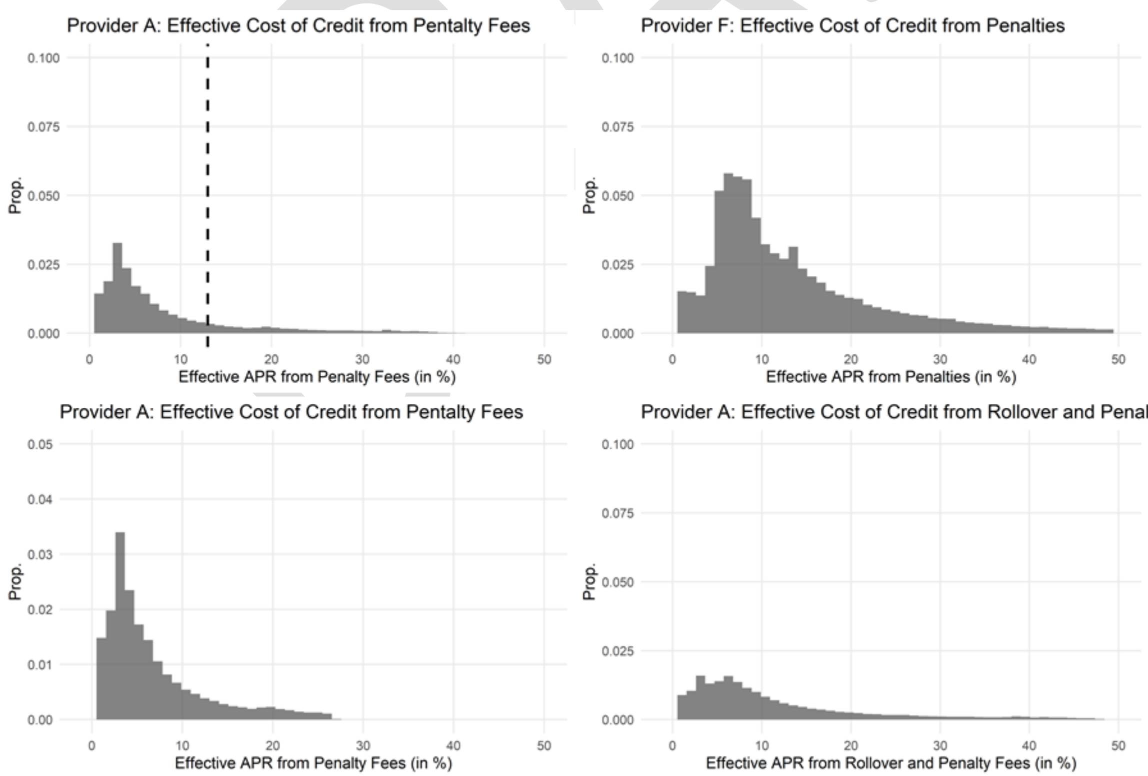

Figure 25: Costs of penalty fees for Providers A and F

Another large source of cost for borrowers of digital credit providers are penalties and rollover fees -- which are charged when loans are repaid late or are rolled over (often to avoid late repayment). We observe penalty fees for both providers A and F and rollover fees for provider A in Figure 25. We first note that a much larger proportion of borrowers pay penalty fees to Provider F as opposed to Provider A. In particular, **while 66.86% of borrowers at Provider F have paid penalty fees, only 6.9% of borrowers have paid penalty fees at Provider** A. Considering only those who do pay penalty fees, the penalties paid by borrowers of Provider F are again larger than those paid by borrowers of Provider A. However, it may be the case that fewer of the consumers at Provider A pay penalties because of the ability to rollover loans. This is a costly strategy, not only because it kicks the can down the road and can lead to additional debt if one borrows to cover the loan plus fees, but also because each rollover introduces additional fees to the account. Considering these rollovers for Provider A, we see that they are used by 17.2% of consumers (it is not yet clear if these are the same consumers who pay penalty fees) and only a small amount to the APR. Comparing the average effective APR from penalty fees at Provider F to the average effective APR from all conditional fees at Provider A, Provider F still leads by a wide margin: 52.0% to 13.0%.

H. <u>When are fees charged?</u>

To get a sense of the dynamics of fees -- when the most expensive fees are charged relative to disbursement -- we perform a case study with the data of Provider A. To process the data, we work from the transaction data to find the first disbursement for each account, and then compile the timelines of fees happening in the day of that disbursement and in the next 99 days. This allows us to understand how fees behave in these first three months of a loan cycle. We then average the total fees paid by day after the disbursement and visualize this data.

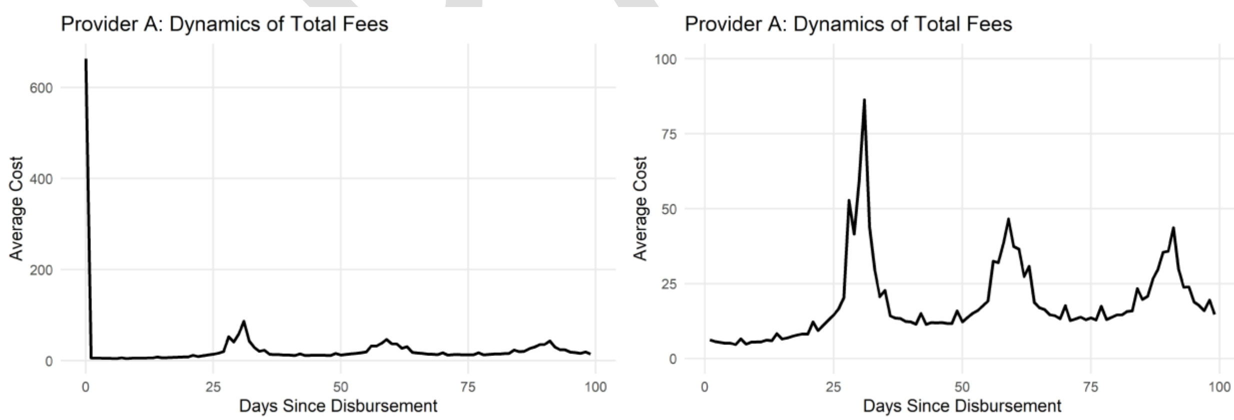

Figure 26: Average cost of fees including fees charged at origination (at left) and without (at right), from Provider A's administrative data

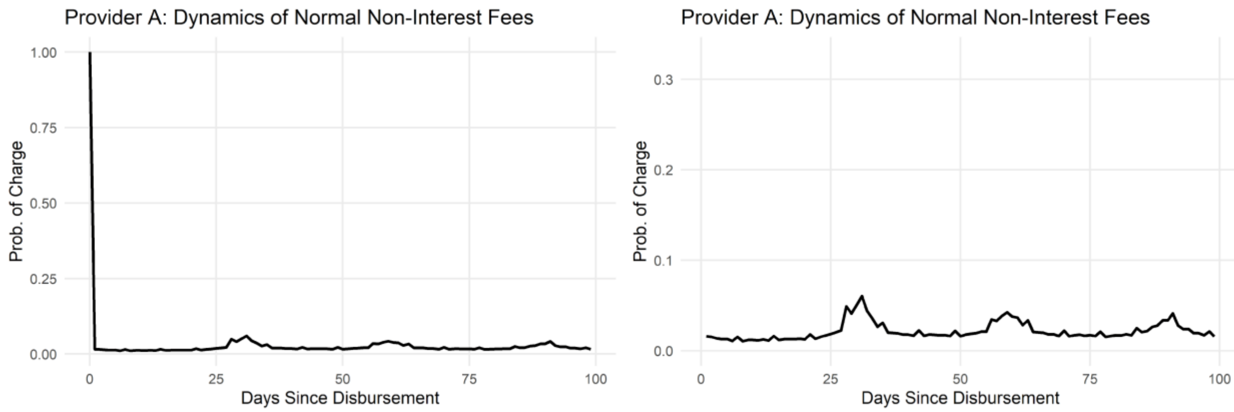

Figure 27: Average probability of any fee charged including fees charged at origination (at left) and without (at right), from Provider A's administrative data

As a first pass, we visualize all fees charged in the first 99 days after the first disbursement, plotting average total fees in Figure 26 and the average probability of being charged a fee in Figure 27. We can clearly see that **the largest fees are charged at origination of a loan with spikes in fees occurring at roughly one month, two months, and three months.** To understand what drives fee dynamics, we desegregate these fees into the same four categories we defined above -- interest, normal non-interest fees, penalties, and rollovers. We start with what we term normal fees, including interest fees and normal non-interest fees. Visualizations of these fees are presented in Figures 28 and 29 which plot the average cost and probability of being charged of these fees, respectively. We note that Non-Normal Interest Fees drive the entirety of the upfront cost -- which is consistent with their role as described in this provider's T&Cs.

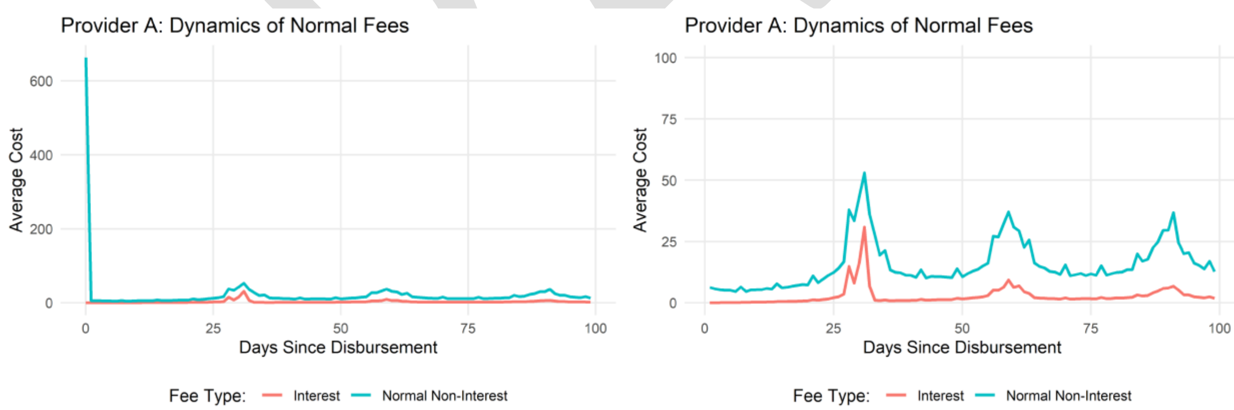

Figure 28: Average cost of normal fees including fees charged at origination (at left) and without (at right), from Provider A's administrative data

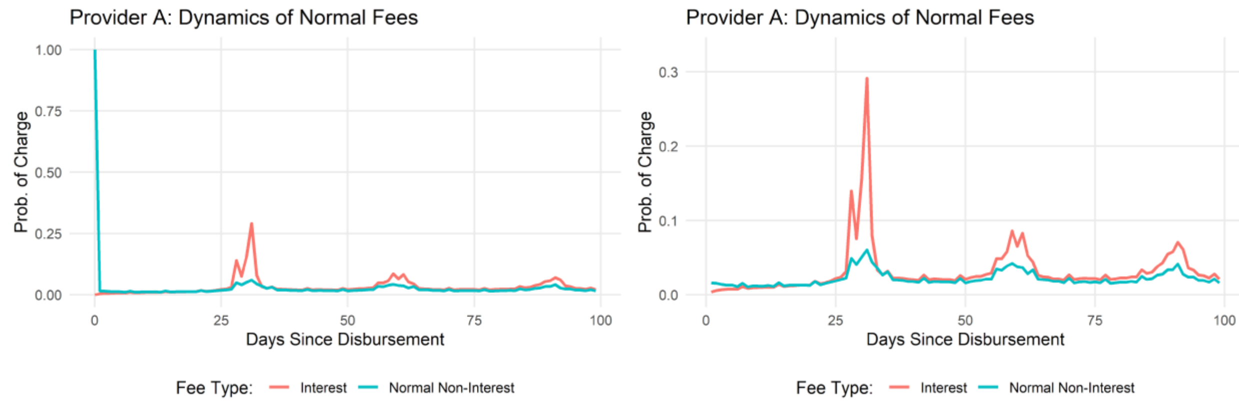

Figure 29: Average probabilities of normal fees charged including fees charged at origination (at left) and without (at right), from Provider A's administrative data

By contrast, interest fees do not contribute to the upfront cost but do contribute to the spikes in cost at the end of each month. While interest is spelled out in the Terms & Conditions (T&Cs) on Provider A's website, it's unclear if first time borrowers know they have not yet been charged interest when they go back to pay back their loan. We also note that normal non-interest fees tend to increase as the end of each month. Our sense is that this is due to additional loans being originated in accounts directly after the closing of the first loan.

This brings us to conditional fees, which are presented in Figure 30. Notably, penalties and rollover fees track very closely, both in their cost and when they are applied. Considering the T&Cs once again, we note that they refer to unsettled loans being rolled over with the same terms as before. **This auto-rollover behavior (which is not unique to this provider) could be a major consumer protection risk. In particular, while late repayment is often a signal of debt stress, such rollovers continue to extend credit and could lead to debt traps. This rollover also incurs additional costs, including a new loan appraisal fee and penalty fees that are not clearly laid out in the Provider's T&Cs.**

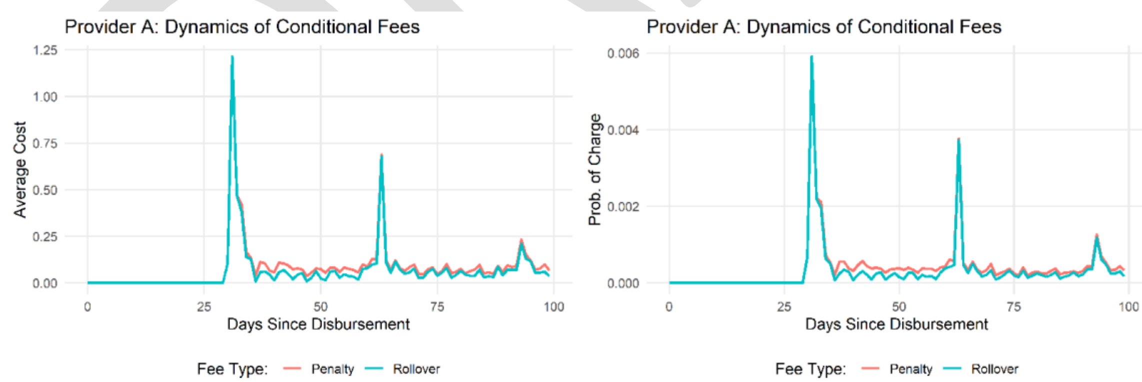

Figure 30: Conditional fees assessed over first 99 days of loan, Provider A

Overall, the dynamics of fees suggest a few places where we might worry about consumer protection. First, the incidence of fees at the closing of loans might obscure these fees to borrowers. In particular, even with disclosure via T&Cs, a first time borrower might feel confident that they had been charged all non-conditional fees on receipt of the loan, and since the balance does not reflect these fees, they may underestimate what is left to pay back. Second, penalty and rollover fees due to loans that are automatically rolled over do not appear to be clearly spelled out in the T&Cs. In addition, these automatic rollovers may lead to borrowers who are not creditworthy to find themselves in debt traps.

I. Risk-Based Pricing

Risk-based pricing refers to a provider offering different pricing for loans based on their perception of the borrower's probability to not pay back the loan. In recent years in Kenya there have been calls for increased use of risk-based pricing by lenders to reward borrowers who have positive loan repayment history. This includes an explicit expectation for banks to use risk-based pricing articulated in the Central Bank of Kenya Banking Sector Charter (2018).

Given the high prevalence of repeat borrowing and short tenure of most digital credit, risk-based pricing could be particularly beneficial for digital credit customers. It has the potential to improve credit markets for both the established and marginal borrower. Ideally, borrowers who have established a good credit history would see a reduction in their cost of credit. On the other hand, more risky marginal borrowers will be able to receive loans at a higher cost of credit, allowing them to enter the market and access credit. Some providers are already utilizing risk-based pricing strategies, adjusting price based on the risk of default. While not all providers submitted sufficient data to measure this, to provide evidence around risk-based pricing, we use data from Provider F as a case study. We find mixed evidence for risk-based pricing, with both loan size and pricing seeming to respond to borrowers' late repayments on prior loans, although not responding to borrowers' prior on-time repayment.

We take a random sample of accounts at Provider F.[35] We graph penalties by loan number in Figure 31. Notably, while we see a decrease in penalty fees charged on the first few loans granted, penalty fees tend to rise once again as borrowers reach around 10 loans over this span, before falling again as the number of loans rises to 15. At this point, we have reached a point where the average effective tenure of such loans must (by definition), fall below one month. It is not surprising that these loans have lower late fees than loans made earlier to those borrowers, since they would in most cases have been repaid early. We see a large number of borrowers who take many loans over our 15-month sample. Therefore in each graph we denote the 15th loan to differentiate behavior on loans taken by these "early repayers."

[35] In particular, we sample 1/3 of accounts and use all transactions from those accounts. This does not impact the results from this analysis, all results are robust to drawing alternate samples and all analyses are sufficiently powered to find effects where they exist (In fact, much smaller subsamples could be successfully used). Given that it will not impact the analysis, it is more convenient to analyze a representative subsample as opposed to relaxing the computational constraints.

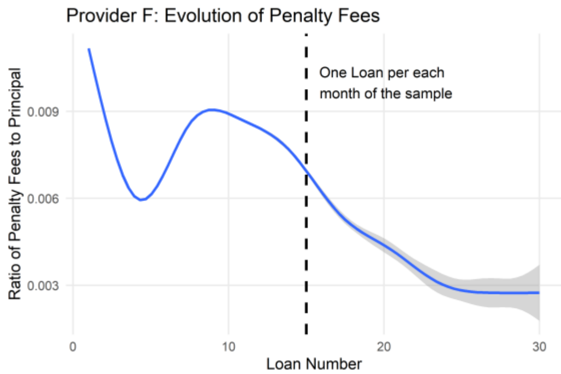

Figure 31: Penalties charged by loan number, Provider F

It's difficult to ascertain exactly what drives this higher incidence of penalty fees around 10 loans, though a few mechanisms could explain it. For example, if number of loans taken is a proxy for debt stress, or if borrowers take further loans to pay back previous loans, we might observe an increase in the risk of late repayment for the subset of borrowers who is borrowing often. [36]

Figure 35 presents evidence that we do see risk-based pricing for this provider. In particular, we plot a proxy for APR, assuming loans of one month, though loan sizes may in fact be shorter. Here, we see that those loans by borrowers who have previously been charged a penalty for lateness are both more expensive and smaller on average than those who have not been charged these penalties for prior loans.

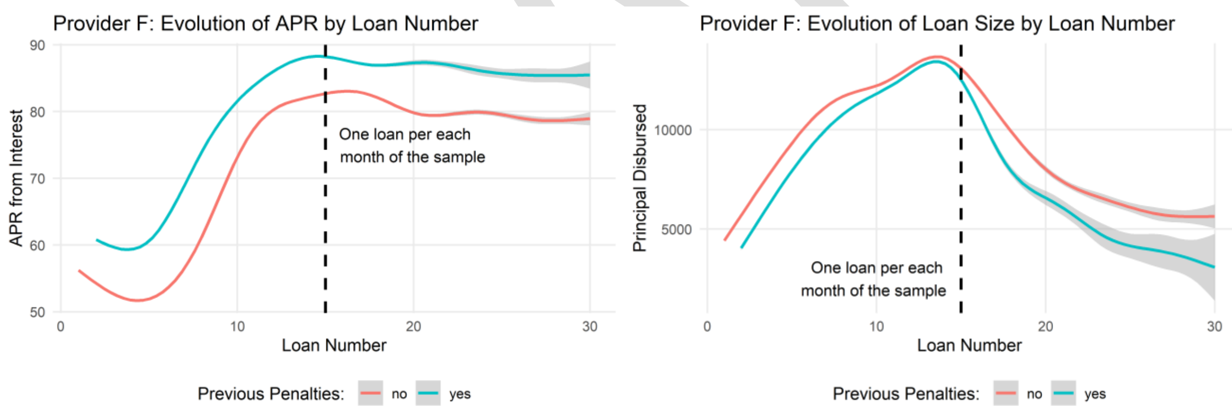

Figure 32: APR dynamics over loan cycles

Once again, the speed of credit matters. In particular, we see the price of loans rise as the loan number reaches 10 for borrowers who have clean credit histories as well as those who have repaid late in the past. This might suggest that the credit model prices in the pattern of late repayment depicted above in Figure 32. Because interest rates were raised in August, about halfway through the time period, this might explain why later loans are higher cost as well. When considering the size of loans over loan

[36] Other possible explanations might include borrowers who have worked to defraud the lender by building up a high credit limit before defaulting on later larger loans or simply borrowing at amounts that are too high for their ability to repay. However, while the correlation between lateness and loan size is positive, it is likely too small to explain these results.

number, as more loans are given the size of loans increases. Again, this pattern spans both those with totally clean credit histories and those who have repaid late in the past.

To get a cleaner estimate of how loan sizes and price change after late loans, we use regression analysis to control for number of loans taken, the total disbursed in those loans, individual effects, and whether or not there had been a general increase in the price of credit yet.37 The results of these regressions are presented in Table 16. After controlling for these factors, we find that a one Ksh increase in the value of cumulative penalties accrued is associated with a 0.65-basis point increase in annualized interest (not counting interest related to penalties or excise tax). Likewise, a one Ksh increase in the value of cumulative penalties accrued is associated with a 1.16 Ksh decrease in the size of loan disbursed. However, despite controlling for a variety of factors, we still see an increase in the average cost of loans to clean accounts. In fact, these accounts pay an above average cost of credit for loans after their seventh, as can be seen in the graph above, “Building Credit?” which plots the cost of credit over the first fifteen loans for an average borrower who is never penalized over these loans. This is not consistent with a model of “building credit,” where repeated successful repayments tend to drive down the price of credit over the long run.

Table 18: Regression analysis of impact of late payment on loan size and fees

	Dependent variable:	
	Interest (Basis Points)	Principal Disbursed (Ksh)
	(1)	(2)
Post Rate Hike	32,620.210***	−1,770.688***
	(17.661)	(9.611)
Lagged Cumulative Penalty Fees (in Ksh)	0.645***	−1.161***
	(0.014)	(0.019)
Lagged Cumulative Total Principal Disbursed (in Ksh)	−0.005***	0.044***
	(0.0001)	(0.0002)
Individual FE	Yes	Yes
Loan Number FE	Yes	Yes
Observations	5,389,929	5,327,586
R^2	0.824	0.912
Adjusted R^2	0.784	0.892
Residual Std. Error	9,737.266 (df = 4401896)	4,039.660 (df = 4339554)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 33 plots the trajectory of an average account that has not repaid late. The points are the average cost of loans to “clean” accounts, where no penalties have been charged in our sample, considering the average loan size of these accounts, netting out the rate hike, and averaging out individual effects. We see that those borrowers who keep their credit clean do see a reduced cost of credit on the first few loans. However, we find the same odd result as before, despite working to address intervening factors.

[37] More specifically we regress interest rate and principal disbursed on an indicator that equals 1 if the loan is taken August or after, 0 otherwise (Post Rate Hike), individual fixed effects, loan number fixed effects, lagged cumulative penalty fees, and lagged cumulative total penalty disbursed.

As borrowers continue to borrow, they enjoy less of these benefits. Moreover, after the 7th loan these borrowers actually begin to pay more than average for their credit, even though they continue to maintain clean credit histories. This is not entirely consistent with a model of "building credit," where repeated successful repayments tend to drive down the price of credit over the long run. Thus, the degree to which borrowers benefit from risk-based pricing may be small in this case.[38]

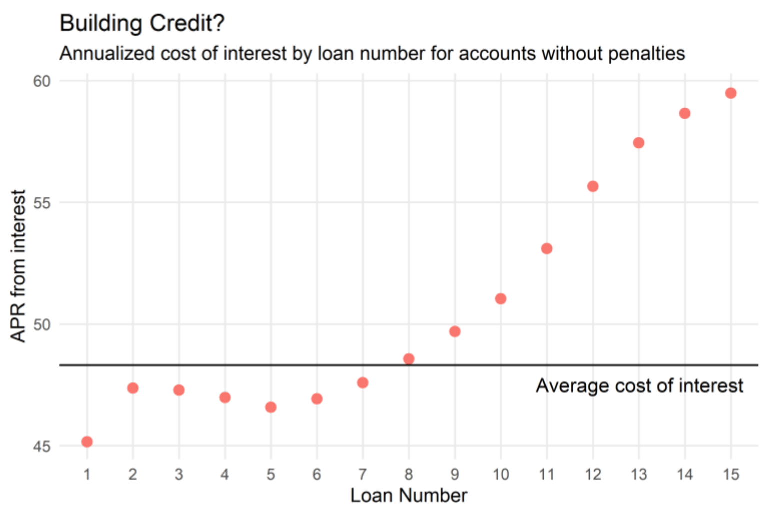

Figure 33: APR Dynamics for an average clean account

[38] In fact, back of the envelope calculations suggest that the average loan to a borrower who has kept their credit history clean from the start of 2019 is granted loans only 0.16 percentage points of APR from interest lower than an average loan. Given that this is a relatively small effect, we argue that keeping one's credit history clean prevents further increases in the cost of credit but does not benefit these consumers with reduced cost of credit.

4. Address probable fraud in digital financial services

Fraud in mobile financial services has emerged as a key risk for consumers, and can take many different forms.[39] The consumer survey conducted for the Digital Credit Market Inquiry confirms the high prevalence of attempted fraud, in particular third-party fraud. **82% of respondents report receiving a call or SMS from an unknown person asking for money or sensitive personal information, or offering a product or service.** The vast majority–77%–of scammers asked consumers for them to send money for a variety of reasons (for example, to reverse what appeared to be money sent to the consumer in error but was in fact fake). (Figure 34) Other common requests included asking for a password or PIN (21%), personal information (19%), or account details (13%). **Most scammers do not identify themselves (63%), though of those that do identify themselves, 72% claim to be an employee of an FSP, suggesting that systems to help verify communications with FSPs may be beneficial.**

DFS phishing scams seem to be thriving during the COVID-19 period; 77% of those who ever received an unknown call or SMS received one in the 90 days prior to the survey, and 56% of all consumers report receiving a scam or fraud attempt since the pandemic began in March 2020. SMS is the most commonly used channel, though phone calls and social media are also used by scammers.

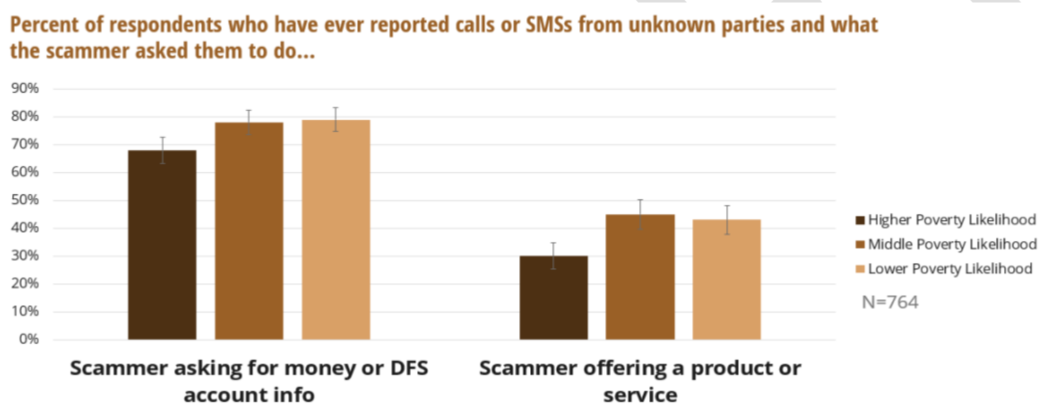

Figure 34: Prevalence of attempted scams by poverty likelihood

Male and female consumers appear approximately equally likely to receive these scam attempts, as do urban and rural consumers. However, older, better educated, and better off consumers are more likely to be targeted than their younger, less educated, and worse off counterparts. As with other challenges reported in this survey, the reason for these differences warrants further investigation. Are scammers targeting these consumer segments? Do these consumers' DFS usage patterns make them more vulnerable to phishing attempts? Or are these consumers simply better able to identify and/or more likely to report these attempts?

[39] Buku and Mazer, 2017.

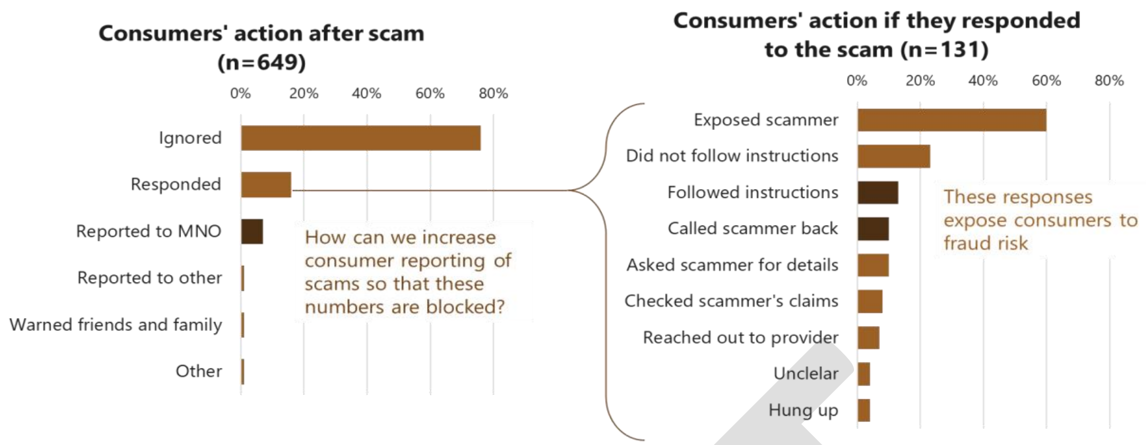

Figure 35: Consumer responses to scam attempts

While phishing scams are quite common, consumers seem to be relatively good at identifying these attempts. 16% of consumers responded to scammers messages, but of these only 13% followed the scammers instructions. 76% of consumers simply ignore these phishing attempts. (Figure 35) Consumers identify scams using a variety of methods. Noticing that the call or SMS comes from a regular number rather than a business line or short code is the most-reported method. Others report hearing about the scam from others, or from their own prior experience. Finding holes in the scammer's story is also common if the scammer asks about a service the consumer does not use or greets the respondent with the wrong name. **However, while many consumers know to ignore these scams, just 8% reported the scams to anyone.** If they do report, most consumers report to their network provider. CAK and others in government and industry could consider utilizing the fraud detection tips of survey respondents to increase awareness amongst all DFS users of how to detect fraud, and encourage more sharing of cases of fraud—even when the consumer does not fall victim—to keep ahead of new types of fraud and to flag phone numbers or accounts perpetrating fraud attempts.

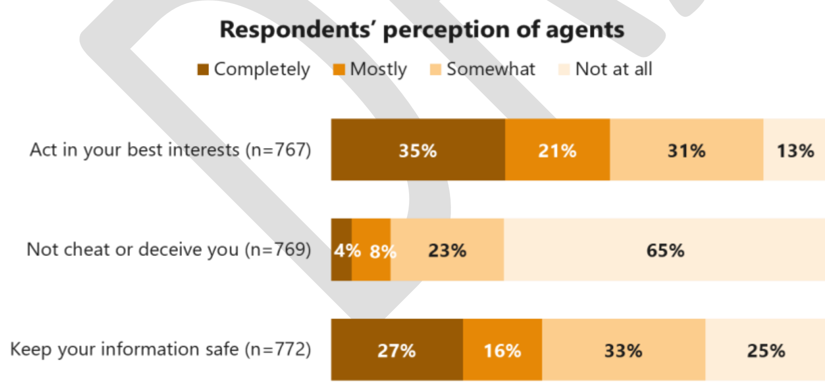

Figure 36: Consumer perception of agents

Consumers also show a healthy degree of caution regarding agents. (Figure 36) While consumers do not generally believe agents will cheat them, they do have less trust with agents regarding keeping their information safe, and acting in their best interests. It is also worth noting that only 2% of DFS users have shared a PIN number or other account details with an agent.

5. Improve consumer redress for digital credit products

Access to effective and efficient redress mechanisms is an essential element of consumer protection regimes. As more and more products and services shift to digital delivery channels, redress mechanisms need to keep up with both the shifting nature of consumer risks and the need for new engagement channels. DFS products require timely and easy to use redress channels to ensure trust, continued usage, and value for money for consumers.[40] The consumer survey on consumer protection conducted for this Market Inquiry sought to deepen our understanding of the challenges consumers experience with DFS, as well as how they engage with available redress mechanisms when these challenges arise. This section reviews consumer experience with redress channels and how redress mechanisms can be enhanced in Kenya's DFS ecosystem.

A. Key challenges consumers face in DFS

The survey asked consumers about a set of common DFS challenges, to understand how many consumers may experience these issues across two periods: 1. Any challenges experienced since January 2020; 2. The most significant challenge ever experienced—to not miss any issues which may have caused substantial difficulty or harm in the past.

Figure 37 presents the portion of consumers who reported experiencing any of the more common DFS challenges since January 2020. **As the data makes clear, phishing scams were the most common issue experienced, followed by incorrectly sending money to the wrong recipient. There is also a substantial portion of consumers who raised issues related to customer care, or challenges understanding the DFS product's interface or it's terms and conditions, which point to the need for potential policy reforms related to complaints handling and transparency of content on DFS platforms and communications channels.** When analyzed by service type the majority of issues are related to mobile money, (excluding being denied a loan or having someone take a loan in your name, which of course is only possible with mobile loans).

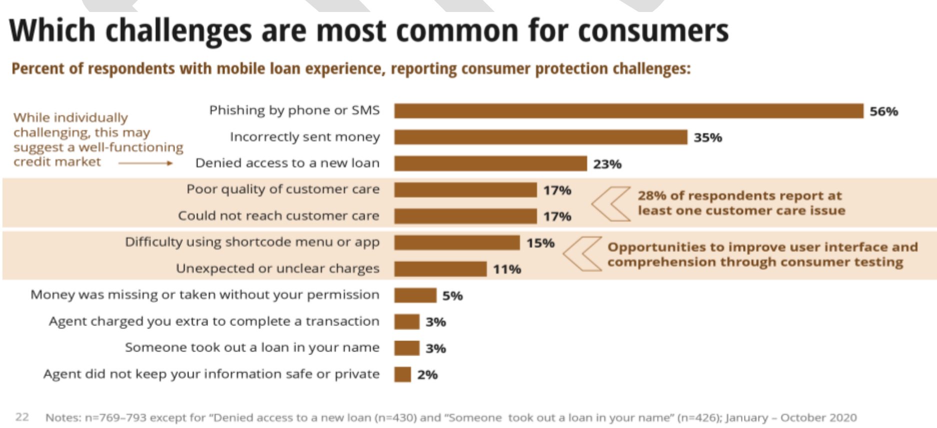

Figure 37: Common challenges reported by DFS consumers

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[40] Nitin Garg and Rafe Mazer. February, 2016. Recourse in Digital Financial Services. CGAP: Washington, D.C. https://www.cgap.org/research/publication/recourse-digital-financial-services

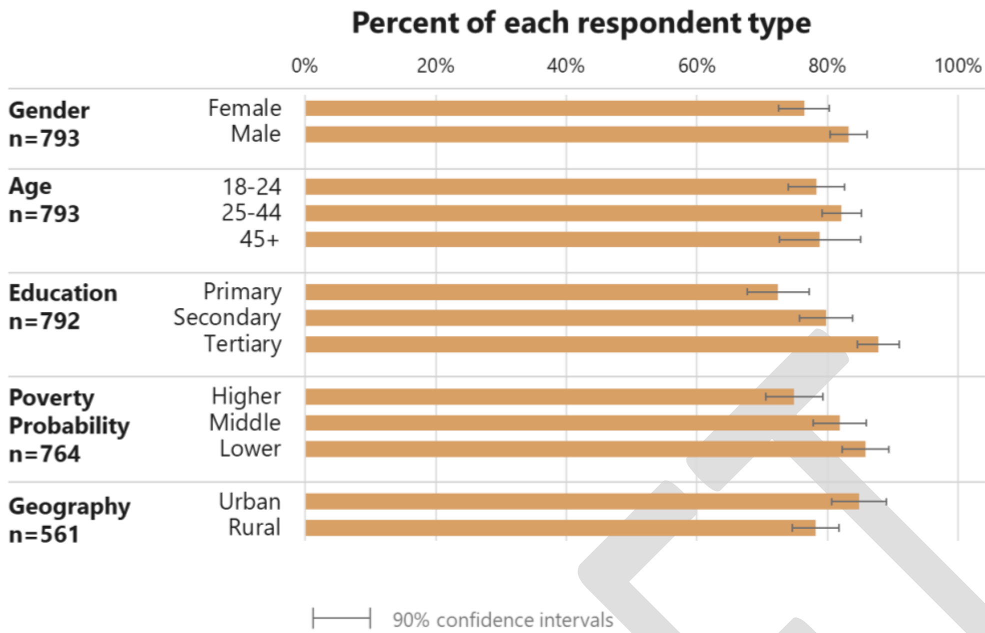


Figure 38: Experience of DFS challenges by demographics

When broken down by demographics, it appears that male, better educated, better off, and more urban respondents report more challenges at a statistically significant level. (Figure 38) While these segments may be more likely to experience challenges, differences could also be partially driven by higher DFS usage, higher awareness of these issues occurring, or greater willingness to report these issues to surveyors. **Unpacking the causes for these differences could be an area for further future research, and we propose that CAK consider further research into this to determine if there are any populations which experience challenges but do not either identify these challenges or report them.** For example, mystery shopping and customer care log data could help explore this issue from different angles.

B. Phishing and scams

As the survey demonstrates, phishing scams have unfortunately become quite common in DFS. To better understand this risk, the survey asked several follow-up questions to consumers who had been targeted for scams.

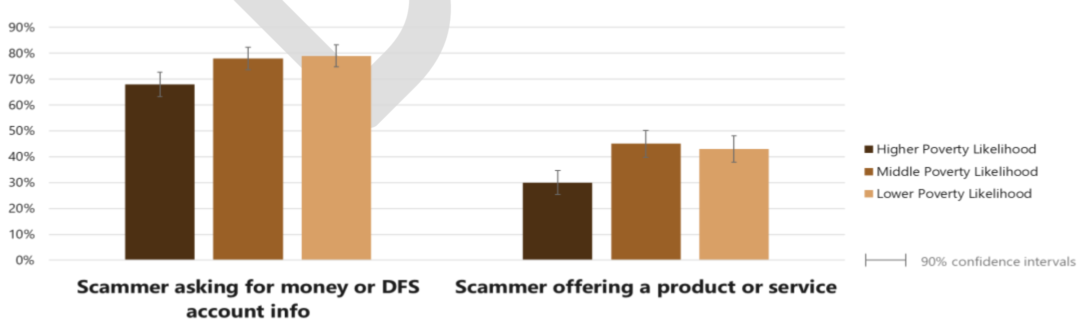


Figure 39: Scam incidence and type of request by poverty probability

Most scams involved asking for money to be sent or for the consumer's DFS account information, while a smaller portion purported to be offering a scam or service. (Figure 39) Regarding the specifics of the request made, **the five most common requests fraudsters made were: For money to be sent (72%); Password or PIN (21%); Personal information (19%); Account details (13%); and Payment reversal (5%). Fortunately, most consumers are able to identify the scam, with only 16% responding to the scam, and only 13% and 10% either followed the instructions or called the scammer back**. (Figure 40)

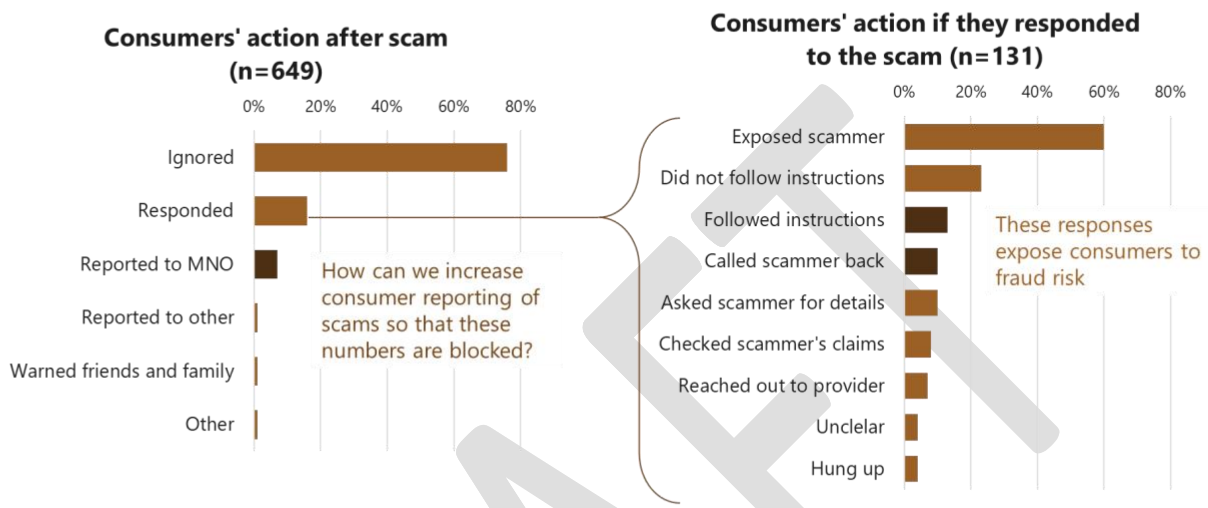


Figure 40: How consumers respond to DFS scam attempts

The survey also asked consumers how they identified the call or SMS was a scam, which is summarized in Figure 41. Tricks like noticing it was a regular number not a shortcode, what they learned from others' experiences, or the nature of the request, could be useful tips to use in anti-fraud awareness campaigns to the broader population, since they appear to have worked for this sample of DFS users. Part of this success could be due to pro-active efforts by providers to increase consumer awareness regarding third-party fraud, such as the "Kaa Chonjo" fraud awareness campaign led by Kenya Bankers Association.

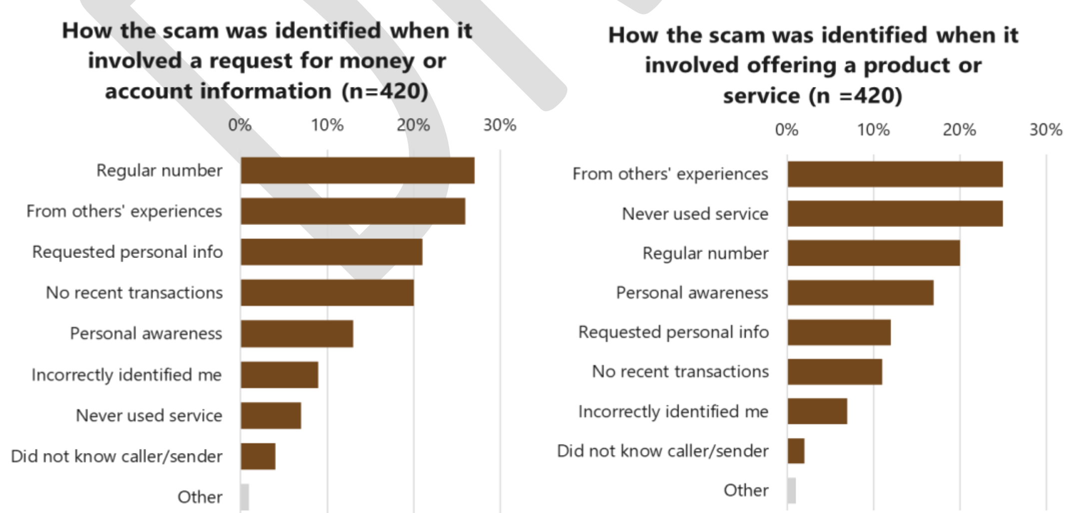


Figure 41: Ways consumers identify likely scams

C. How consumers respond to DFS challenges

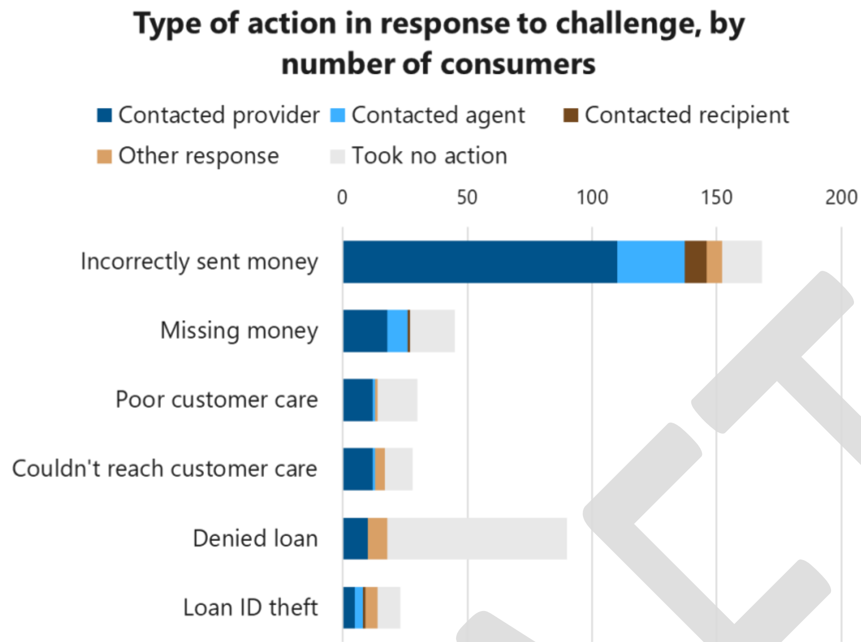


Figure 42: Reporting of attempted scams to redress channels

When challenges occur consumers have several choices to make, including whether to take action or not to try and resolve the complaint. Our survey respondents' actions shows the most common response is to contact the provider, but that in some cases—such as incorrectly sending money or missing money—a significant portion of consumers will also contact an agent of their DFS provider. (Figure 42) **Overall, there was a relatively high level of action taken by consumers, in particular when financial loss was involved—with 88% of consumers reporting taking some action to try to resolve the issue. Better still, 86% of these consumers reported the issue resolved within a day or less, and 77% said they were successful in resolving their issue.** Finally, the survey sought to understand if consumers who did not view their problem as resolved changed their behavior in any way. While not overwhelming, there is some noteworthy difference in behavior change of consumers who reported the problem resolved versus those who did not. (Figure 43)

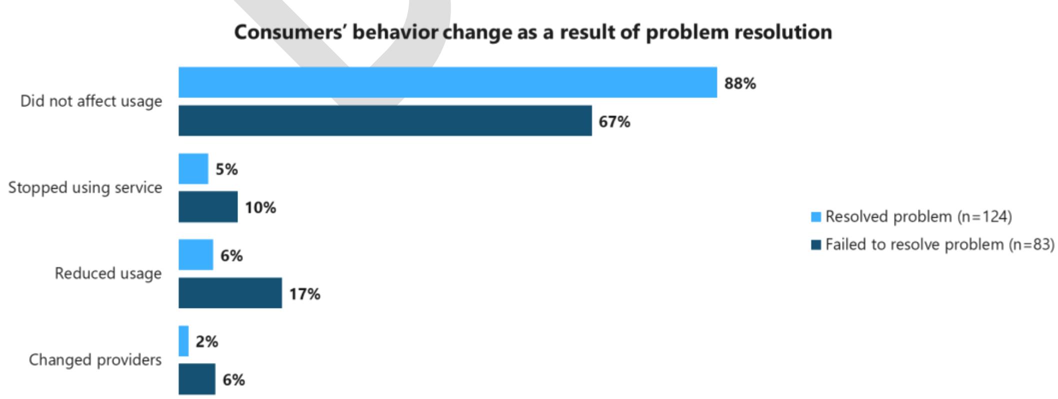


Figure 43: Behavior changes prompted by challenges experienced with DFS

6. Increase consumer control over personal information to expand choice and competition

Kenya's payments system, and the DFS ecosystem which rides primarily on this payments system, has been characterized by levels of market concentration that are unmatched in any other mobile money market, with M-PESA accounting for 99% of market share in mobile money. Similarly, the CAK's 2017 Banking Sector Market Inquiry Phase II identified lack of effective price competition in the banking sector, resulting in increasing efficiencies not being passed on to consumers via reduced pricing and instead being captured in increasing profitability of banks.[41] The Digital Credit Market Inquiry has likewise found that consumers do not always prioritize price when shopping around for products, relying most on the advice and experience of families and friends.

A. Consumer choice in providers

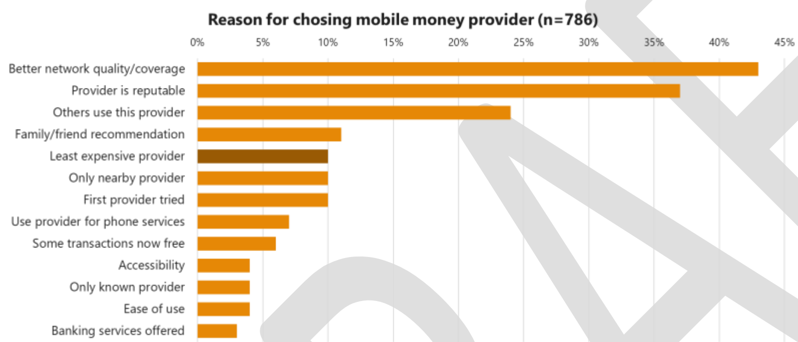


Figure 44: Mobile money provider choice

Survey respondents were asked to share the reasons they chose their primary DFS provider for mobile money, mobile banking, and mobile loans. As Figure 44 shows, **price is only the fifth most important factor for choice in mobile money provider, with network quality/coverage, provider reputation, and use of this provider by others dominating reasons for using the mobile money provider.** Further evidence of the lack of price-based decision-making by consumers can be seen by the limited impact of the temporary removal of fees for mobile money transfers below Ksh 1,000 which coincided with the dates of this survey. For agent selection, mobile money users focus first on the agent they trust, and second on the agent closest to them. Rural consumers, who comprised 64% of our survey sample, are more likely to focus on trust (55% of rural respondents versus 44% of urban respondents), while urban consumers are more concerned with proximity (43% of urban respondents versus 33% of rural respondents).

In mobile banking, consumers tend to use the provider which is linked to their traditional bank account or their salary deposit (46%) and cost factors do not rank higher than fourth in consumers' reasons for using their particular mobile banking provider.

[41] Competition Authority of Kenya, 2017.

Most surprising of all is how little price is a factor in digital credit. (Figure 45) Only 12% of users of mobile loans cited price as a factor in their choice. Speed of loan disbursement and ease of repayment terms were the most common reasons. It is interesting to note that "Only provider I am allowed to borrow from" was a greater factor than price in consumers' decisions. These responses reflect the fact that consumers who do not use a device able to download apps are restricted to the lender or lenders which their mobile money provider allows access to their SIM Toolkit or USSD menu and mobile money channels. This may help explain why **only 27% of mobile loan users in the survey reported they know the fees charged by other mobile loan providers, meaning that awareness of price differences is relatively low in digital credit.**

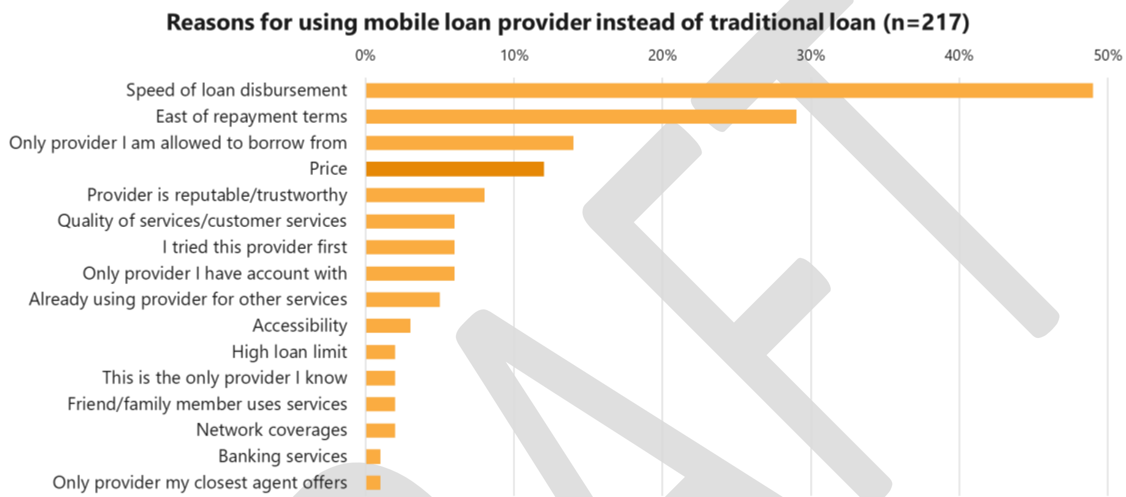


Figure 45: Reasons for selection of digital credit provider

B. Competition in digital credit

As noted in the sub-section of this report "Size and nature of the DFS and digital credit market", the digital credit market is diverse in terms of number or providers, but most consumers primarily use one of the three M-PESA affiliated loan products. **The consumer survey found some evidence of consumers borrowing from multiple lenders, with 33% of borrowers having had multiple mobile loans active at least once prior to the pandemic.** The administrative data, found at least 6% of borrowers had taken loans from multiple lenders across a four-lender sample from January 1, 2019 through March 31, 2020. The absence of the two largest digital credit products as well as smaller but significant FinTech lenders in the data means that the level of multiple account holding is a "lower bound" on the true degree of multiple account holding, which is likely much higher.

To ascertain the true level of multiple borrowing, it is important that a subsequent audit of digital credit administrative data be conducted which includes a larger sample of lenders, submitting standardized data including identifiers such as MSISDN or, ideally, National ID number. This new transaction-level analysis is important because credit reference bureau data will not be comprehensive enough for true multiple borrowing analysis due to two factors:

1. Lack of participation by all non-bank lenders traditionally, and their full exclusion from the credit reference bureaus since April, 2020 per CBK's orders;

2. Lack of full compliance with reporting of digital loan records by digital lenders historically—as noted, for example, in the Banking Sector Market Inquiry Phase II report. The purpose of this analysis would be to determine what the potential loss in competition and risk management is from incomplete information-sharing in the Kenyan market. The analysis would likely focus on the following research questions:

- How many borrowers who did not repay a loan at one provider were able to borrow with another provider later, and did they default again? This would allow for estimations of the costs to digital credit providers and over-indebtedness risks that lack of comprehensive information sharing contributes to.
- What is the state of switching behavior in the digital credit market? Where borrowers can be linked to accounts across different providers, the disbursement dates of their loans from each provider can be used to create an index of switching behavior. This index could include the frequency with which borrowers switch providers, which types of borrowers switch providers, and the impact of switching on the loan size and price paid by borrowers.
- Loan stacking. Loan stacking is when multiple loans are taken out at the same time. This can be a sign of distress—borrowing from a new lender to cover a prior debt—or of capital scarcity—the initial loan is not large enough to cover the needed investment so capital is aggregated from multiple lenders.

To what extent do lenders show evidence of risk-based pricing, and do lenders compete for well-qualified borrowers based on price? Where consumers use multiple lenders, the differences in loan amounts and APR for each loan with different providers, as well as the change in terms on subsequent loans when the prior loan was paid off on time, could provide clues as to how much price is based upon individuals' risk factors versus uniform pricing for all borrowers. The administrative data analysis already points to the potential of such analysis, as one provider did in fact give larger, longer tenure loans to consumers later in the year at a lower average APR, demonstrating the potential consumer benefits if all provides are required to do risk-based pricing that offers discounts to repeat borrowers in good standing. Finally, accurate risk-based pricing is dependent on strong credit information sharing systems, that capture borrowers' full portfolios of debt. In turn, information sharing among all digital lenders should be a priority.

III. Policy recommendations

The Digital Credit Market Inquiry takes place during a pivotal policy moment in Kenya. Nearly a decade into the digital credit revolution there remain significant gaps in coverage of different digital credit service providers, and lack of a clear consumer protection strategy to ensure digital credit maximizes it's potential to benefit Kenyan consumers. There are important policy reforms under consideration currently, such as a new supervisory architecture under CBK; formation of provider associations and codes of conduct; and reforms to credit information sharing mechanisms and data portability across financial services.

As the Government of Kenya considers these and other policy options, consumer protection should be hard-wired into all policy formulation as an essential component. To develop the right policy responses to these priorities will require a mix of new policy formulation, improved market conduct supervision, and further research to unpack the driving forces behind these consumer protection challenges. We propose six actions which CAK and other sector regulators may consider to address these challenges:

1. Develop policies which will contribute to a more competitive digital credit ecosystem

Survey findings point to limited use and awareness of digital credit product alternatives by borrowers. Only 27% of digital credit users in the survey were aware of the charges of other digital credit providers in the market. Meanwhile, historical use of digital credit and use in the past 90 days was predominantly with the three products tied to the M-PESA platform. The analysis of administrative data shows the market consolidated further in 2019 with the entrance of a new overdraft product. It is particularly noteworthy that all lenders besides the overdraft facility increased their average loan sizes over the course of the sample, which could mean that smaller value borrowers have shifted to that overdraft provider. To fully assess this, transaction level data with account identifiers would be needed for the overdraft product, which could be pursued in follow-up research.

While data was limited to analyse multiple borrowing due to lack of consistent submission of MSISDNs and lack of any transaction-level data from two large digital lenders, the analysis still found overlap of approximately 8% of borrowers in our sample. Particularly noteworthy is how one FinTech had 65% of it's borrowers with loans at other lenders in our sample. As it currently stands, these overlaps will not be captured by different providers, which could lead to multiple borrowing that is not sustainable. Or on the other side, this lack of visibility may lead borrowers to stick more with one provider for subsequent loans, as that provider has information on their past positive repayment history which other providers do not. In this way switching and choice could be reduced.

These two trends—Increasing concentration of loans linked to mobile money providers, and multiple borrowing in an environment with high information asymmetry on positive repayment between banks and non-banks—raise potential risks for competition and consumer choice in the long-run. To address these, we propose four policy measures:

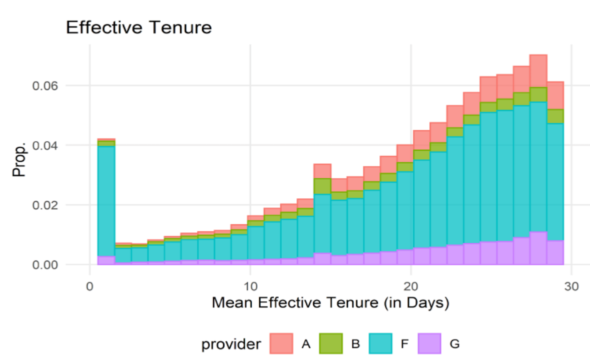
- Develop standards for channel access, product placement and revenue-sharing for digital credit services on mobile money menus to ensure fair competition and consumer awareness of a diverse set of product options—in particular for those without the ability to download apps due to device or network limitations.

- Establish rules regarding the use of competitors' data by mobile money providers and their partner lenders. Mobile money providers hold significant data on their competing digital lenders which could provide them a competitive advantage by leveraging this data for their competing credit products and to target good paying borrowers from other providers. To avoid this risk of unfair advantages for lenders linked to mobile money providers, rules on utilization of competitors' data that is accessible due to being a mobile money provider or other facilitator of digital lending transactions.
- Expand sharing of consumer information for bank and non-bank digital lenders through both credit information systems and other information-sharing schemes. This would include real-time or same-day sharing of positive and negative credit history, mobile money data, and KYC information. Once information-sharing systems are developed, facilitate the creation of third-party services which allow consumers to receive competing offers from digital credit providers based off common borrower information, to increase switching and risk-based pricing competition.

2. Develop standards on structure and timing of fees in digital credit to ensure comprehension for consumers across bank and non-bank products

While many lenders have relatively simple fee structures, analysis of administrative data identified some fee structures and fee dynamics which could make product comparison difficult and obfuscate charges. This includes applying multiple fees at once, applying fees late in the loan cycle, administrative charges, and penalty fees. The frequent payment of penalty fees for some products in our data also indicates that consumers may not be sufficiently attentive to penalty fees and their costs. Improvements in presentation of information and consumer education could help reduce complexity and improve consumers' usage of digital loans, reducing late repayment.

3. Develop pricing rules which ensure that consumers exhibiting positive repayment behavior receive improved terms of credit over time



Digital borrower data analysis showed many borrowers repay their loans in less than 30 days, include more than 4% who repay in less than one day. The analysis also found frequent repeat borrowing is common—in the case of one provider more than 50% of borrowers took 5 or more loans during the 15 month sample period. Some providers already reduce interest and other charges for early repayment, and reduce interest rates on subsequent loans after prior positive repayment. There are potential consumer benefits if all providers are required to do risk-based pricing that offers discounts to repeat borrowers in good standing. These practices should be standardized across the industry by refunding a portion of finance charges for the many borrowers who repay digital loans well before their due date; and reducing the proportion of fees to loan value charged to repeat borrowers who consistently repaid prior loans. These schemes should further be supported by information sharing schemes which allow providers to manage multiple borrowing risks where customers present a false representation of being in good standing with one lender while defaulting on obligations to another lender, have multiple loans active at the same time, or borrow from one lender to service an outstanding debt with another lender.

4. Require digital lenders to provide periodic reports on the actual total charges paid by borrowers

Early repayment, late payment, and loan roll-overs can shift actual costs far from advertised costs. Loan repayment varied significantly. To better monitor pricing trends in the market, data on actual amounts charged and duration of loan cycles should be reported quarterly to assess the effective costs incurred by borrowers and monitor trends in pricing over time.

5. Expand use of administrative data analysis as a digital credit market monitoring tool

Transaction and account level data has proven useful to identify competition and consumer protection indicators, and should be utilized for future market supervision. While there were inconsistencies and incomplete submissions, the administrative data analysis was still able to produce new and important insights regarding true cost of credit products; behavior of different borrower segments; and competition in digital credit. A second round of analysis with more complete data submissions and full participation of leading digital lenders should be done to build a new data-driven market monitoring tool. This tool could be developed in partnership with IPA's data science team by CAK and CBK—which currently oversees bank-based digital lenders and may soon take on supervision of non-bank digital lenders—and designed in a way that the analysis could be transitioned to CAK and/or CBK staff once a common template for data submissions is established and enforced across DFS providers.

6. Require providers to submit aggregated complaints information to monitor consumer risks in DFS

The Market Inquiry identified several variations in the experiences of different demographic segments with key DFS challenges. More research is needed to understand why traditionally vulnerable population segments report lower levels of consumer protection challenges with DFS, and monitor new risks like fraud going forward to address new types of fraud as they emerge. A starting point for this analysis should be requiring that all providers—not just banks—submit monthly complaints reports detailing the types and volumes of issues raised by customers, demographic breakdown of these complaints, and the actions taken to remedy these complaints. This will allow for proactive monitoring and addressing of consumer protection risks early on across providers within the DFS industry.

Appendix A. Effective APR

To compute Effective APR, we adjust the formula for APR slightly. As a reminder, APR is traditionally computed,

$$\text{APR} = \left(\frac{\text{Cost}}{\text{Principal}}\right) \times \left(\frac{365 \text{ days}}{\text{Tenure}}\right) \times 100\%$$

where in the standard computation Cost = Interest + Fees. However, APR uses the tenure as contracted as opposed to the effective tenure. If a loan is given for 31 days but is paid back within a week, this should be considered a more expensive loan as it’s true APR will be higher than if it is paid back at day 31. Where we are able to observe the effective tenure of loans directly, we could compute the true effective APR, accounting for early payments as well as late payments and penalty:

$$\text{Effective APR} = \left(\frac{\text{Cost}}{\text{Principal}}\right) \times \left(\frac{365 \text{ days}}{\text{Effective Tenure}}\right) \times 100\%$$

However, we cannot do this for all of our datasets, notably because in some cases consumers have overlapping loans with the same provider, so there is no clear ending date for one loan and start date for the next. To address those cases, we instead use a proxy for the denominator of effective APR:

$$\text{Effective APR} = \left(\frac{\text{Cost} \times 365 \text{ days}}{\%\text{Disbursed} \times \text{Total Balance Days}}\right) \times 100\%$$

where

$$\text{Total Balance Days} = \sum_{t=1}^{T} \text{balance}_t$$

and

$$\% \text{ Disbursed} = \frac{\text{Total Disbursements}}{\text{Total Debits}}.$$