Digital Credit Market Monitoring with Administrative Data: Evidence from a Collaboration with the Competition Authority of Kenya

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Abstract

I analyze a novel dataset of digital credit transactions in the Kenyan market collected as part of the Digital Credit Market Inquiry undertaken by the Competition Authority of Kenya. This information request yields detailed transaction data on over five million consumers, allowing exploration of consumer outcomes including the size, nature, and evolution of the market; the price, size, and tenure of loans; the timing and type of fees applied; and late repayment and default. Moreover, a unique de-identification approach allows me to match consumers across providers without observing direct identifiers, allowing for the study of multiple borrowing behavior among these consumers. Additionally, I disaggregate these outcomes by gender, age, and provider type. In reflection, I identify five stylized facts about digital credit in Kenya, along with six working hypotheses, and set the stage for future use of administrative data-based market monitoring tools.

Keywords: Digital Credit, Market Monitoring, Consumer Protection, Administrative Data

JEL Codes: G51, D18, G28, C55

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1 Introduction

Kenya is one of the most mature digital financial services markets in the world. Built on the widespread adoption of mobile phones and mobile money products, digital credit emerged in Kenya in 2012 with the introduction of M-Shwari from Commercial Bank of Africa (now NCBA) and Safaricom (Totolo, 2018). In the time 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 (Gwer et al., 2019).

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. Chen and Mazer (2016) identify three primary attributes of digital credit products–"Instant, automated, and remote." These three aspects of digital credit can be both beneficial or harmful to consumers. A main benefit come from the ease of access of credit, reducing the transaction costs for both providers and borrowers. For borrowers, credit comes more quickly, with less paperwork, and without a costly journey to a providers' office. Likewise, the underlying costs of screening credit falls with the usage of alternative data for borrowers who have traditionally operated outside of the the formal credit market, meaning that "marginal borrowers" can be more competitively served by digital credit providers. This ease of borrowing in turn serves to drive greater financial inclusion (Björkegren and Grissen, 2018, 2019). Early work suggests positive impacts of these small digital loans, such as increased resiliency to shocks (Bharadwaj et al., 2019).

Digital credit tend to be short term, high cost, and marketed to those who have limited financial experience (Francis et al., 2017; Gwer et al., 2019). Therefore, despite the great promise of digital credit for financial inclusion, this same ease of access can lead to consumer risks. For example, in Mexico, Burlando et al. (2021) find that reducing the speed at which credit is disbursed meaningfully reduces the default rate on those loans, suggesting some borrowers may be taking on loans without properly evaluating their ability to repay. More generally, in the eyes of regulators, risks including high prices and overindebtedness have grown with the expansion of digital financial services (Garz et al., 2020).

As a first step in understanding the risks of digital credit products, market monitoring is essential. From this perspective, administrative data has clear value in observing the behavior of consumers, lenders, and the resulting market outcomes, but is difficult to access for the use of consumer protection research. Analysis around consumer protection topics may not always appeal to these providers, which may limit the access of consumer protection researchers to such data. An alternative route is to utilize regulator driven information requests, though these may miss non-bank digital lenders. In many contexts, including Kenya, there is limited regulation of non-bank digital lenders and therefore little regulator monitoring. This research project overcomes these hurdles through a collaboration with the Competition Authority of Kenya (CAK), who hold an economy-wide mandate to regulate competition and consumer protection. Through an information request done in collaboration with CAK, I obtain transaction level data from four large digital credit providers (three banks and one non-bank) and aggregate data from an additional two products.

Our first objective is to conduct exploratory analysis to make clear and transparent insights about the state of the digital credit market in Kenya. The analysis explores consumer risks and outcomes including the size, nature, and evolution of the market; the price, size, and tenure of loans; the timing and type of fees applied; the prevalence of late repayment and default, multiple and revolving borrowing, and risk-based pricing. The second objective in doing this analysis, is to demonstrate how how the tools I use–including descriptive statistics, regression analysis, data visualization, and clustering–can be used to advance consumer protection market monitoring. Finally, my results speak to several of the objectives of a Digital Credit Market Inquiry taken on in collaboration with the Competition Authority of Kenya (The Kenya Gazette, 2020).[1]

We start by describing digital credit in Kenya as depicted by the administrative data in the

[1]This market inquiry was designed around a set of objectives to gain evidence around the state of digital credit in Kenya. This particular analysis best speaks to three items from this digital credit market inquiry. In particular, I "provide evidence regarding size and nature of DFS and digital credit markets" (item 1), "identify potential consumer protection risks within Kenya's digital credit sector" (item 2), and "inform development of policies to ensure adequate consumer protection across regulated and unregulated lenders and equal protection of all consumers" (item 7). Additionally, the analysis presents results related to the "transparency and comprehensiveness of product information and terms and conditions"

sample. Considering both transaction and aggregate data, I find that there has been major growth and some segmentation in out sample largely driven by a new overdraft product which serves to provide short term credit at lower values. While demographic data is limited in the transactional datasets, I are able to characterize the age and gender of those who have data and do borrow from these providers. I find that the majority of accounts with gender data in the sample are held by men (64.5%). I also find that most borrowers are younger, with a majority between the ages of 25-44 (66.5%). In comparison, about 48.9% of Kenyans older than 18 fall into this age group.[2] Loans tend to be relatively small: an average borrower takes loans of 6593 KSh (about $161 PPP), though loan sizes vary considerably by provider. Loans tend to be short in tenure, often given as single-month, single-repayment "bullet loans" and repayment times mirror that. Median effective tenure, or the actual time from when the loan is disbursed to when it is repaid, is around 35 days.

We then move on to characterizing the first potential risk within Kenya's digital credit sector: the price of credit and the application of credit fees. I find that digital credit loans tend to be expensive. This measurement can be done using a statistic similar to APR which I call Effective APR, calculates the cost of the loan based on the number of days the loan is active, instead of the loan tenure at origination and includes all fees and penalties charged on the loan as well. I find that the cost of digital credit in the 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 price of credit is highly right skewed, meaning I observe a long right tail of high cost credit. 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 effective APR is in effect.

Second, I document the application of fees to understand how much they contribute to the overall price of credit. Considering two of the four providers, I find a number of different charges applied, including interest, facilitation fees, conditional fees including penalties and rollover fees, and excise tax. I find that when fees at origination are disaggregated (i.e., in Provider A's data),

[2] Author's own calculations with data from US Census Bureau's International Data Base.

that interest rates bunch near the rate allowed by a nominal interest rate cap which was in place during the first 11 months of the sample. However, the majority of the cost in Provider A's data came from facilitation fees charged at origination, which circumvented this interest rate cap. Based on the terms & conditions of Provider A, these fees alone would yield an APR of 86.4%. I find that interest fees are only *charged* when the loan is repaid, which could result in these fees surprising the borrower. Finally, I note that rollover fees at this Provider serve the same purpose as facilitation fees in circumventing the interest rate cap (they are the same size), and that loans are automatically rolled over so these fees are automatically applied.

Third, I characterize the risk of late repayment and default. While I do not have tenure information for all providers, I have been able to reconstruct repayment estimates for two of the providers in the sample. The estimates, which are intentionally conservative, still show that there is a high prevalence of penalty fees charged to digital borrowers, indicating that late repayment is a common event. For one major provider, almost two-thirds of accounts featured at least one charge for late repayment.

Fourth, I were able to identify the same individual across multiple providers' data using borrowers' phone number as a unique identifier.[3] Using the common identifiers at four lenders, I investigate multiple borrowing and multiple account holding in the sample. I are able to trace borrowers across providers to see if they hold multiple accounts, if they take multiple loans over short periods of time, from both the same or different providers. Because the data I received did not allow me to identify individual users for all providers in the market, I cannot estimate the extent of multiple borrowing. However, the estimates give me a clear lower bound. 6% of borrowers in the sample are observed to borrow from multiple providers, and 81.2% of those who hold multiple accounts also multiple borrow, meaning they have active loans with multiple providers at some point during the sample. Additionally, 86.8% of borrowers borrow again from the same provider before the tenure of their past loan has expired, which I refer to as early or repeated borrowing. Using data from a single provider as a case study, I find that those borrowers who

[3]Using a unique approach to de-identification, I are able to de-identify phone numbers without losing the ability to link borrowers across lenders via MSISDN.

solely multiple borrow without repeated borrowing tend to end up defaulting at a higher rate than average. However, those borrowers who also borrow early from the same provider have defaulted at a lower rate than others at the provider.

Finally, throughout the results I characterize these outcomes using disaggregation by gender and age. I find large disparities in outcomes by gender. Men received larger, cheaper loans on average, despite somewhat worse repayment behavior. Additionally, I find strong "lifecycle effects" in consumer credit. Borrowers aged 25-44 tend to be the dominant borrowers in digital credit. Likewise, average loan sizes grow by age cohort until the late 30's when loan size begins to level off. These begin to fall around the age of 55. Effective tenure falls dramatically from age 20 to 30 before leveling off. Finally, those aged 25-64 tend to pay more for credit relative to their older and younger peers.

To synthesize these insights, I conclude by presenting five stylized facts about digital credit in Kenya that follow from the exploratory analysis. Additionally, where I have incomplete or suggestive evidence, I propose three working hypotheses that suggest avenues for future research into risks in the Kenyan digital credit market. Finally, I conclude by discussing the potential for the analysis techniques within to contribute to future consumer protection market monitoring strategies and potential advances that can be made in producing market monitoring tools for more effective consumer protection regulation and supervision in digital credit.

2 Data and Context

2.1 Digital Credit in Kenya

2.1.1 Defining Digital Credit

Drawing on Chen and Mazer (2016), the definition of digital credit begins at the premise that it is "instant, automated, and remote." Loans are disbursed quickly, often being delivered within hours of application. As opposed to employing many loan officers, decisions about loan approvals, interest rates, and credit limits are often made via automated systems utilizing credit scoring algorithms in place of human decision making. Finally, credit can be requested from remote locations provided that cellphone service and or internet for the potential borrower to use. In Kenya, relevant channels include lending via mobile phones (built with USSD or SIM Toolkit), apps, and web based lending.

2.1.2 Providers

Digital credit in Kenya emerged in 2012 with the launch of the M-Shwari product by NCBA and Safaricom and grew rapidly thereafter (Totolo, 2018). While the early partnership between Safaricom and NCBA (and later KCB) was built on linking TelCo data including mobile money and call detail records (CDR) to one's lending account to assess credit risk, a wide variety of providers have entered the digital credit space since (Gubbins and Totolo, 2019; Björkegren and Grissen, 2019). At one point it was estimated that several hundred different providers were operating in Kenya, largely non-bank digital lenders (Gwer et al., 2019). However, despite the fact that the great majority of lenders are non-bank digital lenders, the majority volume of digital lending is done by banks.

A number of competing models have arrived with this wide number of providers. Digital credit providers differ along a wide number dimensions including data used to determine creditworthiness, how loans are linked to other financial products, access channel, and regulatory status. Among providers of digital credit, banks use the aforementioned CDR and mobile money data, salary linked accounts, and credit bureau data to determine creditworthiness. Some efforts have been made to mirror the success of the TelCo partnerships without their CDR data. For example, Branch, a non-bank digital lender, collects data on contact lists, SMS logs, GPS location, and handset type to assess creditworthiness (Branch International). I also see heterogeneity in the digital credit market based on the channel of provision. In particular, one major channel of provision is SIM Toolkit/USSD-based lending which can be accessed via feature phones. This contrasts with the use of application based mobile loans, which one needs a smartphone to access. Finally, as I will discuss in the next section, bank and non-bank lenders are asymmetrically regulated.

2.1.3 Regulators

There are two regulators are of interest when discussing consumer protection regulation in Kenya. First, the Central Bank of Kenya (CBK) is the regulator of banking activities in Kenya and is empowered to intervene in the interests of depositors and members of the public. In practice, this has meant that CBK has regulated banks and not non-bank lenders. CBK has issued consumer protection guidelines which set rules for banks and deposit-taking microfinance banks.

In a more recent step, CBK has moved to limit non-bank digital lenders' access to credit bureaus (CRBs) in response to the COVID-19 pandemic. On April 8th, Parliament passed a prohibition on listing debts below 1000 Ksh, retroactive to April 1st. Additionally, on April 15th, non-bank digital lenders were prohibited from accessing Credit Bureaus (CRBs) (Munda, 2020). However, it is useful to note that not all non-bank providers had been using the credit bureau prior to this change regulation. In fact, 13 of 22 lenders audited by Gwer et al. (2019) did not submit information to any of Kenya's three CRBs.

The second regulator of interest is the Competition Authority of Kenya (CAK). CAK's mandate includes an economy-wide mandate for consumer protection. Additionally, they have taken particular interest in digital lenders. The combination of these two regulatory agencies leaves those non-bank digital lenders in a regulatory grey area, unregulated by the CBK, but regulated by CAK. However, CAK's mandate derives from the Competition Act, which is relatively limited in it's coverage of financial sector policy and financial consumer protection policy, which creates some restrictions on the types of policy remedies they may be able to consider for non-bank digital lenders.

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

Table 1: Providers submitting data for Digital Credit Market Inquiry

2.2 Administrative Data

2.2.1 Information Request

CAK sent letters to all digital credit providers requesting all transactions associated with a loan product to be submitted as part of digital credit market inquiry information request. In particular, Providers were asked that all fees, charges, and/or penalties directly and indirectly related to the loan should be included in the submitted records even if these transactions occur as records in auxiliary accounts, for example: mobile money, savings, current, or other deposit accounts. Likewise, for fees and charges, I requested charges from third parties.

In the data request template, I request nine variables for each transaction: MSISDN, Gender, Year of Birth, De-Identified Loan ID, Transaction Type, Transaction Value, Loan Balance Prior to Transaction, Loan Balance After Transaction. Where there is need for clarity, details on the variables requested are provided below:

- *De-Identified Loan ID*: While I left it up to the discretion of providers how to generate this ID, I required an ID that uniquely identifies transactions associated with each loan disbursed by the provider. I asked that all transactions directly or indirectly related with this loan should be identified using this same loan id, regardless of where they are recorded in the loan account, auxiliary records, or third party transactions

		Provider				
Category	Variable	A	B	D	F	G
ID	De-Identified MSISDN	✓		✓	✓	✓
	MSISDN Prefix	✓		✓	✓	✓
	De-Identified Account Number		✓			
Demographics	Date of Birth	✓	✓	✓	✓	✓
	Gender	✓	✓	✓	✓	✓
	Branch/Location	✓	✓			✓
Transaction Record	Loan ID				✓	
	Transaction Type	✓	✓	✓	✓	✓
	Transaction Date	✓	✓	✓	✓	✓
	Transaction Time				✓	✓
	Transaction ID/Number	✓				
	Debit/Credit	✓				
	Transaction Value			✓		
	Transaction Absolute Value		✓		✓	✓
	Fees Charged		✓	✓		✓
	Interest Fees				✓	
	Penalty Fees				✓	
	Excise Tax				✓	
	Balance Before Transaction		✓	✓		✓
	Balance After Transaction	✓		✓		✓

Table 2: Variables in Transaction Data

- *Transaction Type*: Providers were asked to include transaction type labels for all transactions. These transaction types might include disbursement, fee, charge, penalty, repayment, interest repayment, principal repayment, or write-off.
- *Transaction Date and Time*: Providers were asked to submit this information in the format DD/MM/YYYY hh:mm:ss, or similarly unambiguous format, e.g., YYYY/MM/DD hh:mm:ss.
- *Transaction Value*: The net value of the transaction here where positive values indicate a credit (and negative values indicate a debit) to the consumer.
- *Loan Balance Prior to Transaction*: The loan balance remaining unpaid prior to the transaction taking place.
- *Loan Balance After Transaction*: The loan balance remaining after the transaction has taken

		Product	
Category	Variable	H1	H2
Demographics	Gender	✓	✓
	Age Band	✓	✓
Disbursements	Count	✓	✓
	Total Value	✓	✓
	Average Value	✓	✓
	Minimum Value	✓	✓
	Maximum Value	✓	✓
Repayment	Total Outstanding Principal	✓	✓
	Total Defaulted	✓	✓
	Default Rate	✓	✓
Fees and Charges	Facility Fees	✓	
	Rollover Fees	✓	
	Interest		✓
	Penalty		✓

Table 3: Variables in Aggregated Data Received from Provider H

place.

Additionally, I asked providers to give information about location of transactions and consumer occupation when they were able, but did not require this information.

2.2.2 Data Received

We received raw data from eight providers, which I index A-H. Based on this data I found that Providers C and E had not submitted transaction data and tended to be small players in the market (on the order of thousands of loans per year).[4] Additionally, I received data from Provider H, a large player who submitted aggregated data. Information about the providers and products used in the analysis are presented in Table 1. Table 2 presents the data submitted from the remaining providers. Likewise, Table 3 presents the aggregated data submitted by Provider H.

[4] In particular, one submitted a snapshot of account data, whereas the other submitted loan level data.

2.2.3 Data De-Identification

Before receiving the data, it was de-identified by CAK using tools produced by the IPA research team. To de-identify the data, I focused on two variables featuring personally identifiable information (PII): MSISDN and date of birth. For MSISDN, I wanted to mask this information without losing the ability to link data across providers using this method. Therefore, to de-identify MSISDN, I salted and hashed these numbers to produce a unique identifier that cannot be replicated without the "salt."[5]

2.2.4 Data Harmonization and Processing

Upon receiving the data, I processed each dataset to harmonize as closely as possible across datasets. As seen in Table 2, the data was received in a wide variety of formats. For each provider I stared by cleaning the data – formatting variables, harmonizing transaction types, and variable definitions. After cleaning, all datasets included variables for ID (hashed MSISDN), MSISDN prefix, gender ("M," "F," or "N" for no data), age, transaction date, transaction type ("disbursement," "fee," or "repayment"), transaction value (net absolute value of money changing hands), fees charged (absolute value of fee), flow (negative denominated amount loan balance increased or decreased by, including fees, etc.), loan balance pre, and loan balance post (= loan balance pre − flow).

Many of the datasets were quite large, and often were split up into multiple files with transactions from a single account spread across files. Therefore, as I cleaned the data I saved a file recording the ID and demographics of each account holder. Using this ID file, the next step was to re-organize the data so all transactions related to an account were located in a single file, and the file id stored with their ID.

[5]More specifically, unique MSISDN numbers were extracted from the dataset and a random string of numbers and letters (salt) is stored with these MSISDN numbers. MSISDN and the salt are concatenated, and the resulting string is hashed. When new data was received by CAK, this data is checked against the numbers already existing in their dataset. For those numbers which already exist, the already generated salt is used, keeping this constant across providers. 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.

For the main analysis, I relied on account level data, so I aggregated accounts, computing the total disbursed, total repayments, total fees charged (overall and by fee type), number of disbursements, repayments (where these were listed as separate transactions), and the total number of transactions. Additionally, for Provider B and F, I built account by day timelines of transactions, documenting the balance and flow on each day from when the loan was disbursed, to 100 days after 30 or 61 days, depending on the provider and loan tenure (where available). Finally, I compute the number of days the account was non-zero, the total balance days, the mean disbursement, the mean effective tenure, and the effective APR.

For Provider F, I also used the provided loan ID to aggregate loans, including the total repaid, the total fees charged (interest, excise tax, and penalties), the number of repayments, the number of transactions, the the percentage repaid, if the loan was not fully repaid, the effective tenure, and effective APR (overall and by fee type).

2.2.5 Sample Representativeness

How representative is the sample of Providers? While I capture a large portion of the market, it is important to be aware of the blind spots. Using auxiliary survey data as a guide, I can characterize what proportion of the market I capture transactions and aggregates for. While this data itself is not a perfectly representative sample of Kenyans, it may still do a good job tracking market shares among those who use DFS. Based on this sample, 95.8% of those who used digital credit used at least one of the Providers that submitted transaction or aggregated data in the data request. 42.8% of respondents to the survey used one of the providers submitting transaction data, and 86.1% used one of the providers submitting aggregated data (Blackmon et al., 2021).

These numbers are encouraging and suggest that this administrative data reaches a wide variety of consumers of digital credit. However, I may still worry about sample selection. Given that not all Providers who were contacted submitted, I would expect that those who chose not to submit might have more negative behavior within their data, even if these differences are small. Additionally, I note that some providers may be more used to these types of submissions and more likely to respond. In this case, when considering the largest providers, those banks who are under the purview of the Central Bank of Kenya were likely to submit their data, whereas only two large non-bank lenders submitted. Finally, the COVID-19 pandemic took hold in Kenya shortly after the data request forms went out. Many providers struggled, reducing lending and other business activities (Guguyu, 2021). For Providers who were more capacity constrained during this period, this may have limited their ability to submit data.

3 Digital Credit in Kenya

Before addressing consumer risks in digital credit in Kenya, I begin by looking at trends and characteristics of the Kenyan Digital Credit Market using the administrative data submitted. This exercise is both valuable in itself as a exploratory analysis of digital credit in Kenya and will also be useful to contextualize later findings about consumer risks. In this section, I chart the size and evolution of the digital credit market, the demographics of borrowers, the size of loans, and their effective tenure.

3.1 Size and Evolution of the Market

We start by using administrative data to size the digital credit market and chart its growth. When I consider both transaction level data and aggregated data I received, and considering the survey results, I find it likely that the data covers the large majority of borrowers. Therefore, it's useful to use this data as a measure of the size of the digital credit market, even if it is incomplete.

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 I 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

Figure 1: Disbursements by Month from January 2019 to March 2020

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

Table 4: Loan disbursement by provider, January 2019 - March 2020

grew 213% (Table 4). Competitors F and H1 both shrunk in terms of their number and total value of disbursements. Finally, every other providers' average loan size grew, suggesting a degree of market segmentation took place.

Looking closer at the trends, as can be seen in the top panel of Figure 1, disbursement counts are clearly driven by H2. The overdraft product differs a bit from the the other digital credit products here in that borrowers are charged fees for each day they have a positive balance in their overdraft account. Thus, it is not unlikely that a single account has multiple overdraft disbursements per month. In Table 4, I see that the number of disbursements are an order of magnitude higher than other major products.

Considering total volume, this increase is also driven by the increase in lending via H2, though this is not as stark in Figure 1 (middle panel). However, the early growth seems to have driven total lending volume. This finding fuels a hypothesis that there is or at least was unmet demand for more flexible digital credit lending. In particular, the working hypothesis is that there is unmet demands for loans of shorter length accompanied by lower fees (as compared of disbursement

	Proportion				
Gender	A	B	F	G	Market
Female	32.45	23.21	19.59	8.87	19.12
Male	67.41	67.33	29.54	16.55	33.31
No Data	0.14	9.46	50.87	74.58	47.58
Total	100.00	100.00	100.00	100.00	100.00
	Proportion				
Age Group	A	B	F	G	Market
18-24	4.71	5.44	5.23	21.34	8.43
25-44	67.69	80.18	23.49	66.90	40.37
45-64	24.73	13.67	7.97	11.48	10.94
65+	2.87	0.48	0.91	0.27	0.98
No Data	0	0.22	62.41	0	39.27
Total	100.00	100.00	100.00	100.00	100.00

Table 5: One-Way Account Demographics by Age and Gender

size).

Finally, the average size of credit disbursed fell considerably over this period, as can be seen in the lower panel of Figure 1. However, all other providers/products in the sample except H2 actually increased the average size of their loans. This may be indicative of two different forces. Borrowers may have moved from other Providers to H2 if they found the overdraft product more amenable to their needs. On the other hand, other lenders may have worked towards market segmentation, increasing the size of loans disbursed to borrowers to vertically differentiate themselves from smaller, shorter loans.[6]

Based on this analysis, I see an industry that was growing at least up until the COVID-19 Pandemic, which directly succeeded the time period of the sample. Overall, the results suggest that the digital lending industry disbursed a yearly average of over 34.5 Billion KSh in loans ($\approx$ 300 Million USD). Much of the growth was driven by a new entrant offering an overdraft product, which resulted in segmentation either via consumer switching or product differentiation by lenders.

[6] These two hypotheses are difficult to tell apart, in particular because I do not have transaction data for Provider H2 that I might be able to link to accounts at other Providers to analyze switching behavior.

3.2 Borrower Demographics

Who are the borrowers? Considering the demographics of borrowers in the sample, I find that the majority of accounts who have gender data associated with their accounts are male, a fact which is consistent across providers regardless of the percentage of borrowers they lack gender data for. The data features gender information for 52.4% of accounts. Of the accounts I have information on, 36.5% belong to women and 63.5% belong to men.[7]

Likewise, I have age data for 60.7% of accounts. Here I see that those aged 25-44 tend to form the majority of borrowers, followed by those who are 45-64. Of those accounts I 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. Statistics for individual providers are presented in Table 5. Additionally, a more comprehensive two-way break down of gender and age by Provider is presented in Table A.1.

Of those borrowers in the sample with age data, I find that women tend to be a bit younger than men, and those without gender data tend to be younger than both. Women in the sample are on average 36.0 years old, while men are 36.7 years old, which is reflective of the demographic make-up of adults in Kenya. For reference, the mean adult (over 18) Kenyan is 36.7 years of age.[8] However, those without gender data, on the other hand are about 33.3 years old, much younger than the average adult Kenyan. This is largely driven by consumers at Providers F and G, who make up the majority of consumers without data.[9]

3.3 Loan Account Characteristics

3.3.1 Loan Size

How large are digital credit loans in Kenya? To get a sense of the loan market in Kenya, I take a look at the average loan size by account. In particular, I want to learn about the experience

[7]Considering positively identified multiple account holding, this falls as men tend to men tend to hold more accounts than women.

[8]Author's own computations, with data from the US Census Bureau's International Data Base.

[9]Provider G rarely has gender data but always collects age and tends to have more borrowers of ages 18-24 than other providers.

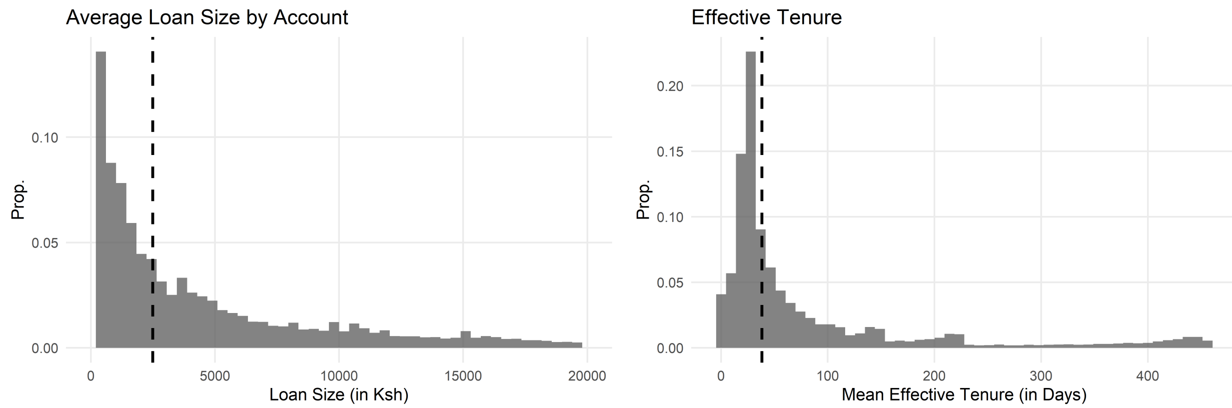

Figure 2: Average Loan Size and Average Effective Tenure by Account, all providers in the market

of an average borrower instead of the average loan taken by borrowers, which would lend more weight to the behavior of frequent borrowers. Therefore I average twice, first taking the average loan size by account and then taking the average over accounts. A similar approach is used for effective tenure in the next section.

Loan size is presented in Figures 2 and 3. In line with previous research, average loan sizes in the digital credit market tend to be small. The average account has an average loan size of 6593 KSh. However, there is considerable heterogeneity in loan sizes by Provider, and within Providers. Provider G, a non-bank lender, has the smallest average loan size at 4034 KSh, followed closely by Provider F, at 6335 KSh, which is closest to the average across the four providers. Provider A tends to give larger loans, with the average account taking loans of 9815 KSh. Finally, the salary loans given by Provider B tend to be more upmarket than any other provider in the sample, with an average loan in one of these accounts being about 12128 KSh.

3.3.2 Effective Tenure

How long to borrowers take credit for? To get a sense of loan lengths I look at average effective tenure i.e., how long the borrower maintained a non-zero balance with the digital credit provider.[10] That is, to compute effective tenure I calculate the number of days a borrower ended with a non-zero balance (i.e., owing the provider money) and divide this by the number of loans

[10]Unfortunately, in general the data request did not retrieve information about the tenure of specific loans.

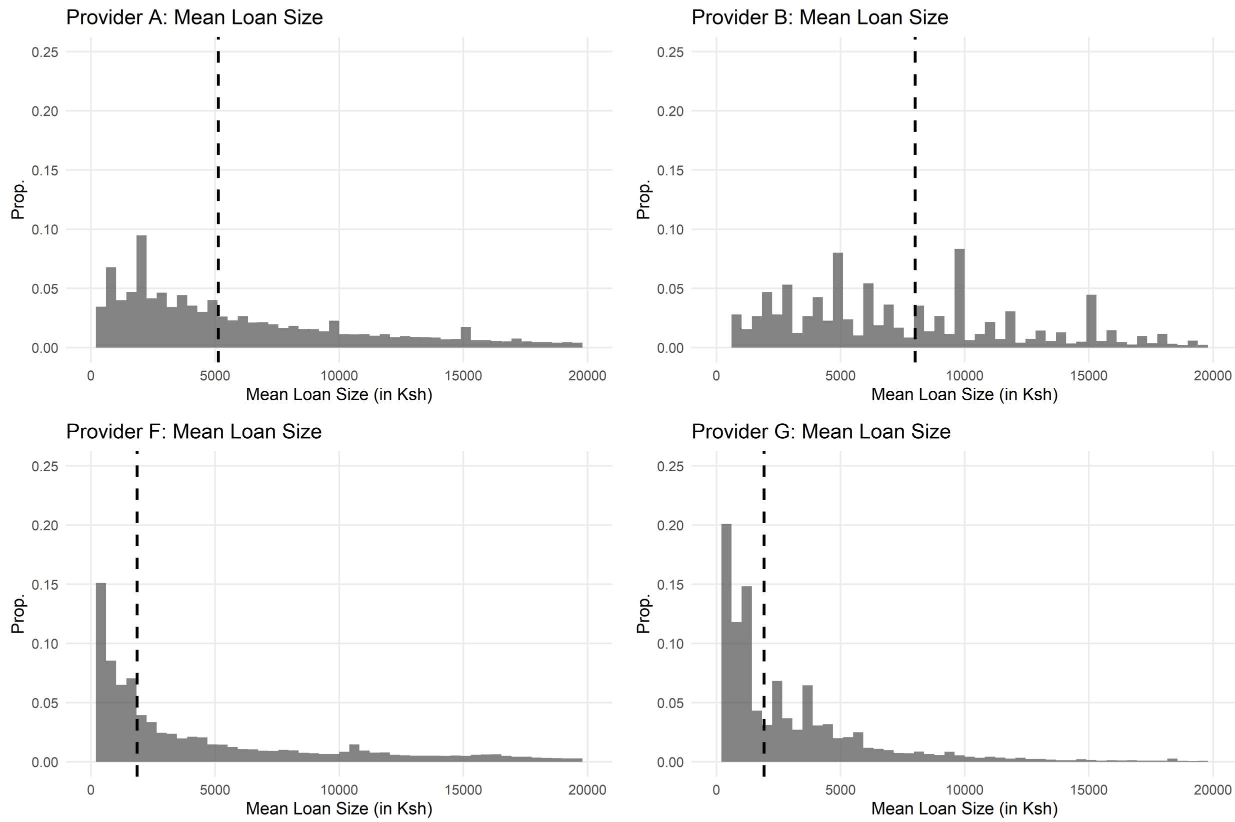

Figure 3: Average Loan Size by Account

they were disbursed over the time frame of January 1st, 2019 to March 31, 2020.

Most digital loans taken in the Kenyan economy are short loans with a single repayment date, referred to as "bullet loans." This is reflected in the data, with relatively short median effective tenures in the market, of about 35 days. The distribution of effective tenure is presented in Figure 2. There is some heterogeneity in effective tenure between borrowers, though it is difficult to tell what is driven by loan flexibility as opposed to late repayment. 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.

At the provider level, that the mean effective tenure tends to be inversely related to the mean loan size. This negative correlation tends to hold at the account level as well, as is presented in Figure A.8.

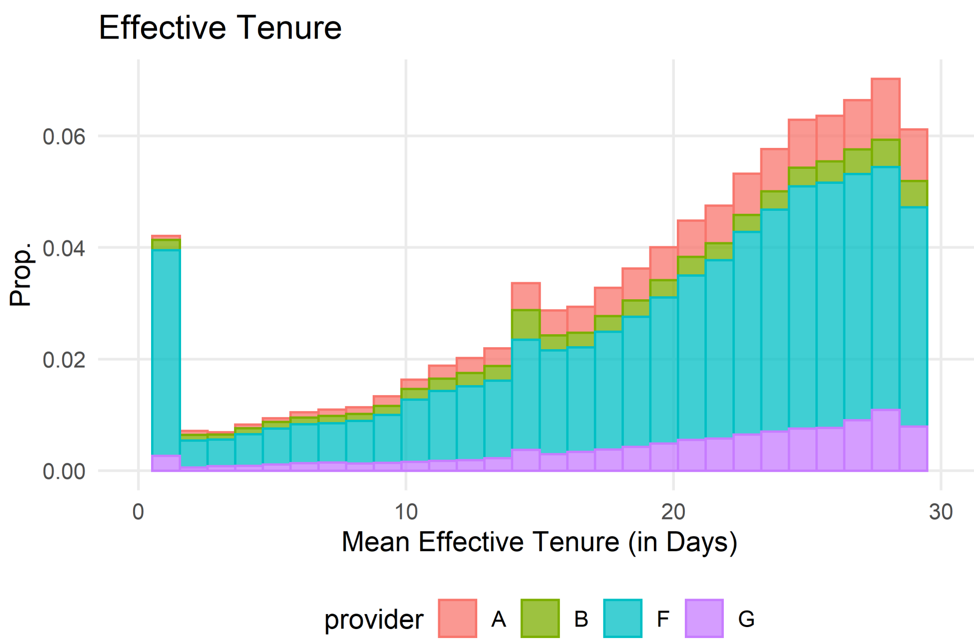

Figure 4: Loan accounts that repay in less than 30 days, on average, disaggregated by provider.

3.3.3 Early and Late Repayment

Looking at effective tenure, what can I say about early and late repayment by borrowers? I tend to believe the accounts found in the left tail are late-repayers. For example, Provider B, who I have information on tenure, offers only one and two month loans. Even on simple inspection I see some average repayment times above 61 days, indicating late repayment. However, I also know that these are salary loans, and thus are paid automatically out of the account of the borrower. Hence, it is unsurprising I do not see a "thick" right tail for this provider's distribution. The few accounts who have these high values of effective tenure tend to drive the averages. As compared to the median effective tenure of 35 days, the mean effective tenure is 81 days among these four providers.

One note when looking at the right tail of effective tenure of loans is that some of the patterns are driven by delinquent loans. In particular, the "bunching" behavior notably in Figures 2 and A.5 reflect this. In particular, if a loan is abandoned or not repaid in the dataset, the effective tenure increases to fill the length of time I observe (about 15 months, or around 450 days). If a borrower took one loan at the start of the dataset and didn't pay it back I would observe a mean effective tenure of around 450 days for that borrower. If they took out two loans, starting at the beginning of the dataset, and didn't repay the second, I would observe a mean effective tenure of 225 days for that borrower. Three, 150 days, and so on. Of course, I see clear bunching to left of these numbers in the histograms of effective tenure.

We also observe some degree of early repayment. It is relatively easy to characterize this as early repayment based on Terms & Conditions for these providers. This deserves a look because it speaks to a degree of flexibility in obtaining loans that might be valuable to consumers (assuming of course, that facilitation fees might vary somewhat with tenure). In particular, despite the fact that providers do not tend to offer loans less than 30 days in length, I see repayment much earlier. As I observe in Figure 4, 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 tenures of less than four weeks and 5.1% have an average effective tenure of one week or less.

This pattern of early repayment represents and important feature of the credit market. While it is difficult to conclude much, it does bring to mind a set of consumer risks. First, if borrowers are paying a month of interest for loans they only need for a week, this represents a very costly approach to credit. Second, it may represent a problem with product suitability in the digital credit market. When surveyed, almost half of digital credit users felt that digital loans in Kenya were insufficiently flexible in their tenure (Gubbins and Totolo, 2019). In particular, respondents were asked about loans being too short. These finding present an alternative issue with flexibility. That is, that borrowers have a shorter term relationship between cash flow in and out and would ideally be offered lower cost (in terms of fee to disbursement) loans of a shorter tenure, or some kind of early repayment rebate. This finding coincides with the growth of product H2, which offers short term credit.

Gender	Mean Tenure (in Days)	Mean Loan Size (in KSh)
Female	68.59	6473.51
Male	76.22	8229.48
No Data	89.86	5460.44

Age Group	Mean Tenure (in Days)	Mean Loan Size (in KSh)
18-24	109.74	1991.65
25-44	81.65	7617.08
45-64	69.73	9373.89
65+	70.95	6270.38
No Data	77.49	5716.31

Provider	Mean Tenure (in Days)	Mean Loan Size (in KSh)
A	63.70	9815.10
B	30.63	12127.81
F	76.08	6334.56
G	118.18	4033.71

Table 6: Effective Tenure and Loan Size by Gender, Age, and Provider

3.4 Account Characteristics by Age and Gender

How do features of loan accounts relate to gender and age? Considering gender, I note that men tend to have longer average effective tenure of loans. In particular, men's average effective tenure is about 76 days, whereas women's average is about 69 days, seven days shorter (Table 6). While such a difference could in theory be driven by early repayment behavior, I find that in practice it is driven entirely by less intense late repayment behavior. Of those who repay within the first month, women and men repay on nearly the same schedule. However, as can be seen in Figure A.7, women are faster at repaying once this period of time has passed.

Men also tend to have considerably larger loan sizes as compared to women, 8229.5 KSh as compared to 6473.5 KSh on average, as can be seen in Figure A.6. Those accounts not associated with gender data tend to have smaller loans on average, but longer tenure. This may accord with the fact that these are younger borrowers, or with the fact that their lack of KYC may be associated with other risk factors.

As one might expect, I see that loan size tends to have a "inverse-U" shaped relationship with age Figure (Figure 5). That is, as one gets older, I 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 ones early 50's and falls until old age, when I see a slight increase, which may be driven by selection.[11] While noisier, this "inverse-U" tends to be borne out even when the data is disaggregated by provider (lower panel, Figure 5).

When considering effective tenure, I see that this statistic falls dramatically over cohorts of borrowers. This pattern also suggests that effective tenure is driven more by repayment behavior than loan length. Again, I see some anomalous behavior for older borrowers, with a subset of older borrowers with long effective tenure. This also seems to be borne out when the data is disaggregated by provider, except in the data of Provider B, who see small increases in tenure across age (lower panel, Figure 5).

Additionally, I can consider how the difference between men and women's average loan size and effective tenure changes throughout the age distribution in the middle panel of Figure 5. For loan size, while women have lower average loan size at each at every age, the difference is most pronounced as I see loan sizes reach their peak. For effective tenure, the effect is more complex: I note that while younger women have lower effective tenure then men, women aged about 55 and up tend to take as long or longer to repay as men do. For further breakdown of tenure and loan size by demographics and provider, see Tables A.2 and A.3, which summarize statistics across these groups.

3.5 Discussion: Consumer Risks and Digital Credit

A number of risks are already suggested by this analysis. One of the most pronounced is a risk of unfair treatment on the dimension of gender. Not only do women get smaller loans on average, suggesting smaller credit limits, but also tend to repay these loans quicker. These themes will be important to continue exploring, so I will make a special point to return to gender disaggregated analysis when considering pricing of digital credit, late repayment and default, and the degree of

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

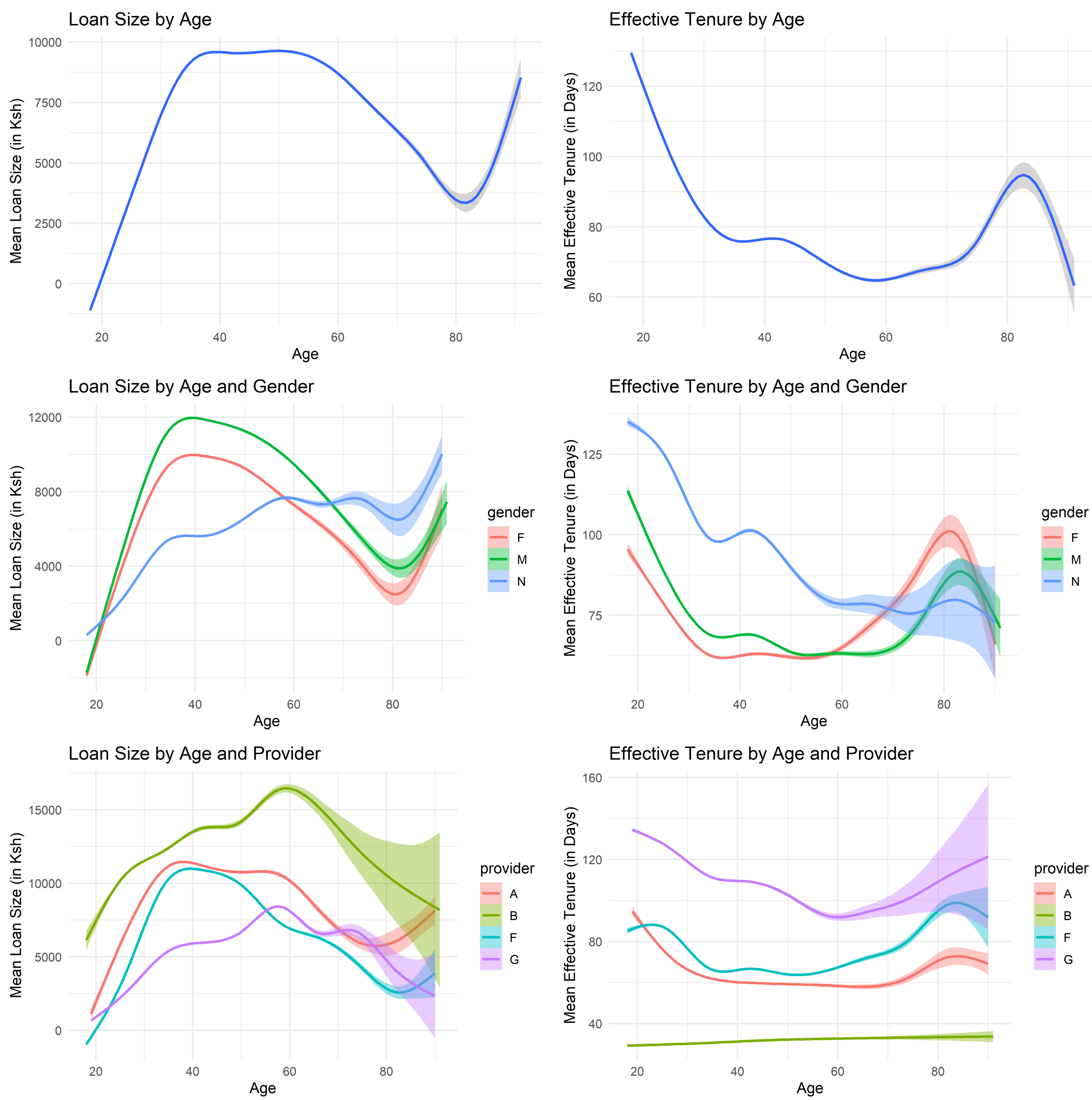

Figure 5: Loan size (left) and effective tenure (right) by age. Middle panel is disaggregated by Gender and the lower panel is disaggregated by Provider.

risk-based pricing.

Additionally, the number of early repayers in the sample, combined with the attractiveness of short term loans brings to the forefront the risk of suitability of credit. Likewise, understanding what drives these early repayers is an interesting avenue for future research.

4 The Price of Digital Credit

The first set of consumer risks I address stem from both the average price of digital credit lending and the application of fees. Pricing is a headline issue in financial inclusion and digital credit is no exception (Francis et al., 2017). In Kenya in particular, an interest rate cap was used over several years to try to control the price of credit (Safavian and Zia, 2018).

However, despite obvious distributional consequences, the overall welfare implications of the price of credit are not simple. As in microfinance before it, if an aim of digital credit is to make credit more mass market and introduce new consumers to lending, it follows that lenders may need to be compensated in order to provide credit to higher risk borrowers (Morduch, 2000). Price can just as easily be influenced by factors unrelated to cost, such as the absence of competition or the shrouding of fees (Gabaix and Laibson, 2006). Finally, interest rates themselves may drive selection into credit due to *ex ante* adverse selection and default due to *ex post* moral hazard (Stiglitz and Weiss, 1981; Karlan et al., 2009).

While the analysis cannot answer the question of what the optimal interest rate is for borrowing or the optimal policy to reach this rate, I can provide evidence about the price of digital credit in Kenya, illustrate comparisons between providers, and provide an understanding of how fees are applied with an eye for fee complexity that might obscure prices. In this section, I measure the effective price of credit at four digital credit providers in Kenya and take a deeper dive into the cost of constituent fees at two providers and the dynamics of when fees are charged. We find that the price of credit is quite high – particularly when one considers effective tenure of credit. In particular, within the sample of providers I find that credit has a mean effective APR of 280.5%

and median effective APR of 96.5%.

4.1 The Effective Price of Digital Credit

4.1.1 Effective APR

To measure the effective price of credit I process each of the providers that I have complete data into summaries of the user accounts. I 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. Longer effective tenure of loans for the same cost is, in effect, cheaper credit. To measure the effective price of credit I include any and all observable fees that are paid to access credit. This measurement can be done using a statistic similar to APR, which I call Effective APR. Ordinarily I would compute APR,

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

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. The cost will once again be expressed as an APR, with some modifications to account for effective tenure. In situations where I are able to observe the effective tenure of loans directly I could compute

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

However, I cannot do this for all of the datasets, notably because in some cases loans overlap. Thus, I instead use a proxy for the denominator of effective APR. In particular, I compute

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

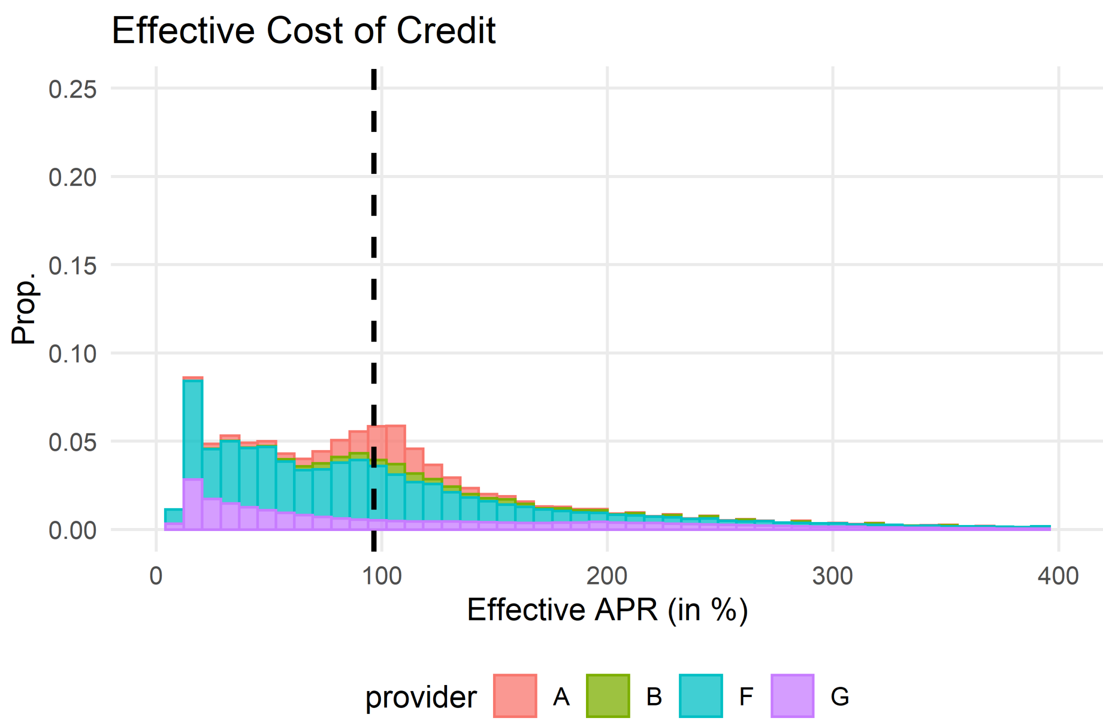

Figure 6: Effective price of credit after aggregating the accounts of four providers. the dotted line is median effective APR.

where

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

and

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

where % Disbursed $\times$ Total Balance-Days $\approx$ Effective Tenure $\times$ Principal.

4.1.2 Data Processing

To limit the influence of outliers in the data, I do minimal cleaning on the data after computation. In particular, in the case that a loan is paid back the same day, I enforce a minimum effective tenure of one day and a minimum effective balance of the loan disbursed plus fees. Likewise, in certain cases I do see that there are typos when entering repayment amounts that lead to consumers repaying more than the loan value, though this is a relatively small portion of the

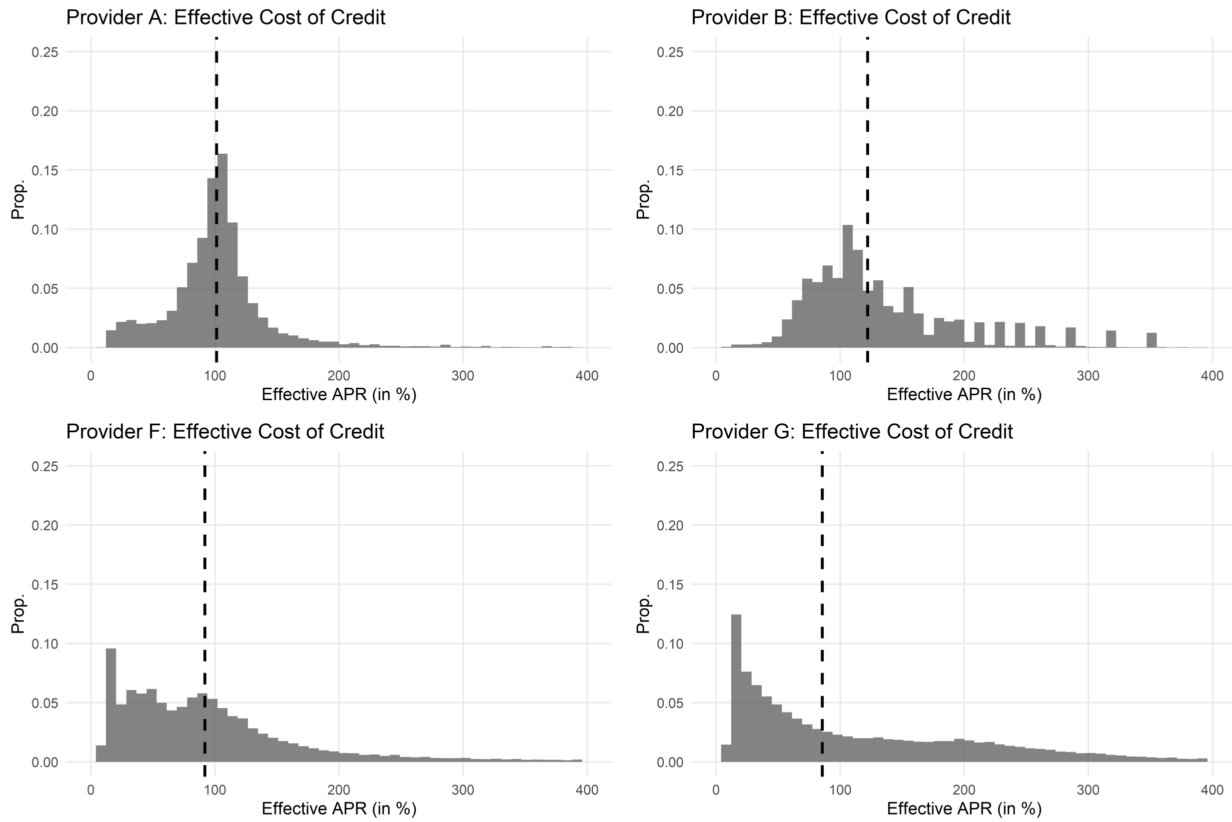

Figure 7: Effective price of credit from various providers. The dotted line in each figure is median effective APR.

data I encounter. I enforce that a given loan can only be paid back to zero to avoid negative APRs (this might happen e.g., due to typos). Finally, after computing effective APR I trim the maximum value above the 99th percentile from each dataset to reduce the impact of outliers on the results, and remove any negative values calculated due to errors in the data.

4.1.3 Effective Price of Credit

We find that the cost of digital credit in Kenya 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 price of credit is highly right skewed, meaning I observe a long right tail of high cost credit.[12] I can see also see this skew in the histograms of price of credit, presented

[12]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.

Provider	Median	Mean	Std. Dev.
A	101.41	103.63	48.44
B	122.07	192.09	281.12
F	91.84	375.97	1078.06
G	85.51	133.47	143.64

Table 7: Effective APR by Provider

Gender	Median	Mean	Std. Dev.	Prop. Sample
Female	99.61	268.96	841.84	19.06
Male	98.34	252.09	788.52	33.15
No Data	91.45	305.76	902.82	47.8
Age Group	**Median**	**Mean**	**Std. Dev.**	**Prop. Sample**
18-24	76.00	193.08	638.19	8.45
25-44	101.52	222.84	655.23	40.25
45-64	101.17	247.90	767.53	10.87
65+	96.34	249.05	830.58	0.98
No Data	90.97	374.04	1077.05	39.46

Table 8: Effective APR by Gender and Age

in Figure 6 with the individual providers highlighted by color. Here I note not only the skew of the distribution but also the incredible heterogeneity in cost, both between providers, and within individual providers. I present these provider level distributions in Figure 7. In particular, this long right tail is most pronounced in providers F and G.

One reason for highly skewed distribution is the presence of early repayment. I do not observe early repayment fees, rather, some of the very high effective APRs are due directly to the short period of time credit is utilized. The shorter the amount of time credit is taken out for, the higher the APR is in effect. For this reason, I 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, I find different results by how I measure the average experience of consumers. Considering the median consumer for each firm, I find that provider G is cheapest (at 85.5%), followed by provider F, A, and B as the most expensive. However, when I look at the

	Provider A		Provider B		Provider F		Provider G	
Gender	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Female	106.1	48.1	193.8	280.4	347.6	1041.4	141.2	135.4
Male	102.4	48.6	191.0	279.9	356.2	1051.2	127.3	131.5
No Data	102.3	41.2	195.6	290.9	399.7	1108.0	133.9	147.1

	Provider A		Provider B		Provider F		Provider G	
Age Grp	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
18-24	102.4	60.8	207.2	308.0	323.3	1009.5	109.6	132.0
25-44	104.7	50.2	195.7	288.0	388.0	1077.9	136.9	146.1
45-64	101.2	41.4	166.5	224.8	393.9	1125.9	156.3	143.9
65+	100.3	37.8	158.2	208.3	349.8	1083.6	172.9	152.6

Table 9: Effective APR at the Provider level by Gender and Age.

mean price of credit, 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% (Table7).

4.1.4 Gender, Age and the Price of Digital Credit

In addition to heterogeneity across and between providers, I see heterogeneity in the price of credit by both gender and age. Table 8 presents costs disaggregated by gender and age in the market as a whole while Table 9 presents price 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, I 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 I are assessing: Provider A, B, and G. Interestingly, women pay less than men at the largest provider in the sample, though this is not enough to drive the market as a whole. The largest difference in effective price of credit comes from Provider G, where women pay 13.9% more in effective APR as compared to men. While both men and women's average price are drawn up by expensive effective APR from early repayers, the difference in the price of credit documented here is not particularly dependent on early repayment. Figure A.7 documents the difference, though the potential for late repayment

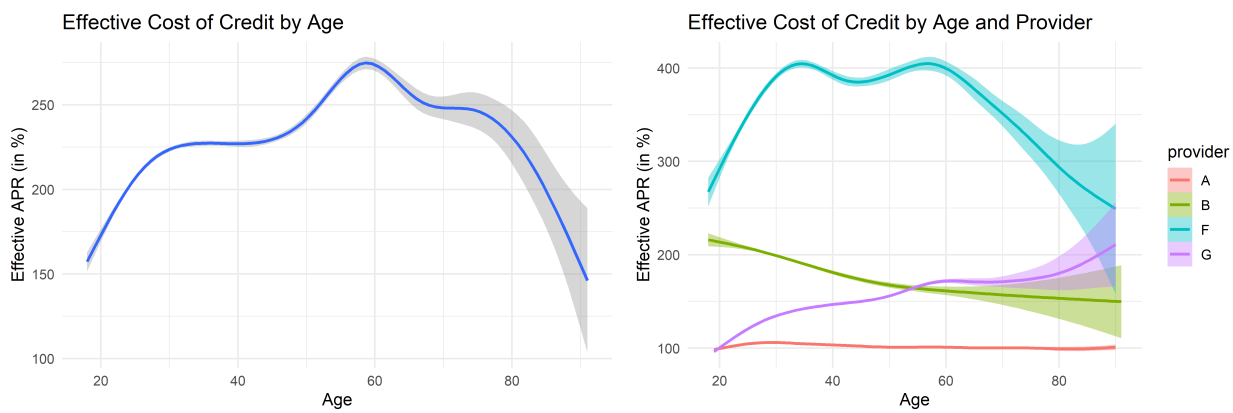

Figure 8: Left Panel: Effective price of credit Rapidly Increases in One's Twenties and then Falls Until Old Age. Right Panel: This pattern is driven by Provider A and F.

may have an ambiguous effect on total cost of credit, given that men tend to repay slower and may be more likely to be penalized (at least by Providers A and F). Additionally, I find that the women's distribution of effective APR is shifted just a bit upward from men's in the range from very low prices to prices nearing 200%. Finally, when I consider both age and gender, I see that women have higher effective APR than men across the spectrum of age (Figure 9. The difference tends to be most pronounced around age 55, though it is unclear what drives this difference.

Considering price of credit by age, I again find different results depending on the measure of price of credit. When I consider the average effective price of credit I see that the most expensive credit in the market is taken on by older adults and the elderly, with those 45-64 pay 247.9% and those 65 and over paying 249.0% in effective APR.[13] However, when I consider the experience of the median borrower, the price of credit follows an inverted-U shape with regards to age. Those borrowers aged 25-44 and 45-64 pay a median of 101.5% and 101.2% in effective APR, respectively. When I visualize effective APR over the age of borrowers in the market in Figure 8, the true story seems to be somewhere in between. I note that the inverted-U pattern seems to be driven by Provider F, the largest provider in the sample. Other providers behave differently however. For example, while provider A features the same U-shaped pattern it is considerably less pronounced.

[13] Age groups are chosen to be directly comparable to those in the Consumer Protection Survey undertaken by IPA (Blackmon et al., 2021). To flesh out more subtle differences in behavior as it relates to age I will visualize cost (and other outcomes) as a function of age.

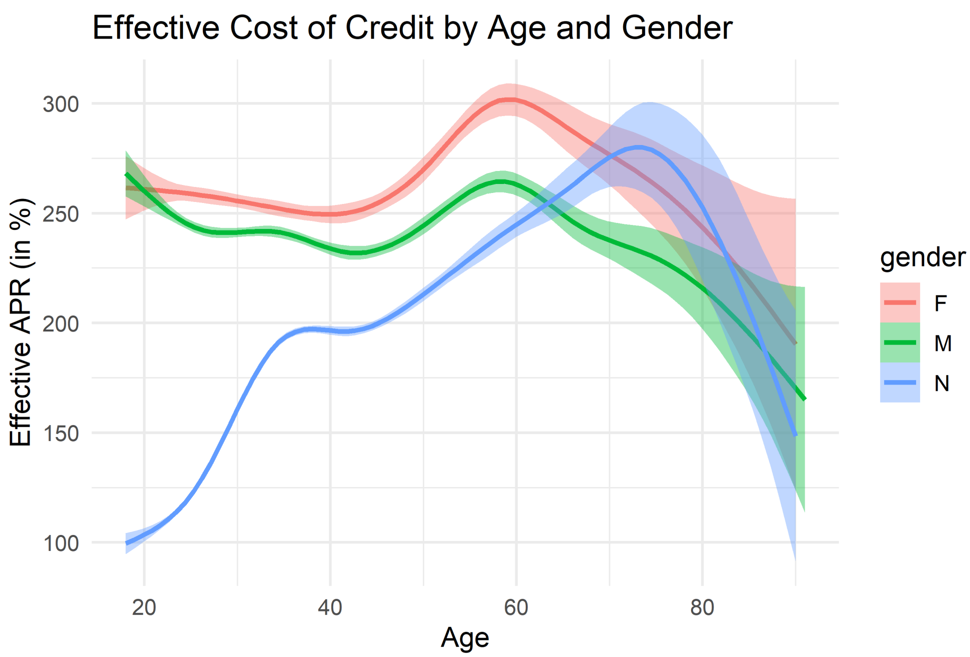

Figure 9: Effective APR

Elsewhere, Provider B features price of credit that falls with age and provider G sees price of credit that rises with age.

While I 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 differences 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 post or salary to get one of 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 likely differs considerably between the two groups, with younger consumers being more active on their mobile devices relative to their older peers.[14]

The price of credit is difficult to present solely as a consumer protection risk, despite its ob-

[14]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 (Björkegren and Grissen, 2019). Likewise, mobility (as measured by GPS/radius of gyration) has been shown to be highly predictive of wealth (Blumenstock et al., 2015).

vious connection to consumer welfare. Providers' profit also contributes to welfare – balancing the aggregate and distributional welfare consequences of price regulations is difficult Cuesta and Sepulveda (2019). Despite this, it is not unreasonable to note that the price of credit is very high among digital lenders at the current moment.

The next two subsections dive into the details of what fees are charged and when to more clearly present features of the credit market and enunciate a set of consumer protection risks surrounding the application of fees and charges in digital credit. Likewise, the final subsection deals with price comparison across a wider group of providers to think about how competition in the credit market may drive price.

4.2 What Types of Fees are Used in Digital Credit?

What types of fees are used in digital credit in Kenya? To understand this, I dive into the data of individual providers, using different providers as case studies for the types and application of fees in the Kenyan digital credit sector.

There is a great deal of heterogeneity in the data received regarding fee types, both in the actual fee types recorded, whether or not fee types are disaggregated, and in the types of fees charged themselves. Table 10 summarizes the data received and how it can be used to understand fees in the market. Overall, of the transaction data I analyze in depth, only providers A and F submit. This is done with the caveat that these providers are not perfectly representative of the rest of the market.

4.2.1 Data Processing

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. For example, Effective APR from Interest is computed

$$\text{Eff. APR from Interest} = \left(\frac{\text{Cost from Interest} \times 365 \text{ days}}{\text{\% Disbursed} \times \text{Total Balance-Days}} \right) \times 100\%.$$

	Provider						
Fee type	A	B	D*	F	G	H1**	H2**
Interest	✓		✓	✓			✓
Facilitation	✓					✓	
Penalty	✓		✓	✓			
Rollover	✓					✓	
Excise tax	✓			✓			
Other				✓			✓
Aggregated only		✓			✓		
Fee format	A	B	D*	F	G	H1**	H2**
Recorded with disbursement		✓		✓	✓		
Recorded in own transaction	✓		✓				
Not tied to a transaction						✓	✓

* indicates data was otherwise incomplete and therefore not analyzed.

** indicates that provider only supplied CAK with aggregated data.

Table 10: Fee Types and Formats Observed in Data by Provider

Fees will be split out into a number of categories including interest, facilitation, tax, and conditional fees (penalties, rollover fees). The same checks and adjustments are made to factors entering the calculation as well.

4.2.2 Interest Fees and Facilitation Fees

We start by considering interest fees to understand their importance in the price of credit. Consistent with a nominal interest rate cap which spanned roughly the first ten months of the sample, interest fees for Provider A tended to be under 15% Effective APR (even allowing for the effective tenure of loans to become short). More specifically, more than 99% of these loans have an effective APR from interest under 15%. The interest rate cap cap tied the allowed nominal interest rate to 4% above the Central Bank Rate, which was 9% over the relevant period. Due to this was set at 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.[15] Additionally, visually inspecting the distributions reveals "bunching" near the interest rate cap as can be seen in the left panel of Figure 10. This leads to a median Effective APR that is below the cap, around 9.6% (Table 12).

[15] The cap, which is illustrated in Figure A.9, was repealed on November 7th, 2019.

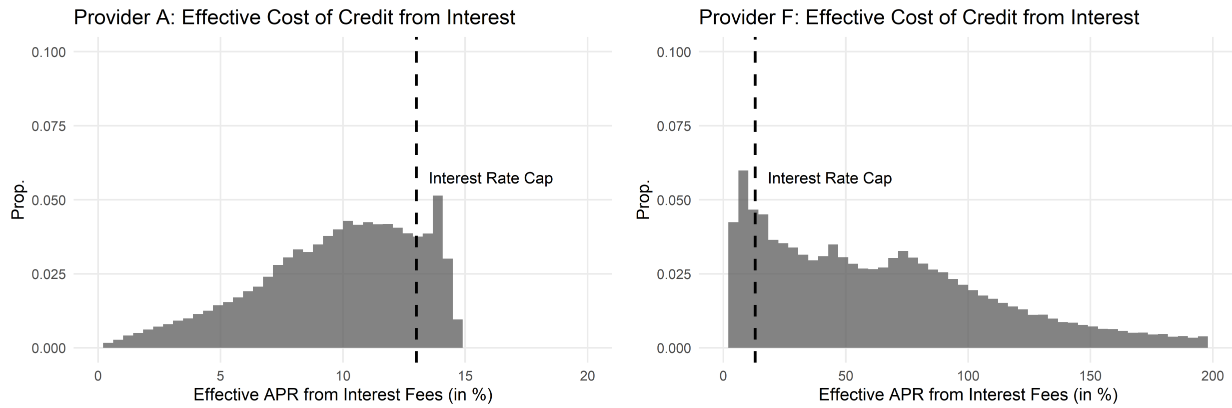

Figure 10: Effective price of credit from Interest Fees: Providers A (left) and F (right). The interest rate cap marked above was set at 13% for all but a few months of the sample, when it was removed. Please note that the x-axes differ between the figures.

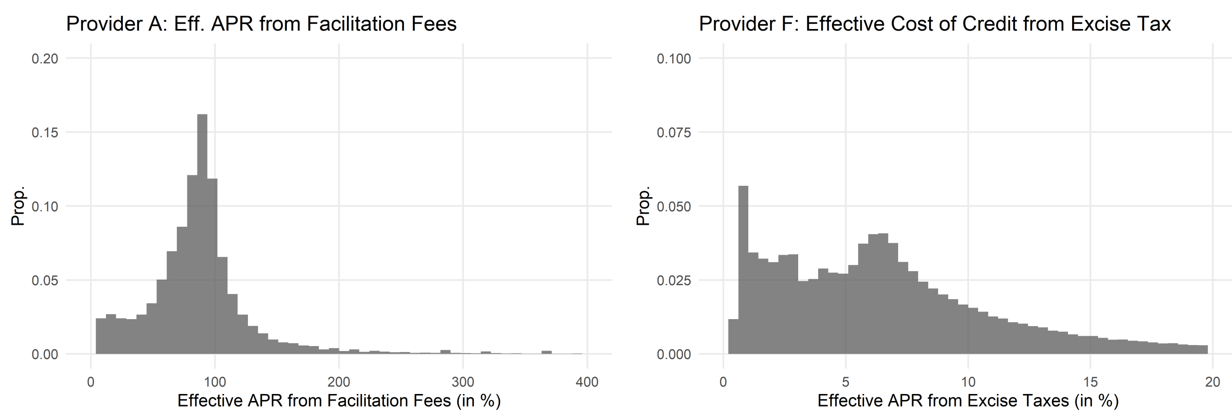

Figure 11: Facilitation Fees for Provider A (left) and Excise Taxes for Provider F (right). Note that the x-axes differ.

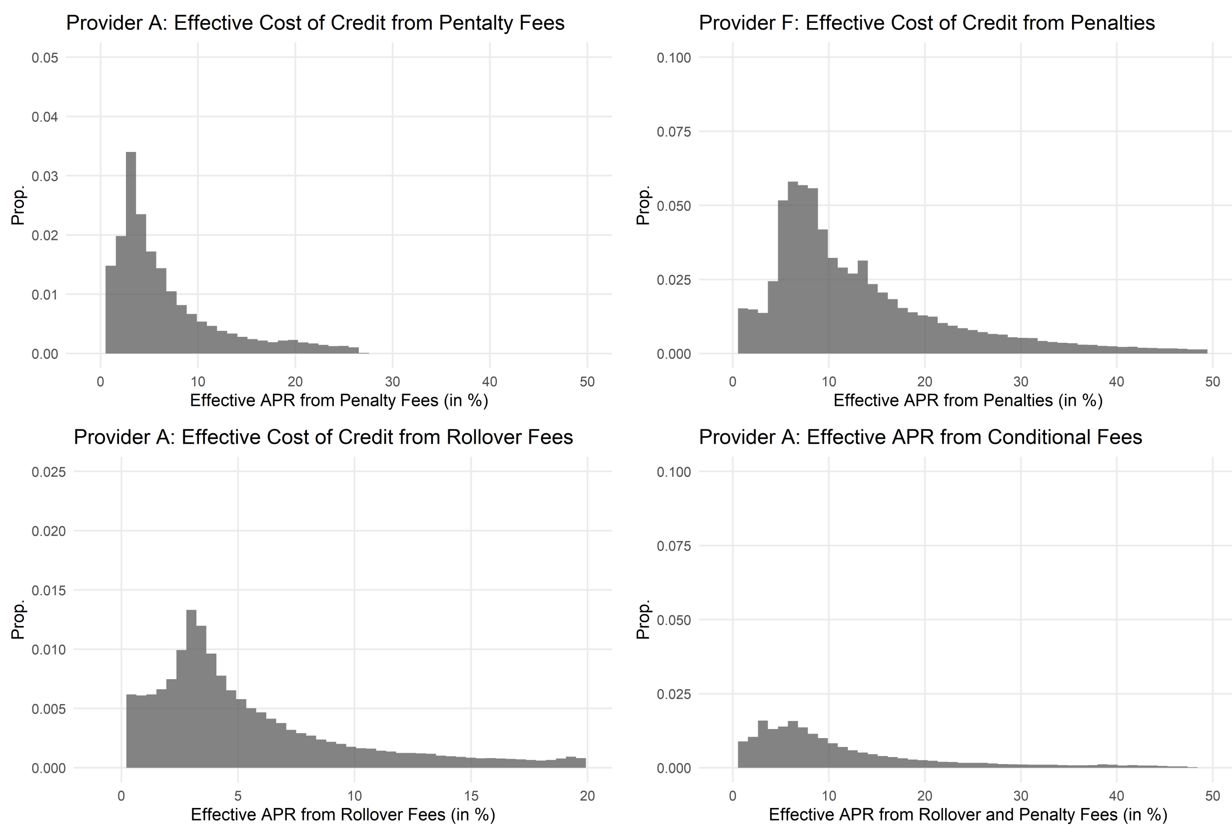

Figure 12: Cost due to conditional fees. Top left: penalties from Provider A. Top right penalties from Provider F. Bottom left: Rollovers from Provider A. Bottom right: Rollovers and Penalty Fees fees from Provider F.

Fee Type	Cost
Interest	Central Bank Rate+4% per annum
Loan Appraisal	Maximum of $0.05\times$ Disbursement
Excise Tax	$0.1\times$ Loan Appraisal (or maximum of $0.005\times$ Disbursement)
Insurance	Maximum of $0.01\times$ Disbursement

Table 11: Loan Terms and Conditions for Provider A

Considering Provider F, I do not see the same type 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 Facilitation Fees.[16] I observe a median effective APR of 72.9% and an average effective APR of 294.8% (Table 13).

Fee Type	Median	Mean	Std. Dev.	Prop. Charged
Interest	9.56	8.55	4.36	100.00
facilitation	86.38	88.8	49.32	100.00
Penalty	0.00	1.60	4.78	6.91
Penalty (Non-Zero)	5.44	6.97	5.36	100.00
Rollover	0.00	0.98	3.07	17.22
Rollover (Non-Zero)	4.13	5.98	5.25	100.00

Table 12: Effective APR From Different Fee Types for Provider A

Fee Type	Median	Mean	Std. Dev.	Prop. Charged
Interest	72.93	294.78	843.8	100.00
Tax	6.49	33.37	102.16	100.00
Penalty	7.96	38.39	134.11	66.86
Penalty (Non-Zero)	11.76	51.96	153.75	100.00

Table 13: Effective APR From Different Fee Types for Provider F

This analysis highlights one source of fee complexity in costs faced by borrowers. In particular, 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

[16]In fact, given that facilitation fees were not submitted, I presume that this is the case.

what would normally be considered interest, with what but whereas labeled "facilitation fees" to avoid having to comply with the cap for digital loans (cof, 2018). This obfuscation, however, doesn't just serve as a loophole, it also increased the complexity of loan fees by pushing interest towards facilitation fees like facilitation fees (Ferrari et al., 2018).

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 I can compute the maximum effective APR for a one-month loan as 91%. From these T&C's I can compute the maximum rate for a one month loan: $\text{APR} = \text{Central Bank Rate} + 4\% + 12 \times (5\% \times 1.1 + 1\%) = 91\%$. 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, facilitation 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.

The effective APR of credit due to these facilitation fees tends to exceed the rate computed using information from the T&Cs for Provider A. For example, this can be seen in 11. In particular, facilitation 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. I do not observe regular non-interest fees for Provider F, which furthers the belief that some fees are miscategorized for the purposes, though I do see excise taxes disaggregated, which tend to be on the order of less than 10% in terms of APR.

4.2.3 Conditional Fees: Penalties and Rollovers

Another large source of cost, and a potential risk, for these borrowers are penalties and rollover fees – which trigger when loans are repaid late or are rolled over (often to avoid late repayment). How much do these fees cost consumers? I observe penalty fees for both providers A and F and rollover fees for provider A.

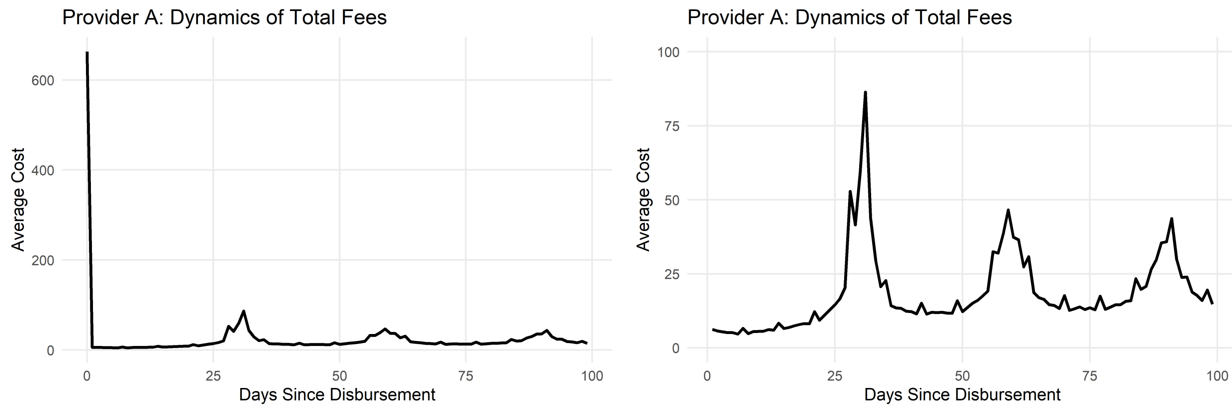

Figure 13: Average Total Cost of Fees in the First 99 Days After Disbursement. Fees charged at origination are included at left, while only fees charged after origination are included at right.

We first note that a much large proportion of borrowers pay penalty fees to Provider F as opposed to Provider A. In particular, while 66.9% of borrowers at Provider F have paid penalty fees, a comparably mild 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, I 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 add marginally to total cost in terms of APR when they are used. 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%.

4.3 When Are Fees Charged?

When are fees charged in the loan cycle? One might expect that all fees would enter the account at disbursement (to be paid at later dates), where fees are introduced as transactions this is not always true. To get a sense of the dynamics of fees – when the most expensive fees are charged

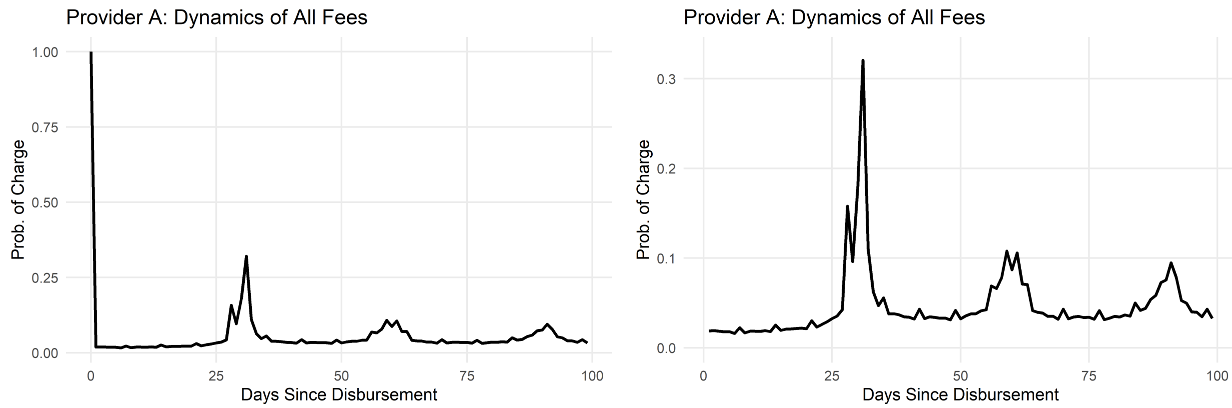

Figure 14: Average Probability of Fees Being Charged in the First 99 Days After Disbursement. Fees charged at origination are included at left, while only fees charged after origination are included at right.

relative to disbursement – I perform a case study with the data of Provider A and find that while most fees are charged at disbursement, interest fees accrue when loans are repaid, and rollover fees will accrue on automatic rollover. This brings to light consumer risks around the complexity and transparency of digital credit.

4.3.1 Data Processing

To process the data, I work from the transaction data to find a 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 me to understand how fees behave in these first three months (as well as shortly thereafter – for comparison). I then average the total fees paid by day after the disbursement and visualize this data.

4.3.2 Dynamics of Total Fees

As a first pass, I visualize all fees charged in the first 99 days after the first disbursement, plotting average total fees in Figure 13 and the average probability of being charged a fee in Figure 14. I 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.

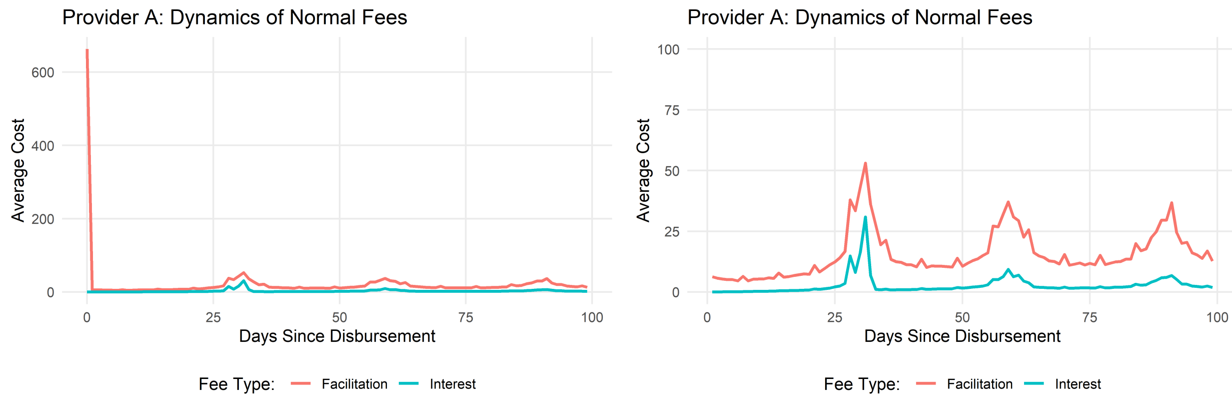

Figure 15: Average Cost of Normal Fees in the First 99 Days After Disbursement. Fees charged at origination are included at left, while only fees charged after origination are included at right.

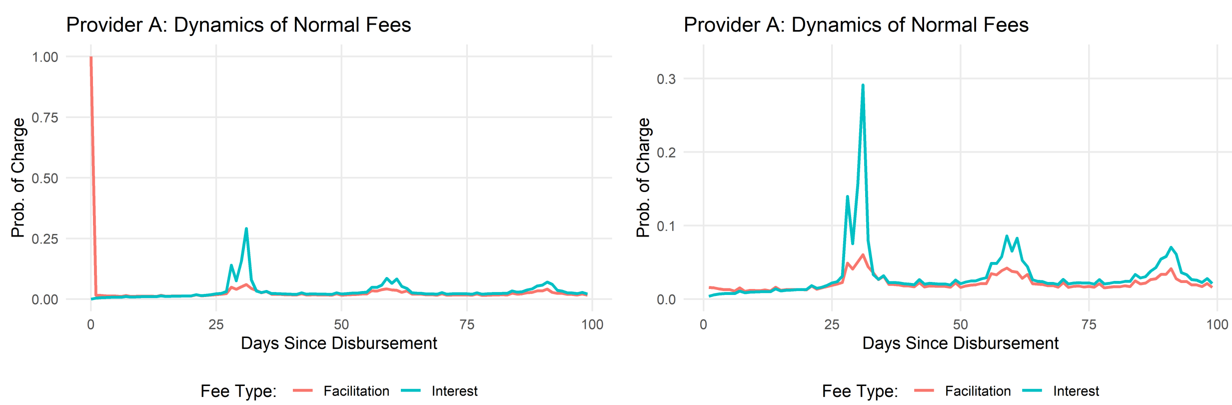

Figure 16: Average Probability of Normal Fees Charged in the First 99 Days After Disbursement. Fees charged at origination are included at left, while only fees charged after origination are included at right.

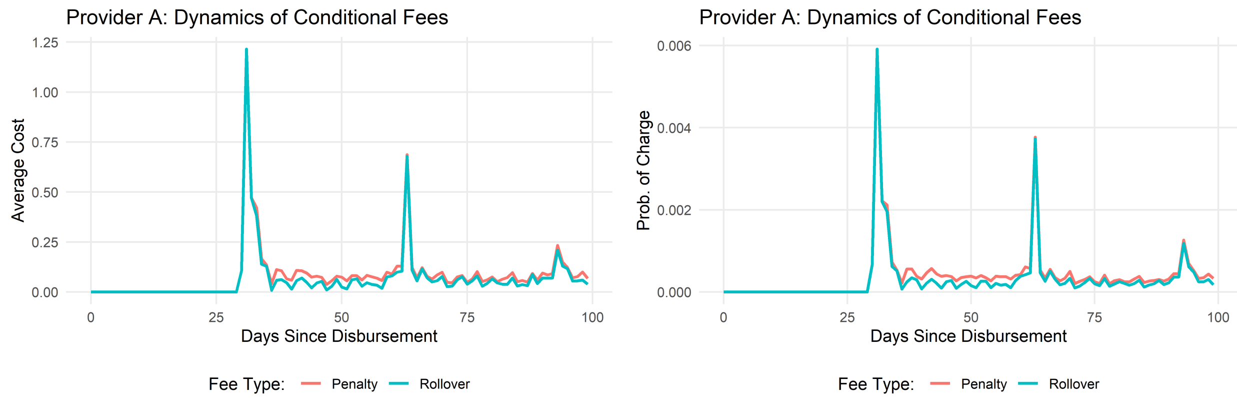

Figure 17: Average Cost (right) and Probability (left) of Conditional Fees Charged in the First 99 Days After Disbursement.

4.3.3 What Drives Fee Dynamics?

To understand what drives fee dynamics, I desegregate these fees into the same four categories I defined above – interest, facilitation fees, penalties, and rollovers. I start with what I term normal fees, including interest fees and facilitation fees. Visualizations of these fees are presented in Figures 15 and 16 which plot the average cost and probability of being charged of these fees, respectively. I note that Non-Normal Interest Fees drive the entirety of the upfront cost – which is consistent with their role in the T& C's from Provider A.

In 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 T&C's, it's unclear if first time borrowers know they have not yet been charged interest e.g., when they go back to pay back their loan.[17] This also may add to complexity – while facilitation fees are quoted as a percent of the disbursement, interest fees are presented per annum. The borrower reading such T&Cs might think of the facilitation fee as 5% per annum (as opposed to what is in effect – per month).[18]. I also note that facilitation fees tend to increase as the end of each month. My sense is that this is due to additional loans being originated in accounts directly after the closing of the first loan.

[17]This turns out to be relatively common across providers (Gwer et al., 2019).

[18]Of course, mathematically gifted consumers may be able to work out these fees. However, in the classic treatment of the similar case of shrouded fees, it is consumer myopia which allows them to exist in the first place (Gabaix and Laibson, 2006)

This brings me to conditional fees, which are presented in Figure 17. Notably, penalties and rollover fees track very closely, both in their cost and when they are applied. Consulting the T&C's once again, I note that they make reference to unsettled loans automatically rolling over with the same terms as previously agreed upon.[19] While this auto-rollover is relatively rare on a per loan basis (no more than 1% of loans), it may persist. For example, rollover fees are applied to approximately 0.6% of accounts on the peak day after the first month, and about 0.4% after the second, which may suggest a propensity to rollover loans a second time conditional on doing so a first time.[20]

4.3.4 Discussion: Transparency, Disclosure, and Fee Complexity

It is important to note that these results falls within a context where disclosure of fees in DFS is now more commonplace (Mazer, 2016). However, even when disclosure takes place, complex terms may still cloud transparency for consumers. The existence of facilitation fees priced differently than interest fees is one example of how disclosed fees might be non-transparent. Likewise, fees that are charged later in a process may also serve to dilute transparency. Finally, loans that automatically rollover may result in fees the consumer did not expect to pay. If consumers remain myopic about fees, such complexity might work similarly to fee shrouding, dampening the ability of competition to reduce the price of credit (Gabaix and Laibson, 2006).

4.4 Competition and the Price of Credit

Competition (or the lack thereof) is one of the most important features of markets for controlling the price of credit. While I have limited data to assess the degree of competition in the market. One way I can provider suggestive evidence around competition is to track how prices between firms vary. If differences in average prices persist between providers, this is suggestive that consumers cannot easily move from a more expensive to less expensive firm. Figure 18 shows the

[19] A similar practice is used by other Providers, including Provider F.

[20] Given the limited data about loan tenure in this dataset, and the fact that overlapping loans are common, it is difficult to nail down such a statement.

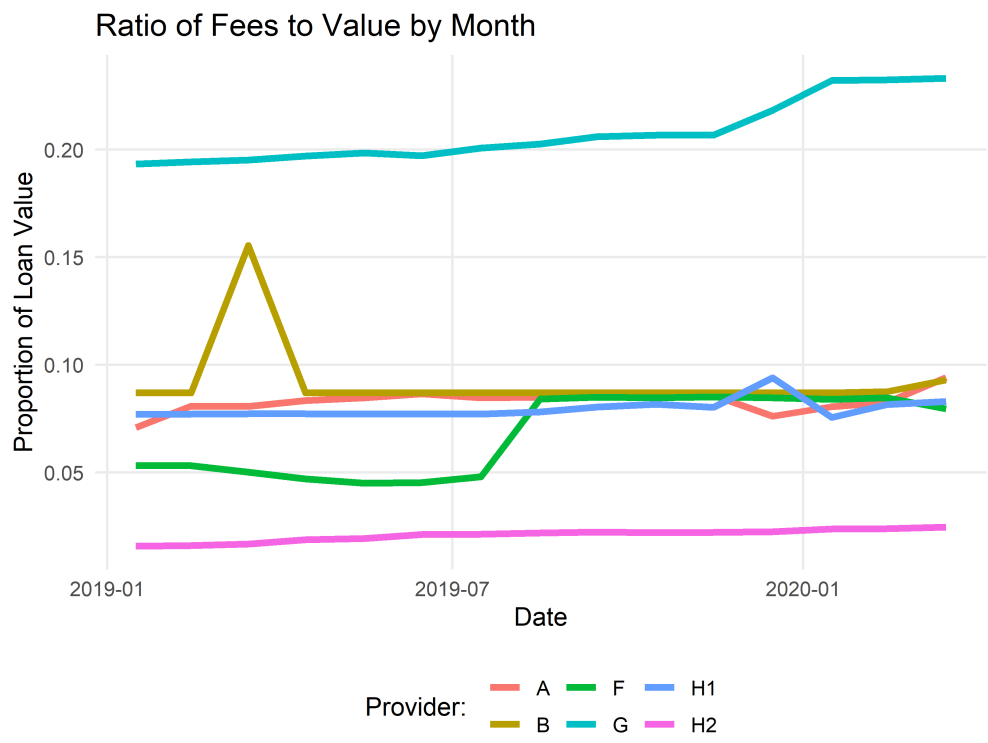

Figure 18: Evolution of Fee Ratios for Digital Credit Providers

evolution of the ratio of fee to over the course of the sample. For Providers A, B, F, and H1 – the regulated digital credit lenders – I see a similar fee to value. While Provider B and Provider F feature different average fee to value ratios early in the sample, these converge to the other providers by the end of the sample. Given that most of these loans are homogeneous 30 day bullet loans, this would suggest that these firms are part of each other's relevant market.

For the overdraft product, Product H2, I see lower fee to value ratio throughout the length of the sample. However, the overdraft product has much shorter tenure as overdraft fees are charged by the day. The price of credit for loans of average size at this Provider are in fact comparable to those at the regulated providers. For example, consider a seven day repayment of a 31 day loan with 94.1% APR (this would have a fee to value of about 8%, similar to the standard digital credit loans). Considering the pricing schedule of Product H2, I see that the two would not differ much until loan sizes become large. For small loan sizes the overdraft product would cost much more (Figure 19). The symmetry in pricing suggests that the overdraft product is a potential competitor

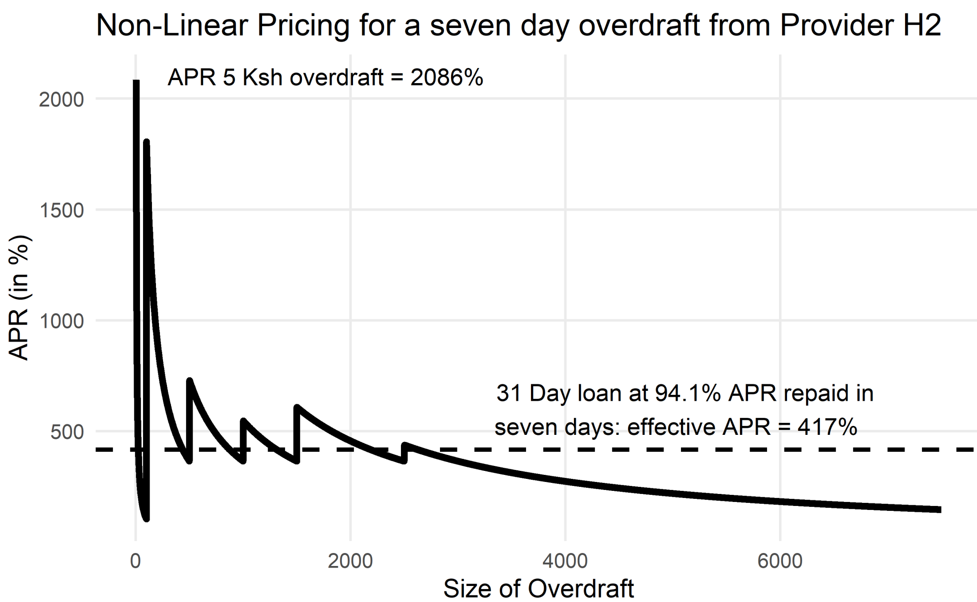

Figure 19: Provider H2 Pricing Example

to traditional digital credit products from regulated providers, as I don't see that the price is much higher or much lower.

On the other hand, Provider G, an unregulated non-bank digital lender, I see much higher fee to value which continues to rise over the course of the sample. The much higher price of Provider G suggests that perhaps unregulated providers do not always compete directly with regulated firms. For example, these providers may borrow to those who did not pass screening for the regulated borrowers. This could be due to their ability to charge variable interest rates that exceed the nominal interest rate cap. This would also allow them to extend credit to borrowers with riskier profiles who might not qualify for loans from the other lenders.

While this analysis does give me useful information about the scope of the relevant market, a limitation of this evidence does not indicate that the market features a competitive equilibrium. First, this analysis of competition would be remiss to omit concentration in related markets. In particular, the mobile money product M-PESA, which is the dominantly used mobile money service in the Kenyan economy, is associated with three of the products in the market. In fact, these products are accessible from the SIM Toolkit (now USSD as of 2020), which may allow such products to receive name recognition and may also be more convenient for customers who already use this account. Second, more favorable repayment behavior given that the widely used M-PESA account serve as "digital collateral," where the lender can digitally "repossess" the account when loans from any of these three products are not paid.[21] Finally, as noted before, consumer myopia with complex or shrouded fees may dampen the consumer benefits of competition Gabaix and Laibson (2006).

While a full analysis of the degree of competition in the digital credit market using administrative data is outside the scope of the current work, such work may have potential in the future. With a more complete sample of aggregate data from lenders, market share and concentration indices might be computed. Additionally, administrative data may also give access to to some measurements of the degree of competitiveness in the digital credit market. For example, one could use the conjectural variation method to learn more about the degree of competition in the digital credit market (Bresnahan, 1982; Lau, 1982).[22] This remains as a avenue for future exploration that could magnify the power of administrative data for consumer protection market monitoring.

5 Loan Repayment in Digital Credit

The second consumer risk I address is non-repayment, either in late repayment or outright default. Of course, there is little debate about the rate of default *per se.* Providers' profits are hurt when borrowers fail to repay and borrowers lose access to credit when they fail to repay and may fall into collections. Aside from those who seek to defraud lenders, both borrowers and lenders alike want to see a low rate of default. However, the optimal rate of default is not zero. While the risks stated above are obvious, from the perspective of financial inclusion, extending credit to higher risk populations will come with some degree of failure to repay.[23] With this in mind, I do not

[21]This concept draws on empirical results from a related context. In particular, Gertler et al. (2021) finds that the potential to digitally repossess (deny the flow of services from) solar panels improved repayment rates of school fees.

[22]Likewise, many other alternative methods and refinements have been introduced in subsequent years (Oliver et al., 2006; van Leuvensteijn et al., 2007).

[23]In a stylized model, this is more true the noisier predictions are. Of course, if one could perfectly predict default, screening could easily allocate credit to those who would be able to repay.

	Provider						
Penalty Information	A	B	D*	F	G	H1**	H2**
Penalty Fees Reported	✓		✓	✓		✓	
Transaction (with Loan ID)							
Transaction (without Loan ID)	✓		✓				
Aggregated Fees on Loan				✓			
Aggregated Fees Overall						✓	?✓

	Provider						
Repayment Information	A	B	D*	F	G	H1**	H2**
Tenure Information		✓					
Repayments (with Loan ID)				✓			
Repayments (without Loan ID)	✓	✓	✓		✓		
Defaults Overall						✓	✓

* indicates data was otherwise incomplete and therefore not analyzed.

** indicates that provider only supplied CAK with aggregated data.

Table 14: Using Fees and Repayment Data to Assess Default at Providers

seek to make a claim about the optimal rate of default, but instead document defaults with the risks to consumers in mind of late repayment and default.

5.1 Data Processing and Data Constraints

5.1.1 Definitions

We arrive on a definitions to track two statistics, late repayment and default. In particular, I define late repayment of loans when the loan is not repaid in full on the date it is due. For a loan not to be late, loans should be repaid, in full, prior or on the date that the loan is due. Then, if the loan is fully repaid within 90 days of the due date, I consider it only late repayment. However, if some portion of repayments are overdue by 90 days, I consider these loans in default in addition to late repayment.[24] Additionally, I will quantify the size of defaults among those who have not repaid.

[24]This tends to match with broader definitions, including provider definitions. For example, default, Provider G includes in their Terms & Conditions "fail to pay any sum payable for a Loan granted under these Terms and Conditions for a period of ninety (90) consecutive days," i.e., a one month loan is in default if it's not repaid after e.g., $30 + 90$ days $= 120$ days.

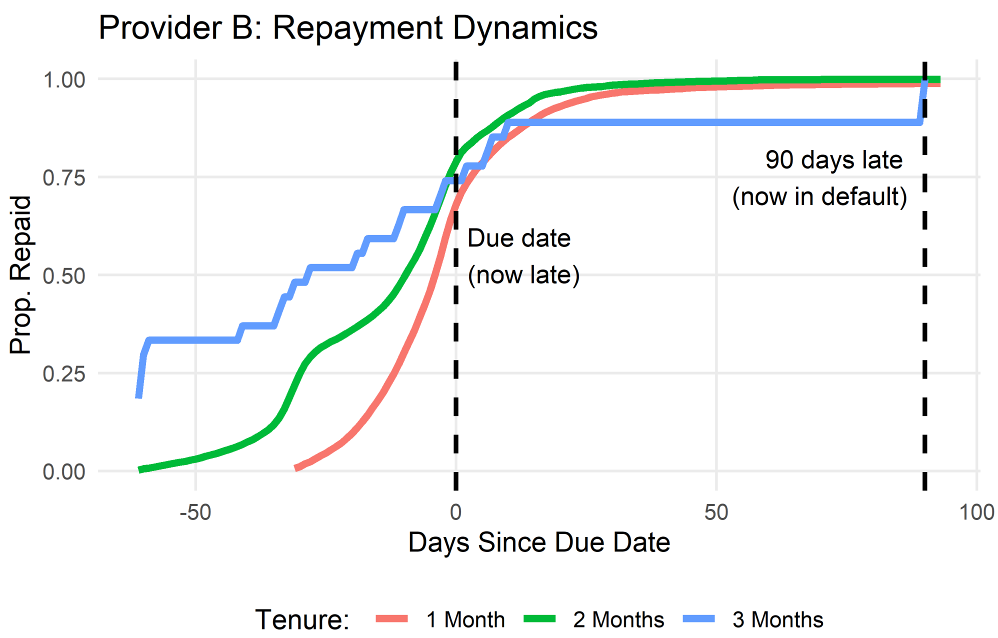

Figure 20: Repayment behavior of borrowers of Provider B

5.1.2 Data Constraints

We present the information submitted in the data request in Table 14. Notably, I do not have the tenure information for all providers. While I can certainly consider abandoned loans that are never repaid, based on the information I have it may be difficult to study the definitions above in all provider data sets. Therefore, it may be best to analyze repayment and default individually at different providers.

We have both tenure and repayment information for Provider B, so I are able to compute both late repayment and default in this dataset based on repayment. However, no other dataset features tenure information for individual loans. Despite this, I are still be able to paint a clear picture of late repayment and default for Provider F due to information on Loan ID and Penalty Fees. I detail the data processing for these Providers below.

Finally, for Provider H I are able to get limited repayment data for both product H1 and product H2. While I get default rates by month for each product directly, this is disaggregated by gender and age group. Moreover, I don't have overall demographics for the users of these products and so

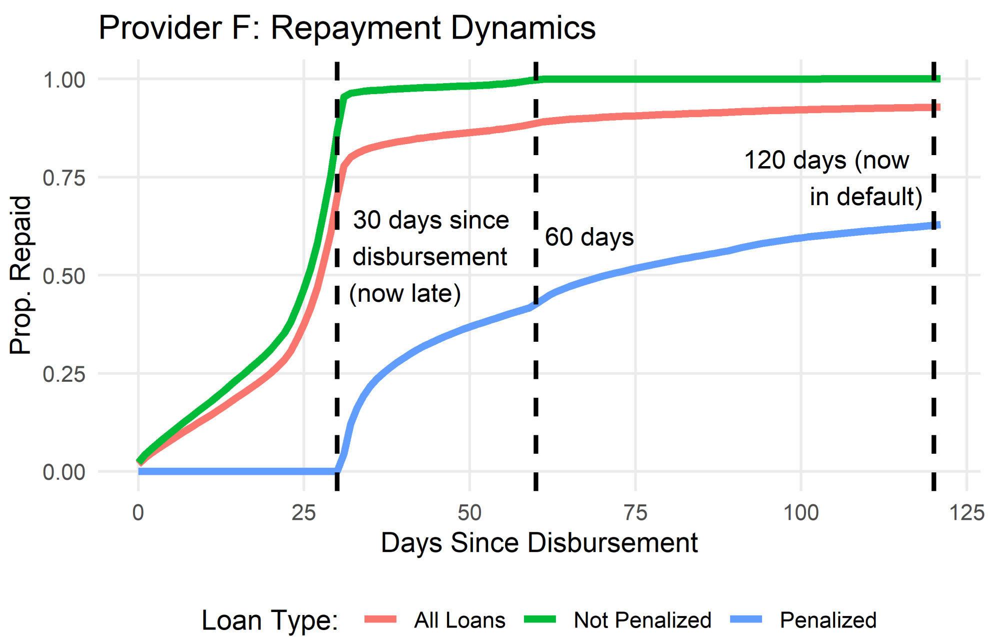

Figure 21: Repayment behavior of borrowers of Provider F

I could only guess at the overall default rate, by, for example, weighting these equally. However, I also received total amounts defaulted, which I use to track repayment at this provider. In order to compare these to others, I compute this by month an chart it in comparison to Provider F.

For the other three Providers with transaction data but without tenure information, I are less successful in painting a picture of their repayment behavior. In particular, a lack of information on Loan IDs for Provider A serves as a binding constraint. For Provider G, the lack of penalties (as no penalties are charged by the provider) hinders the analysis.

5.1.3 Data Processing

We process data from both Provider B and Provider F as a case study of repayment behavior in digital credit. I start by processing the data for Provider B, dropping all repayments from loans that are disbursed before January 1st, 2019. Likewise, I want to drop loans that come due within 90 days of the end of the dataset, hence selecting only loans due on or before December 31st, 2020. I construct a history of the borrower's balance at the end of each day. Then I record loans that have been repaid late as loans that feature non-zero balances when the loan is due. In particular, I assume loans are 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, I record loans in default when I observe a non-zero balance 90 days after the loan has come due. Figure 20 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.

To diagnose the measure, visual inspection of Figure 20 illuminates a potential limitation of this method. In particular, while repayment rates are steeply increasing prior to the assumed due date, the change in the rate of repayment is less sharp than one would expect. I would expect borrowers to hurry to repay just before the due date and therefore have less reason to repay after the due date, sharpening the angle of the curve around the due date. This might suggest some measurement error in the choice of due date, likely due to salary loans being tied to worker salary schedules instead of 30 day increments. A possible refinement here, given knowledge of Kenyan salary schedules, would be to "snap" due dates to likely paydays.[25]

We move on to process Provider F's data, dropping all loans that are given on December 1st or after – to allow the identification of default. Likewise, I drop all repayments from loans that are disbursed before January 1st, 2019. Given tenure information I might compare the repayment behavior to the loan length, as I did in the case of Provider B. Unfortunately, I do not have this information for this provider. However, despite not having information about the tenure of specific loans for Provider F, the ability to track repayment behavior and penalty fees allows me to paint a clear picture of late repayment when combined with the Provider's T&C's. By using penalty fees to measure late repayment I allow the Provider's judgement to guide the definition.

Notably, in Figure 21, I see a much sharper curve in this graph around the due date, which is suggestive of limited measurement error in this definition. However, I do see that a small proportion of loans that are not repaid are not penalized are not repaid in the first 30 days (4.5% remain unpaid). However, almost all of these loans are repaid by day 60 (about 0.3% remain unpaid), indicating that these borrowers may have been able to "work out" their late repayment

[25] For example, biweekly paydays on the 15th and 30th of the month might be appropriate in the U.S. salaried context.

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

Table 15: Provider B: Repayment by Age and Gender

with the Provider (alternatively, they may have been overlooked). One the other hand, virtually no borrower that is charged a penalty fee has repaid within 30 days. From this perspective, the measure of late repayment is relatively conservative. That is, I are more likely to under-report late repayment than over-report it.

Similarly, to operationalize this measure of default, I 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 borrower who have not repaid by 120 days and are not penalized is quite small (less than 1 in 5000 loans), meaning I are not likely to overstate the amount of loans that go into default at this Provider.

To calculate percentage repaid for Products H1 and H2, I take total value defaulted on these products when loans would go to default and divide this by the total value disbursed by these products. I 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.[26] Then to compute proportion of value repaid, I subtract this

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

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

Table 16: Provider F: Repayment Behavior by Age and Gender

number from one.

5.2 Results

5.2.1 Provider B and F: Transaction Data

We present the results of this analysis for Provider B in Table 15. Using definition based on 30 day tenure, I 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. Again, I note that if there is measurement error in the chosen due dates, I may overstate the number of late loans. Despite the low default rates, each given default is large. Only 92.7% of the value of disbursements and fees is repaid – an average amount for a below average percentage of defaults. For those loans that go into default, the average not repaid on these loans is around 55452 KSh.

We present the results of this analysis for Provider F in Table 16. Using the penalty definition, I 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

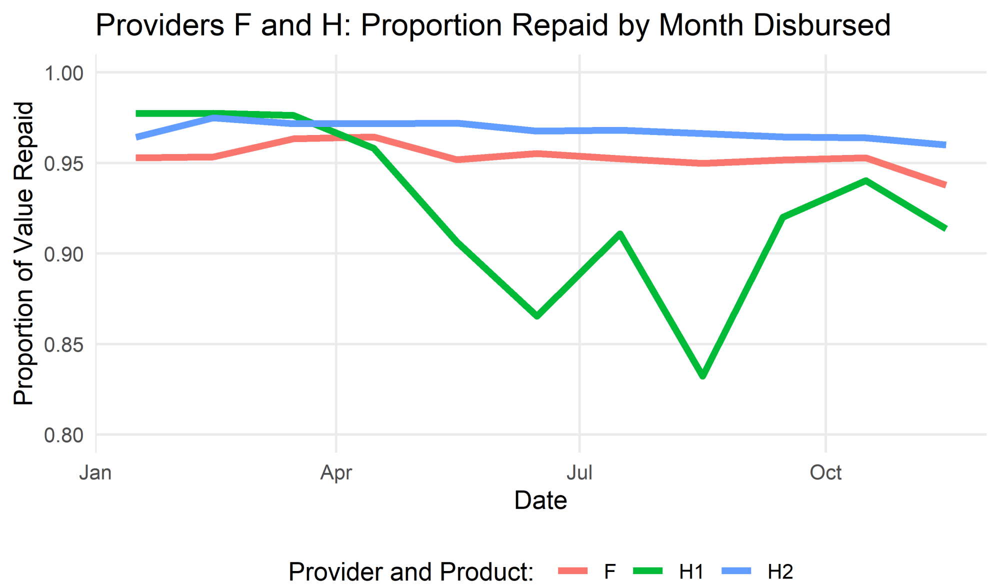

Figure 22: Repayment Dynamics for Providers F and H

37.3% of these late loans go into default.[27] From this default rate, I see that 95.6% of the value of disbursements and fees is repaid. For those loans that go into default, the average not repaid on these loans is around 5272 KSh.

5.2.2 Products H1 and H2: Aggregated Data

Considering Product H1 and H2, I visualize the percentage of value repaid over the first 11 months of 2019 in Figure 22. While the proportion of value repaid declines slightly over the year for Provider F and Product H2, I 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 repaid. While it's unclear what is causing this, I cannot rule out that the provider has chosen to write-off loans that were defaulted upon earlier than these months.[28] Tracking such repayment anomalies (perhaps disaggregated by gender) as part of a market monitoring strategy would be useful from the perspective of consumer protection. For example, regulators could follow up directly with providers when usually high default rates are reported. Such systems are

[27] About 5.7% of loans are never fully repaid over the window I observe.

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

Gender	H1	H2
Female	92.09	96.42
Male	92.76	96.81
Age Group	**H1**	**H2**
18-24	74.17	89.31
25-34	90.74	95.68
35-44	93.32	97.81
45-54	94.02	97.74
55+	93.85	96.06
	H1	**H2**
All Demo	92.47	96.7

Table 17: Overall Repayment Rates for Provider H

likely low hanging fruit as similar market monitoring often exists for prudential regulation.

Statistics for proportion of value repaid for Provider H are also presented in Table 17. As might be expected from these results, 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. I see roughly equal repayment by gender of borrowers for both of these providers. However, when considering age, consistent with expectations, I note that younger borrowers are more likely to not repay their loans, repaying only 74.2% of the value they owe. For both products proportion of value repaid increases in each age cohort until the 55+ cohort in which in declines.

5.3 Discussion: Strategic Default and External Validity

Within the period of the sample, defaults do not seem to be a particularly prominent consumer protection risk for borrowers of Provider B and F. Likewise, Product H1 does see an unusually high proportion of value not repaid on loans disbursed midyear, which is potentially driven by younger borrowers, but has a reasonable proportion of value defaulted overall. Finally, Product H2 is widely in line with Provider F in terms of proportion of value defaulted.

These results could lead one to concluding that default is not a problem in digital credit in Kenya. However, given that those lenders I rely on for this late repayment and default data tend to be regulated and/or large providers, this analysis may not be representative of the rate of default across all digital credit products in the Kenyan economy. For example, borrowers may have differing willingness to default from providers based on factors such as convenience, collateral (or digital collateral such as an M-PESA account), price, and recourse either through dynamics incentives of CRBs (Carlson, 2018; Gertler et al., 2021). Each of these factors would suggest that higher cost non-bank digital lenders, who are less likely to use the Credit Bureaus, and whose loans are not tied to mobile money or salary accounts, would be more likely to find borrowers strategically defaulting on their loans (Gwer et al., 2019). In cases where multiple borrowing, or borrowing from two providers simultaneously, has lenders defaulting on one loan or another, this type of strategic default might become even more prominent. In the next section, I continue on to study what multiple account holding and multiple borrowing I observe in this limited selection of lenders.

6 Multiple Account Holding and Multiple Borrowing

Multiple borrowing is when a borrower obtains overlapping loans from multiple providers. It has often been observed in situations where credit market information systems are not in place, incomplete, or feature incomplete compliance of providers. Multiple borrowing is not synonymous with over-indebtedness or debt stress, it is often thought of as closely related. Little is known about the causal relationship between the two (as well as other omitted variables), but the empirical relationship is well documented. For example, Chichaibelu and Waibel (2017) presents such a relationship in Northeast Thailand, where multiple borrowing and over-indebtedness occur as persistent and interrelated states. Likewise, Vogelgesang (2003) finds that Bolivian borrowers who multiple borrow are more likely to default on their loans. These results accord with theoretical models of microcredit. For example, McIntosh and Wydick (2005) shows that more impatient borrowers will take on loans from multiple providers in the microfinance sector. Thus, from the perspective of consumer protection, it is an important outcome to monitor to understand consumer welfare in credit markets. Moreover, understanding the behavior of multiple borrowers is important when considering implications for risk.

To analyze multiple borrowing, I start by looking at the segment of borrowers with multiple loans across providers, a prerequisite to multiple borrowing. This is made possible using de-identified MSISDN collected with each dataset. I find that I can positively identify 6% of borrowers at Providers A, D, F, and G as having taken a loan from multiple providers over the course of the sample. There is great heterogeneity by provider in what proportion of borrowers have accounts with additional providers. For example, 65% of those who borrow from Provider D have accounts at one of the three other providers, which is notable as they are a non-bank lender. Men are more likely to hold multiple accounts than women. Likewise, those aged 25-44 tend to be most likely to hold multiple accounts.

Considering the set of borrowers who hold multiple accounts, I look for borrowers with overlapping loans, using a definition of any loan taken within 30 days of a previous loan. I define multiple borrowing as overlapping loans from different providers. I find that of the three providers I have repayment data for, 81.8% of multiple account holders multiple borrowed. Similarly, I are interested in overlapping loans at the same provider taken by early or revolving borrowers and find that 86.8% of borrowers have done so. I investigate the relationship between multiple borrowing and credit default and find multiple borrowers are more likely to default than they average borrower, but only if they are not also early/revolving borrowers. Finally, I segment out multiple account holders by behavior.

6.1 Multiple Account Holding

6.1.1 Data Processing and Constraints

We process each provider's data individually. I find all unique combinations of ID (i.e., hashed MSISDN), age, gender, and prefix available in the dataset. The data from the four providers are

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.

Table 18: Gender of consumers who hold accounts at multiple providers.

then linked using the ID as an identifier. This produces a single datasets with the gender, age, and prefixes from each dataset.

As I process the data I note some constraints to the demographic data in the sample. First, at the provider level, I see some missing data in gender, age and prefixes, and inconsistencies in gender and age within providers. Notably these inconsistencies are relatively small compared to the number of accounts at each provider. There could be many sources for these inconsistencies including multiple family members using the same phone, phone numbers being reassigned, SIM cards being sold, or used by multiple households. It is unclear how often each of these individual events happen. One final possibility, if SIM registration took place early in the expansion of digital finance, is that demographic data may have not en collected with the same care during this initial registration. Newer registrations would likely have more have more accurate data. In each dataset, when I encounter inconsistencies in a variable, I default to keeping the data from the first entry where that variable is not missing.[29] This approach is used for both gender and age. When no data can be found for a consumer, that id is passed on without additional data. Missing data by provider is summarized in Table 5.

Second, I also find inconsistencies in age and gender variables across datasets. In this case I keep track of inconsistencies at this stage, which are more prevalent than within datasets. For both gender and age, I 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, I mark that consumer male. Otherwise, I mark the data as inconsistent, or missing in the case that there are no non-missing

[29] That is, sometimes an inconsistency is generated solely by missing data in one variable.

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 19: Age of consumers who hold accounts at multiple providers.

entries. In the case of age I work to rectify some of these inconsistencies. In particular, I 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 I do see this type of inconsistency I 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).[30]

An important note is that the data fidelity is directly related to the number of providers a phone number is associated with. As you might expect, 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 an a consumer id is associated with more accounts, I are more likely to see inconsistent information about that consumer. Both of these patterns can be seen in Tables 18 and 19.

6.1.2 Results from Four Providers

Before diving into multiple borrowing, I look to consider the overlap of consumers at the four providers I have data for. Within these four providers, I see that about 6% of the sample holds multiple accounts. This observation comes with a few necessary caveats. First, if I consider the extent of multiple account holding in digital credit in Kenya, I note that this number will neces-

[30]Unfortunately, I are not able to check if prefixes are inconsistent across provider, though the general agreement in demographic data across providers suggests that I are matching the same individuals across providers.

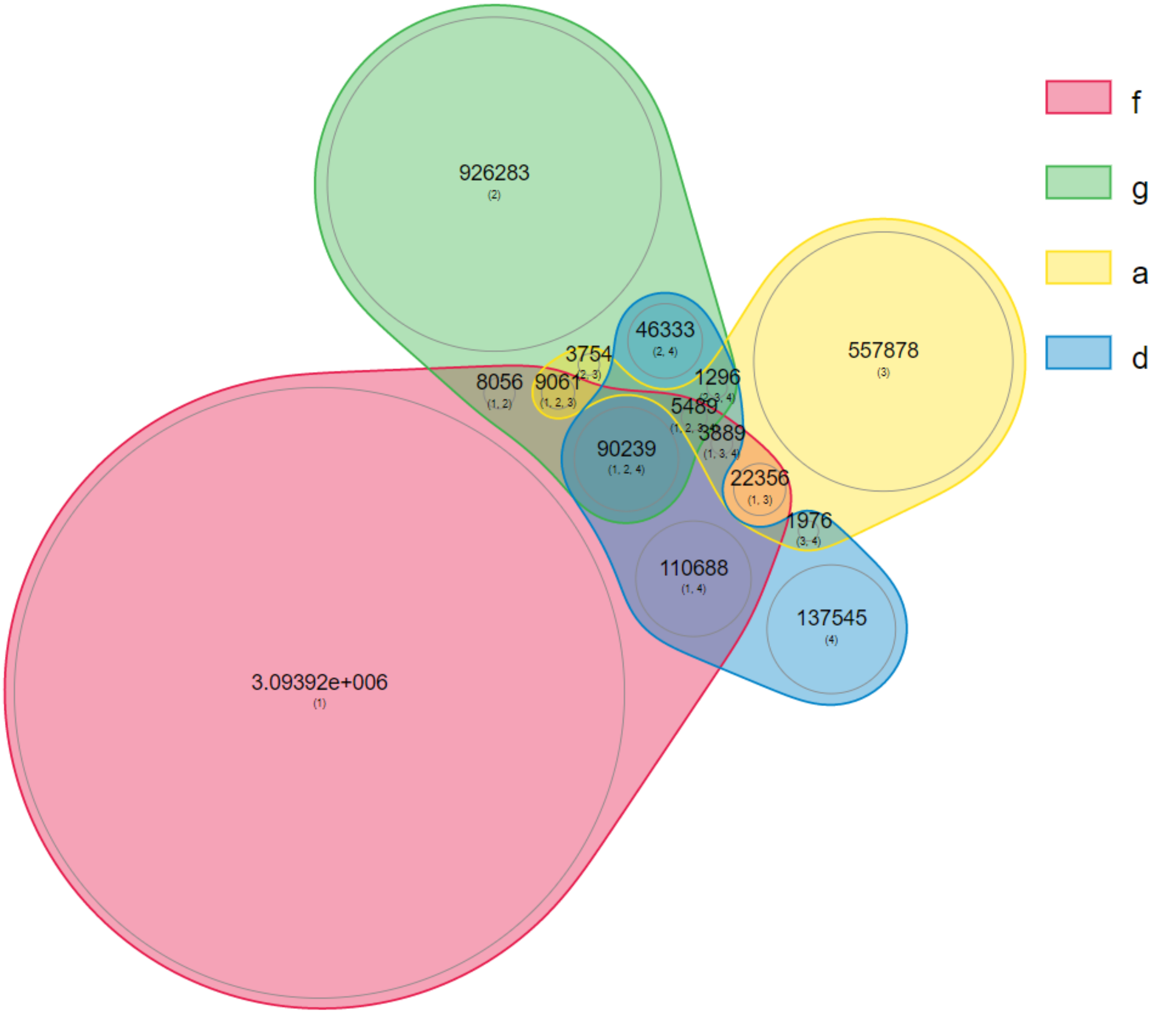

Figure 23: Venn Diagram of Multiple Account Holding

sarily be a lower bound. A first limitation is that I do not observe all providers. In the very likely case that multiple account holding takes place between unobserved providers and those in the sample, this would bias the estimate of the extent of multiple account holding downward. In particular, I do not have transaction data about borrowers at the largest provider in the market in this dataset. However, I can still document the existence of multiple account holdings amongst this set of providers. Additionally, I can explore the demographics and behavior of those consumers who hold multiple accounts.

Looking at Figure 23, I can get a sense of what providers these borrowers have taken loans with, and some sense of where I see multiple overlapping accounts. Likewise, Table 20 gives exact

	% of consumers from provider also borrowing from:				
Provider	Any other provider	A	D	F	G
A	7.90		2.30	6.95	3.45
D	65.39	3.51		53.2	36.39
F	7.47	1.26	6.33		3.41
G	15.06	1.92	13.26	10.47	

Table 20: Multiple Accounts by Provider and Provider Pair

numbers for what percentage of a providers account holders have also borrowed elsewhere. One provider stands out: Provider D, a relatively small FinTech, seems to have many consumers with accounts elsewhere, particularly at providers F and G. While D stands out within the sample it is difficult to say whether this type of overlap is specific to this provider or endemic to smaller FinTechs in Kenya. While I cannot say specifically how Provider D used the credit bureaus over the course of the sample, the tendency of non-bank lenders to neglect these is higher (Gwer et al., 2019). This suggests that any tool using administrative data to gain an understanding of multiple borrowing should consider provider heterogeneity in use of credit bureaus.

6.1.3 Demographics of Multiple Account Holders

Who are the multiple account holders? Starting with the gender of I see that men tend to have more accounts than women. In particular, 9.7% of men have more than one account as compared to 7.7% of women. In Table 21 I present the proportion of borrowers with each number of accounts as well as the mean and standard deviation of the number of accounts by gender.

We also see a higher degree of multiple account holding among adults aged 25-44 as compared to older and younger cohorts, with 11.1% holding multiple accounts. This is followed closely by adults aged 45-64, of whom 8.0% hold multiple accounts. In contrast, young adults and the elderly do not hold multiple accounts at a high rate. In Table 21 I present the full results of the analysis.

Finally, looking at multiple accounts by operator, I notice some interesting patterns. Multiple account holding tends to be higher among numbers with prefixes that are originated by Safaricom. In fact, prefixes associated with other providers have almost no multiple account holding.

	Number of Providers						
Gender	1	2	3	4	2+	Mean	Std. Dev.
F	92.26	4.51	3.07	0.16	7.74	1.11	0.41
M	90.29	5.72	3.75	0.24	9.71	1.14	0.46
Age Group	1	2	3	4	2+	Mean	Std. Dev.
18-24	97.68	1.57	0.72	0.03	2.32	1.03	0.22
25-44	88.92	6.55	4.28	0.24	11.08	1.16	0.48
45-64	91.99	5.05	2.87	0.10	8.01	1.11	0.40
65+	99.09	0.78	0.13	0.00	0.91	1.01	0.11
Operator	1	2	3	4	2+	Mean	Std. Dev.
Airtel	99.76	0.20	0.04	0.00	0.24	1.00	0.06
Equitel	99.96	0.04	0.00	0.00	0.04	1.00	0.02
Safaricom	93.24	4.30	2.33	0.12	6.76	1.09	0.37
Small Operator	99.67	0.33	0.00	0.00	0.33	1.00	0.06
Unknown Operator	92.92	4.72	2.28	0.08	7.08	1.10	0.37

Table 21: Number of accounts held by gender, age group, and operator.

The interpretation of this fact is not completely clear. Notably, in some cases, operators are associated directly with providers. For example, in the case of Equitel, it is unclear if the lack of multiple accounts on Equitel SIMs is actually evidence of reduced multiple borrowing or a symptom of multiple borrowing. In particular 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 much of their multiple borrowing would not be captured by matching MSISDN. This would require use of National ID number, which was not considered for this research due to data privacy concerns. In addition, borrowers who do not have a known operator are also likely to be associated with multiple accounts. The full results are presented in Table 21. I can be relatively confident in the quality of match to the operator because numbers are rarely ported between operators in Kenya [31]

[31] Communications Authority of Kenya (2019): "In Quarter Four, 254 numbers were ported amongst the three mobile operators with Safaricom PLC recording the highest in-ports at 215. Airtel Networks Ltd and Orange registered 23 and 16 in-ports respectively as illustrated in Figure 4."

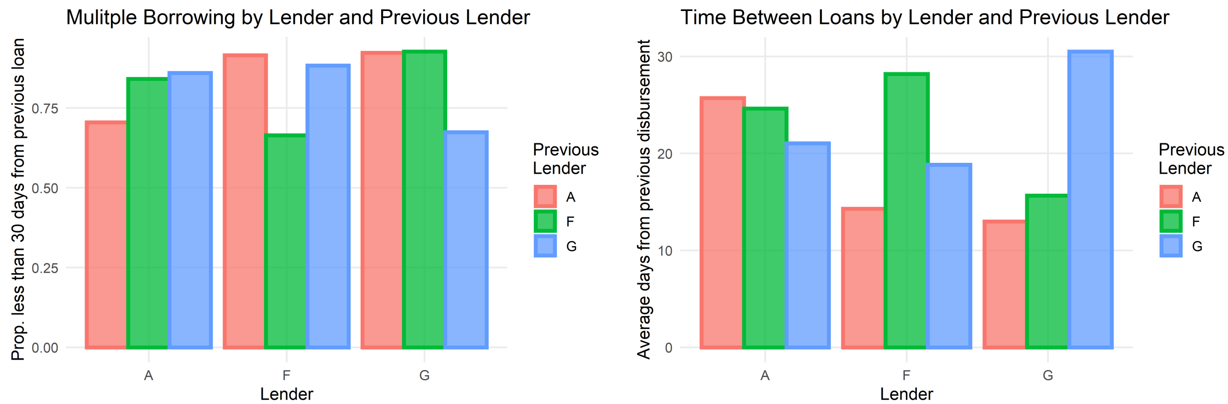

Figure 24: Multiple Borrowing by Lender and Previous Lender

6.2 Behavior of of Multiple Account Holders

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

6.2.1 Multiple Borrowing and Early/Revolving Borrowing

First, I note that most multiple account holders tend to multiple borrow, or at least borrow early. Defining multiple borrowing as those who take a loan from a different provider within 30 days of their previous loan, I see that 81.2% of multiple account holders also multiple borrow. 86.8% of these borrowers borrow from the same lender at some point during the 30-day window, which I refer to as early borrowing. Finally, 95.8% of multiple account holders take a either multiple borrow or early borrow, taking any loan within 30 days of a previous loan. As I 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 24). The difference in time elapsed to the next loan 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. Likewise, those who take another loan within the 30-day window are more likely to take it at a different provider than the same provider.

6.2.2 Default and Multiple Borrowing

In general, I tend to think that the more multiple borrowing a borrower does, the riskier they are as a borrower. While I do not have conclusive data on to answer this question, data from provider F suggests that multiple borrowing is associated with default risk. I split up the multiple account holders into seven sub-samples. At a high level, 5.1% of the same do not multiple or engage in early or revolving borrowing, so I hold these people out as their own category. Then the other 94.9% I report statistics for subsamples. In particular, I report statistics for those who early or revolving borrow, regardless of multiple borrowing status and vice-versa. Then I take those who only early borrow, only multiple borrow, or do both. These results are presented in Table 22.

Considering all borrowers at Provider F as a baseline (including multiple account holders), 67.7% of accounts have ever been late and 36.2% have ever defaulted. In comparison, I see that those accounts who multiple borrow are more likely to have repaid a loan late and are more likely to have defaulted than those in the general population. Considering those who multiple borrow but do not revolving borrow, I find 73.4% have been late in repaying a loan and 39.6% have defaulted on a loan, both higher than the average borrower from Provider F.

However, early borrowing does not have so clear an implication for risk. The relationship between multiple, early borrowing, and default is complex. While multiple and early borrowing are positively correlated ($\rho = 0.24$), early borrowing is not associated with high risk of default, and in fact is associated with a lower risk of late repayment and default. In fact, I find lower default rates among almost every sample split than in the greater population except for those accounts that solely multiple borrow. In the sample, those who both early and multiple borrow still end up defaulting less often than average.

However, multiple account holding overall does seem to be associated with late repayment.

Multiple Borrowing Status	Group(s)	Proportion Ever Late	Proportion Ever Defaulted	Prop.
No early/multiple borrowing	(1)	67.32	31.48	5.11
Only early borrowing	(2)	64.41	27.42	12.08
Only multiple borrowing	(3)	73.36	39.56	20.28
Early and multiple borrowing	(4)	69.77	25.49	62.53
Early borrowing	(2), (4)	68.90	25.80	74.61
Multiple borrowing	(3), (4)	70.65	28.94	82.81
Early or multiple borrowing	(2), (3), (4)	69.85	28.74	94.89

Table 22: Account level repayment for Provider F by multiple borrowing among multiple account holders.

The multiple account holding population tends to have been late at about the same rate as the average consumer or a bit higher, depending on the exact subsample. This is true of all the subgroups I analyze, except those who only engage in early borrowing, where a lower proportion have ever been late (64.7%). This coincides with the need for early repayment among early/revolving borrowers.

Based on this exploratory analysis, the risks posed by early repayment may in fact relate more to the expenses of servicing debt early—increasing the Effective APR for these borrowers—than default.[32] In fact, even those who multiple borrow and early borrow tend to have defaulted at a much lower rate than an average consumer at this provider (25.5% compared to 36.2%). These results suggests that policy interventions related to high frequency borrowers need to distinguish between the issues concerning those who borrow from many providers, and those who borrow frequently but primarily from a single provider.

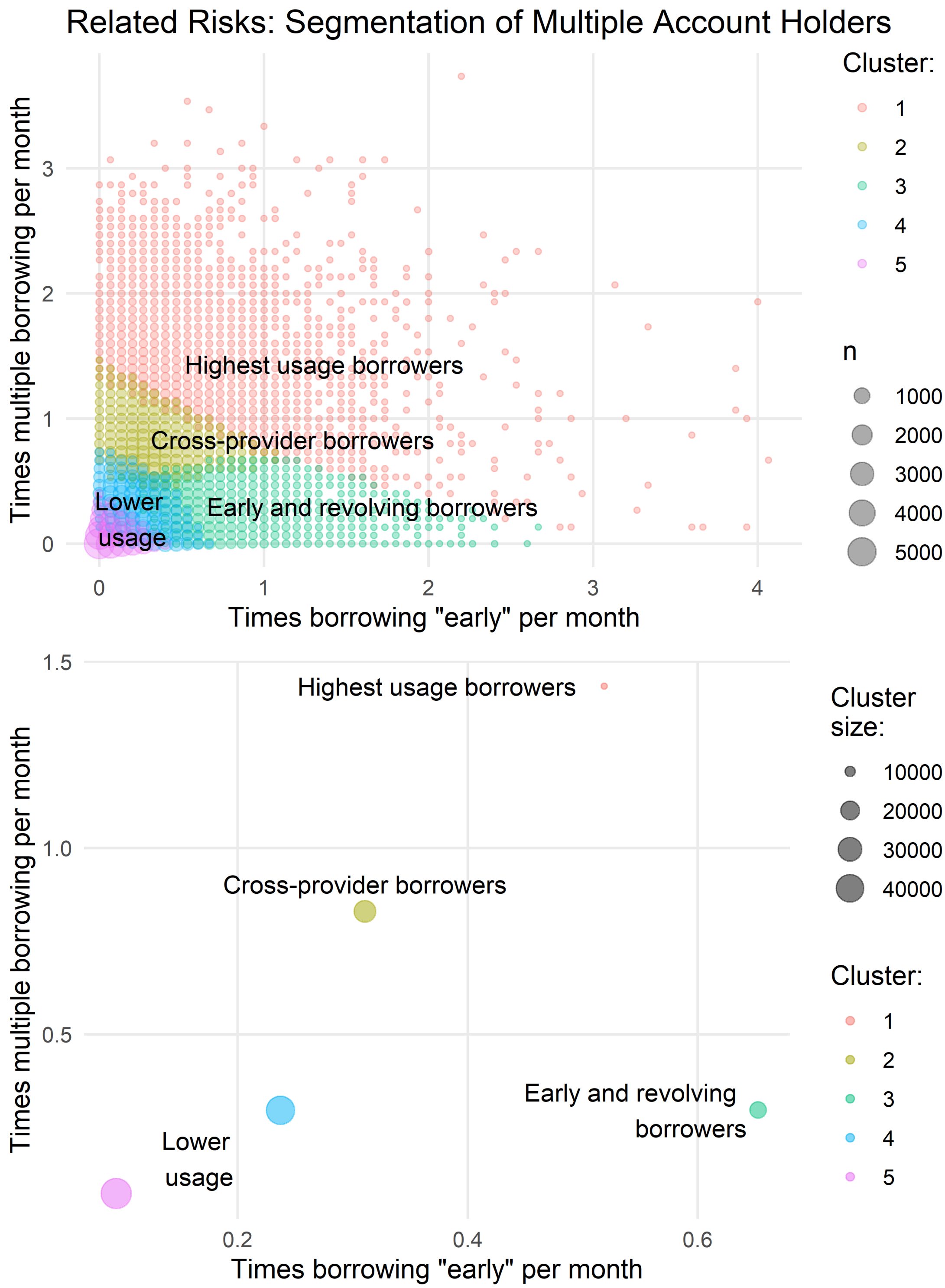

Figure 25: Segmentation of Multiple Borrowers

6.2.3 Segmentation

We also perform a data-driven segmentation of multiple account holders based on their behavior using k-means clustering with 5 clusters.[33] This gives a useful breakdown of the types of multiple borrowers and how they differ. Figure 25 plots this segmentation over the total number of multiple borrower loans, with those multiple loans taken at the early borrowing on the x-axis, and multiple borrowing on the y-axis.

Collapsing these clusters to their central point gives a clearer view, as shown in the right panel of Figure 25. In particular, cluster 3 (marked "early and revolving borrowers") tends to lie out of line with the other clusters. Based on the analysis of defaults, this suggests an important qualitative difference between this an other segments. 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.

6.3 Discussion: Overindebtedness, Default, and Multiple Borrowing

These segmentation results also bring forth new questions about the risks faced by consumers engaging in these activities. I presume the highest volume will be higher risk pf default while the lower volume will be lower risk, but need to interrogate this assumption. How does default risk change with usage in both the dimension of multiple borrowing and also early borrowing?

Additionally, I find that while multiple borrowing has important implications for default, I are not able to speak as well to the burden of debt from overindebtedness related to multiple and revolving borrowing. Are the early and revolving borrowers similar to those seen in Karlan et al.

[32]It's still unclear that this is not a risk *overall*. This subsample of borrowers are often paying high rates, and paying loans back quickly, increasing their effective price of credit. Since they take many loans and loan size may increase, these borrowers spend a large amount of money servicing debt, despite their ability to repay.

[33]Variables used in this clustering include number of times overlapping, multiple, and early borrowing; number of times borrowing from the same provider, number of times borrowing from a different provider, total loans taken, if loans overlapped overall, between providers, and at the same provider, the proportion of loans that overlapped, between providers and at the same provider, the proportion of loans taken at each of the three providers, and the total number of accounts held. To choose $k = 5$ I ran clustering with 4, 5, 6, and 7 clusters. Within this set, the qualitative implications of the clustering remained consistent with the results presented here. However, I found five clusters tended to yield the cleanest presentation of the story.

(2019), who quickly run up large debts and continue is a cycle of repayment? As I move on to risk-based pricing in the next section, I will also see that borrowers who take many loans from the same provider tend to pay more for credit, despite low default rates.

Finally, it is important to note possible limitations in the analysis. As is the case with the analysis of defaults earlier, I note that I might not observe those lenders who are most prone to default in this analysis. If, for example, Provider F was a preferred lender, I might see that Provider F could impose multiple borrowing externalities on other providers in this scenario (Green and Liu, 2019). In this way, it is quite possible that the relationship between multiple borrowing and default is understated in this analysis.

7 Discussion

To synthesize the findings about digital credit in Kenya I start by presenting a set of stylized facts about the state of the digital credit market in Kenya. These facts are those I think should serve as the clear takeaways from the evidence provided within the report. Next, where this work has been suggestive of other possible insights without rising to the level of evidencing those insights, I propose working hypotheses as avenues for future exploration and future research questions. Finally, I conclude by discussing the potential of the tools and analysis techniques used within this research project to contribute to future market monitoring. Additionally, I make suggestions about where and how advances might be made to extend these tools.

7.1 Five Stylized Facts about Digital Credit in Kenya

1. *Digital credit is small, short term, and high cost.* The digital credit industry mirrors other consumer credit products that serve “marginal” borrowers like payday lending. The results tend to reflect the general perception around digital credit: loans tend to be small, short in tenure, and relatively expensive.

2. *Late fees are common, even where the default rate is low.* These fees are not expensive, but

the high degree of lateness may prevent borrowers from effectively building credit through digital credit products. For example, these may slow the rate and which borrowers are able to build their credit limits. This risk is more acute when digital credit providers post negative listings to the credit bureaus, which may affect the terms of credit they get elsewhere in the market.

3. *Multiple borrowing is common.* Though I cannot measure the true extent of multiple borrowing, I find that it is common to hold multiple accounts even in this limited sample. Likewise, I find that multiple account holding usually implies some degree of multiple borrowing.

4. *There are gender disparities in lending outcomes.* Men tend to be over-represented in digital credit relative to their population share. Likewise, they pay less for credit than women, have higher credit limits, repay later, and default more often than women. Finally, women pay more in interest for the number of late fees they take on.

5. *"Lifecycle" effects are prominent in lending outcomes.* Digital credit users tend to be adults aged 25-44 and loan terms and borrower behavior varies greatly by age. In particular, the price of credit is most expensive for middle aged borrowers as compared to younger and older borrowers.

7.2 Six Working Hypotheses for Future Exploration

1. *Despite the short tenure of loans, there is demand for even shorter term credit.* While most loans are only one month in length, borrowers may be interested in more flexible alternatives for short term credit. First, I see that early repayment of loans is quite common. Second, overdraft products, which feature greater flexibility in the short term are growing at a rapid pace. These facts are suggestive of demand for short term loan products and may make the case to offer options such as partial refunds of interest fees for early repayment.

2. *Early repayers may have heterogeneous motivations.* There is a small but important set of consumers (referenced in stylized fact 2) who I refer to as "early repayers" who may lack the

flexibility to borrow as they desire. For the moment it is unclear who these borrowers are in particular, though many of them take on high numbers of loans with short average tenure. This behavior may involve true need (e.g., shopkeepers or street cart vendors handling short term cash flow issues), or convenience, but may also be an indication of a commitment device used by borrowers to manage limited self-control.

3. *Despite fee disclosures, contracts are not yet fully transparent.* Fees in digital credit products can be complex. For example, different fees may be presented in terms of APR and monthly interest. Likewise, some fees are only charged near the end of a loan, adding complexity to the balance owed for such products. Finally, automatic rollovers are present in the fine print of loans. These complexities may make credit non-transparent, despite recently improved disclosure.

4. *Multiple borrowers face different risks than early and revolving borrowers.* Despite both groups taking part in overlapping borrowing, the results suggest risks differ considerably. While multiple borrowing is associated with higher default rates, frequently borrowing from the same provider is associated with lower default rates. Despite this fact, revolving borrowers are often treated as risky investments, given smaller loans at higher rates.

5. *Asymmetry in regulation and Credit Bureau usage drives market segmentation by risk.* The limited usage of credit bureaus by non-bank lenders (and subsequent prohibition) may lead to a risk segmentation effect within the digital credit industry. Lenders who depend on credit bureaus will lend to those with a credit file, whereas "thin file" customers, or those with little in the way of credit history, may not have access to this type of credit. In contrast, lenders who depend on alternative data spruces (e.g., CDRs) will have a comparative advantage with these consumers. In particular, I see that bank lenders tend to lend at similar rates while the sole non-bank lender charges over twice as much.

6. *Borrowers prefer banks to non-bank lenders.* Closely related to the segmentation described in 5, I hypothesize that due to the price of credit, loan size, convenience and legacy rela-

tionships, bank digital lenders would be preferred to their non-bank counterparts. If this is true, I would expect that default rates (in particular among multiple borrowers) would be higher at non-bank borrowers, reflecting a lower cost to losing credit over this channel. This may indicate the sample, which draws on a bank digital lender, may not be reflective of broader default rates among this group.

7.3 The Potential of Transaction Data for Market Monitoring

Digital credit transactions have created a rich new source for insights into consumer protection risks and borrower outcomes more broadly. This report serves to illustrate the potential of transactional data to serve in developing market monitoring tools for digital credit. Some examples of these tools include the ability to identify multiple borrowers after de-identification, the use of regression analysis to monitor the degree of risk-based pricing in the industry, the use of cluster analysis to segment multiple account holders, data visualization to illustrate trends and correlations in the credit industry, and the construction of indicators such as effective APR and effective tenure to track average borrower experience in digital credit.

This research project has served as a proof of concept for such market monitoring tools, allowing me to make insights (like the stylized facts presented above). However, while promising the analysis thus far does not represent the full potential of transaction data for consumer protection market monitoring. First, while the tools presented within were applied as a static analysis of the digital credit market, such techniques could be adapted to more short-term or "real-time" monitoring. Such a solution for monitoring digital credit might look like a "dashboard" which would summarize a large number of the statistics introduced and/or tracked within this report, yielding monthly or perhaps even real time insights into tenure, price, default rate, multiple borrowing, concentration, and the use of risk-based pricing in the economy.

Second, administrative data hold the potential to serve as an input for further market monitoring tools. For example, the use of predictive modeling should not be neglected. This might be useful to predict future consumer protection issues in digital credit using a forward looking model, or build proxies for important but expensive or difficult to measure outcomes using transaction data linked to survey data. For example, survey data on overindebtedenss, an outcome which is difficult to measure using administrative data, could be combined with administrative data to build predictions of overindebtedness from this data. The predicted level of overindebtedness would then serve as a real-time proxy for survey measures.[34] Similarly, such tools might be combined with data on policy changes in the financial sector to analyze these policies' effects on the digital credit market and key consumer protection risk indicators.

Finally, more can be done to make the administrative data request process efficient. Importantly, the use of random samples of lenders and accounts might help with the ease of executing such data requests. Likewise, standardization of the information requested and the delivery path could similar streamline the ability of regulators to use such data. Moving forward all three of these objectives will contribute to greater, more useful, and more efficient tools for regulators to characterize and monitor digital credit in Kenya and elsewhere.

[34]For a similar approach see Blumenstock et al. (2015) poverty mapping exercise with CDR data.

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A Additional Tables

		Proportion				
Age Group	Gender	A	B	F	G	Market
18-24	Female	1.35	1.40	2.01	1.46	1.79
25-44	Female	23.76	19.47	8.10	6.50	10.20
45-64	Female	6.87	2.27	2.74	0.9	2.83
65+	Female	0.47	0.06	0.30	0.01	0.25
No Data	Female	0.00	0.00	6.44	0	4.05
18-24	Male	3.36	3.94	3.17	2.72	3.14
25-44	Male	43.88	51.8	13.17	11.93	18.51
45-64	Male	17.8	11.18	4.40	1.85	5.8
65+	Male	2.37	0.41	0.55	0.05	0.65
No Data	Male	0.00	0.00	8.26	0	5.19
18-24	No Data	0.00	0.10	0.05	17.15	3.50
25-44	No Data	0.05	8.91	2.22	48.48	11.66
45-64	No Data	0.06	0.22	0.83	8.73	2.31
65+	No Data	0.03	0	0.05	0.21	0.08
No Data	No Data	0.00	0.22	47.71	0.00	30.02
Total		100.00	100.00	100.00	100.00	100.00

Table A.1: Two-Way Account Demographics by Age and Gender

Provider	Gender	Mean Tenure	Mean Loan Size
A	Female	61.47	8,974.49
A	Male	64.79	10,212.42
A	No Data	60.00	13,304.62
B	Female	30.82	11,442.21
B	Male	30.57	12,374.04
B	No Data	30.63	12,057.14
F	Female	68.00	4,986.68
F	Male	81.30	6,762.84
F	No Data	76.27	6,632.52
G	Female	112.90	7,471.80
G	Male	125.20	6,648.53
G	No Data	117.24	3,044.46

Table A.2: Mean Effective Tenor and Loan Size by Gender and Provider

Provider	Age Group	Mean Tenure	Mean Loan Size
A	youth (24 and younger)	82.38	4,322.49
A	adult (25-44)	64.20	10,004.50
A	middle aged (45-64)	59.23	10,637.21
A	senior (65 and older)	59.84	7,276.43
B	youth (24 and younger)	30.04	9,137.55
B	adult (25-44)	30.38	11,871.17
B	middle aged (45-64)	32.23	14,779.08
B	senior (65 and older)	33.10	13,511.48
F	youth (24 and younger)	89.53	1,625.10
F	adult (25-44)	72.83	8,172.57
F	middle aged (45-64)	65.46	9,075.26
F	senior (65 and older)	77.10	5,257.51
G	youth (24 and younger)	132.85	1,486.53
G	adult (25-44)	116.22	4,369.41
G	middle aged (45-64)	102.86	6,745.61
G	senior (65 and older)	95.60	6,794.38

Table A.3: Mean Effective Tenor and Loan Size by Age and Provider

Number of Providers	Female	Male
1	37.96	62.04
2	32.07	67.93
3	32.88	67.12
4	28.03	71.97

Table A.4: Gender of those who hold multiple accounts taking into consideration only those with complete and consistent gender data.

N Providers	18-24	25-44	45-64	65+
1	15.72	61.72	20.71	1.86
2	4.24	76.42	19.10	0.25
3	3.11	79.53	17.30	0.06
4	2.63	86.26	11.08	0.02

Table A.5: Age of those who hold multiple accounts taking into consideration only those with complete and consistent or rectified age data.

Table A.6: Loan Level Repayment for Provider F by Multiple Borrowing

		Proportion	
	APR from Interest	Late	Default
Loans after multiple borrowing:			
Repeated or cross-provider borrowing	5474.91	17.25	4.36
Repeated borrowing	5293.87	13.43	3.06
Cross-provider borrowing	5651.09	20.96	5.61
All loans		19.36	7.22

B Additional Figures

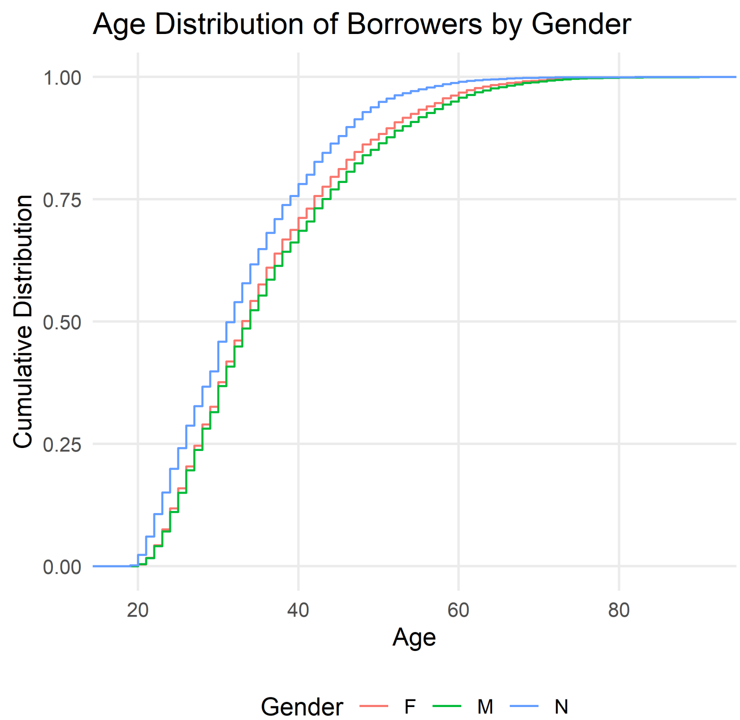

Figure A.1: Cumulative Distribution of Age by Gender

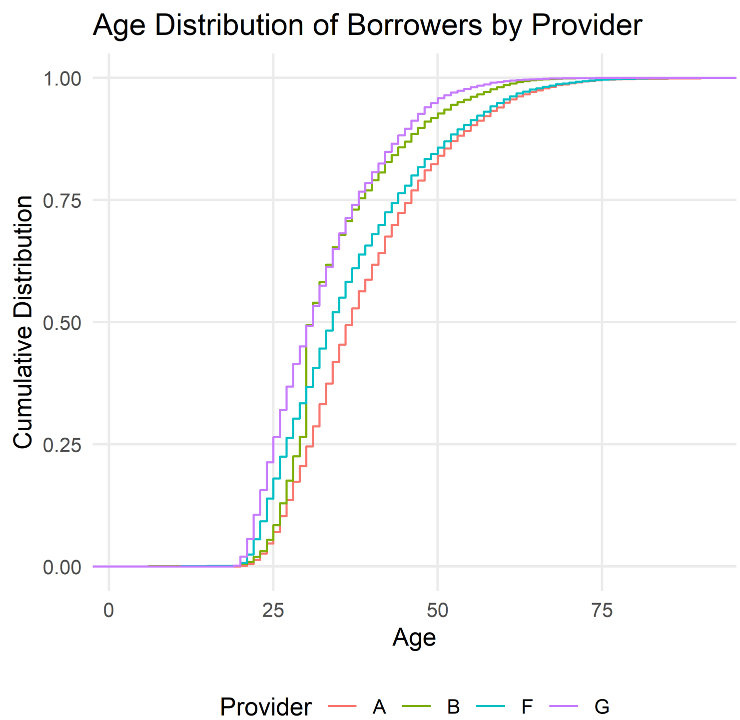

Figure A.2: Cumulative Distribution of Age by Provider

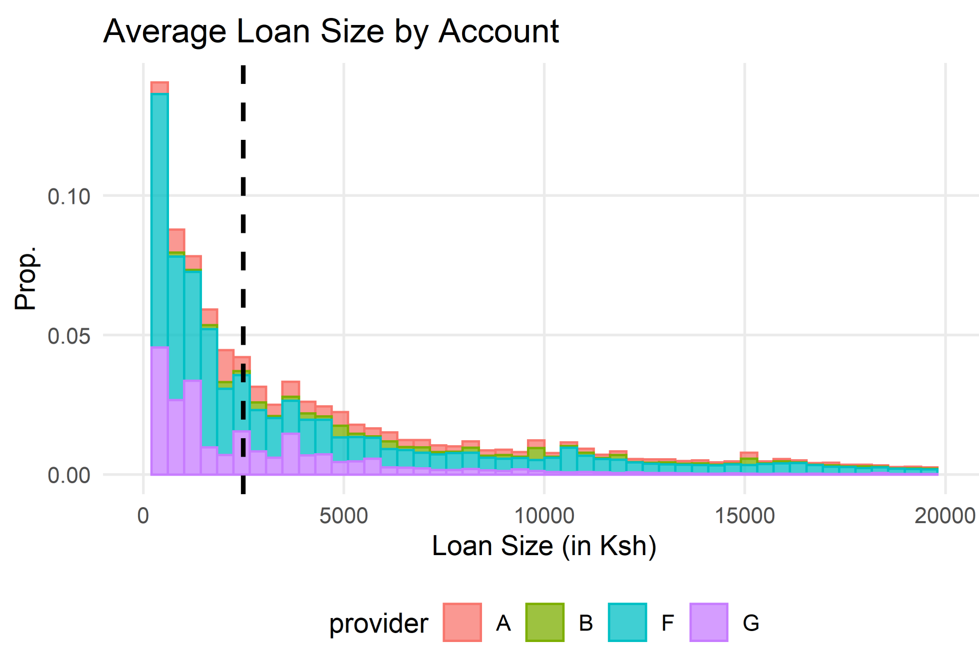

Figure A.3: Average Loan Size by Account, disaggregated by provider for all providers in the market

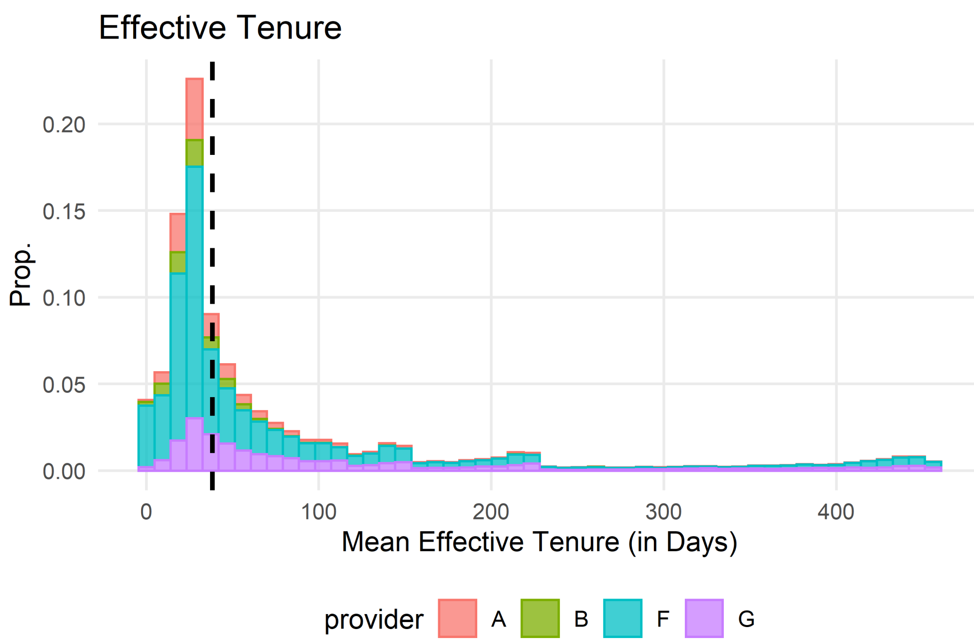

Figure A.4: Average Effective Tenure by Account, disaggregated by provider for all providers in the market

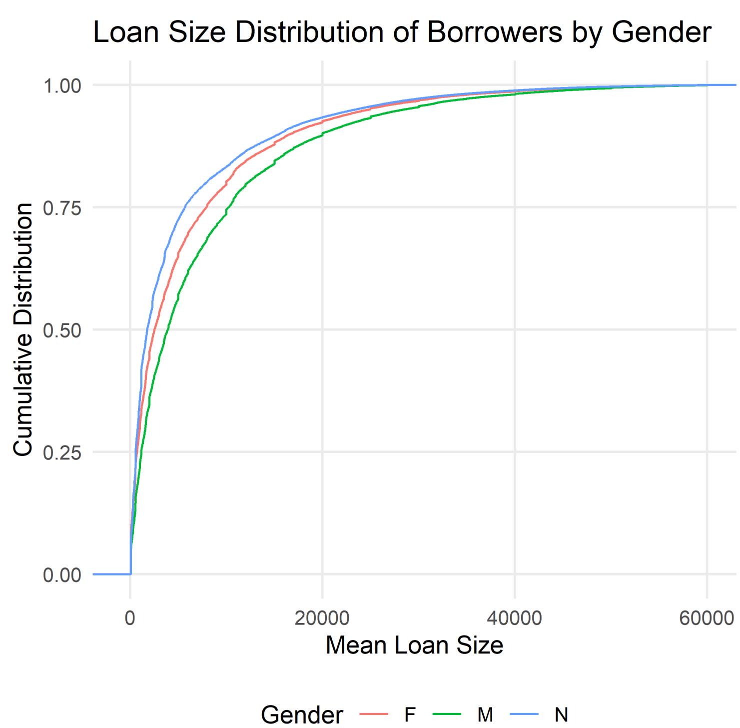

Figure A.6: Cumulative Distribution of Loan Size by Gender

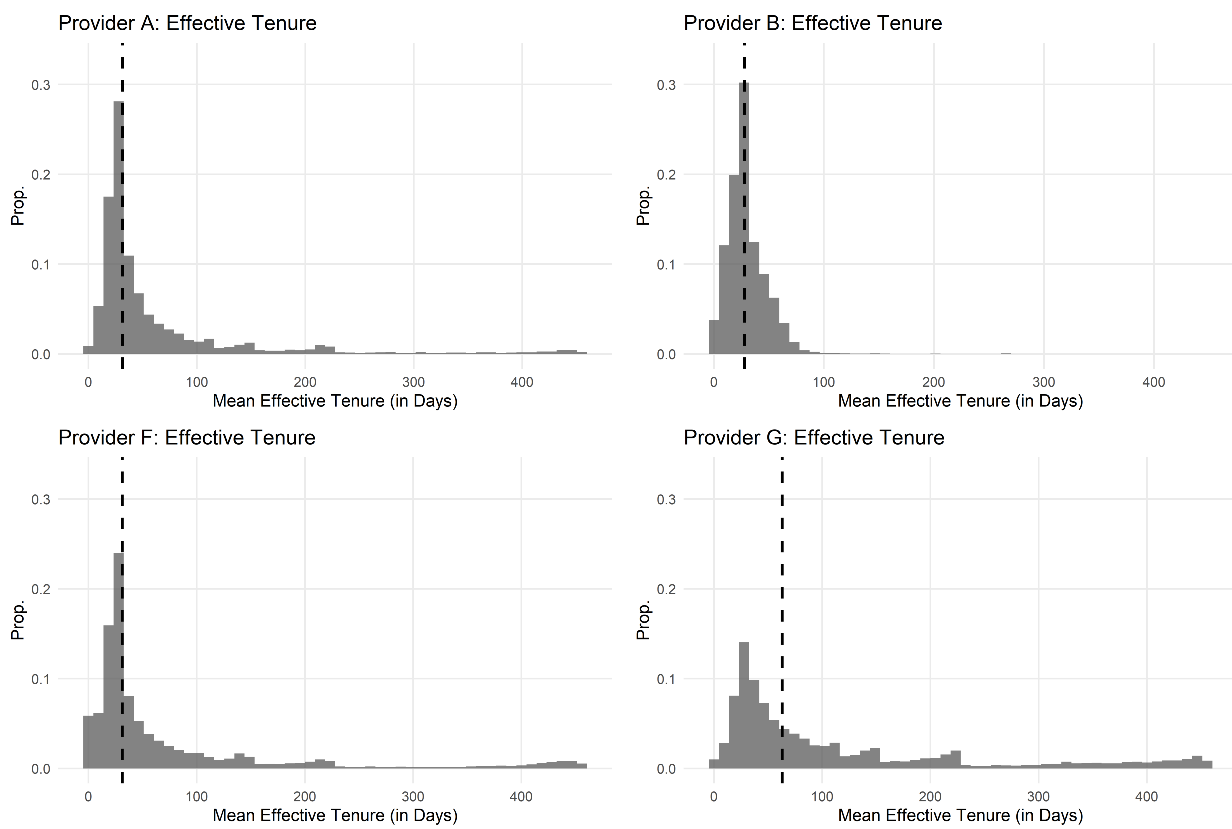

Figure A.5: Average Effective Tenure by Account

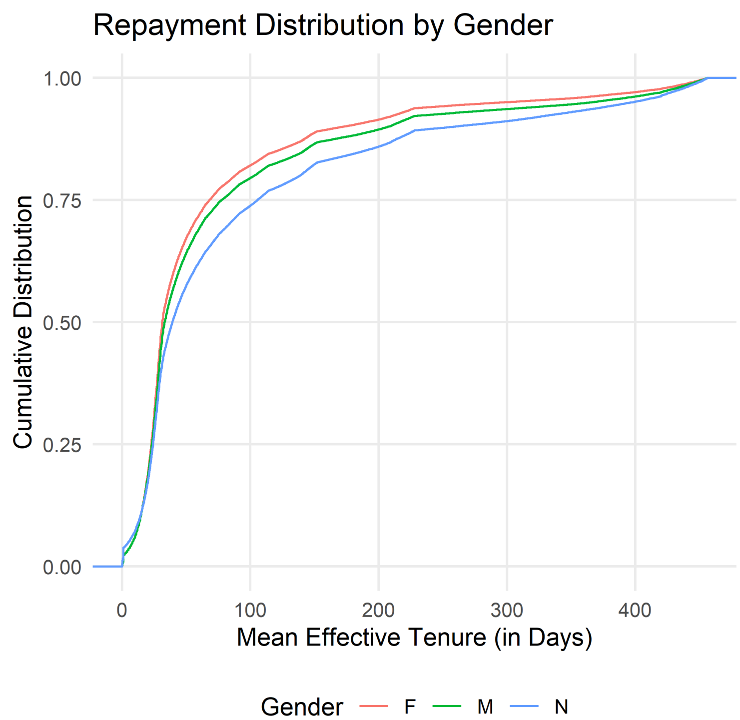

Figure A.7: Cumulative Distribution of Effective Tenure by Gender

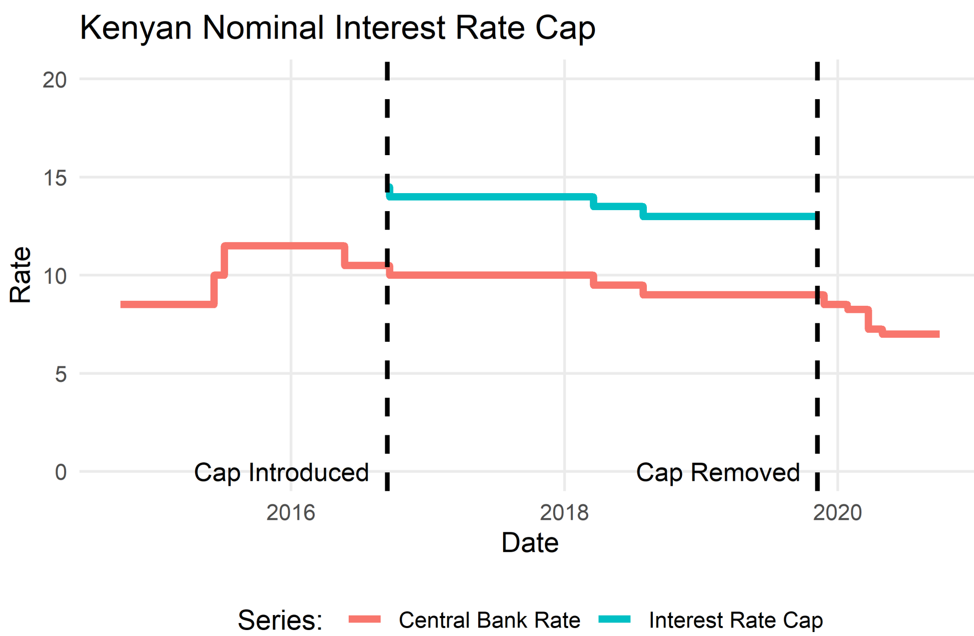

Figure A.9: Kenyan Nominal Interest Rate Cap which was present from the years 2016 to 2019.

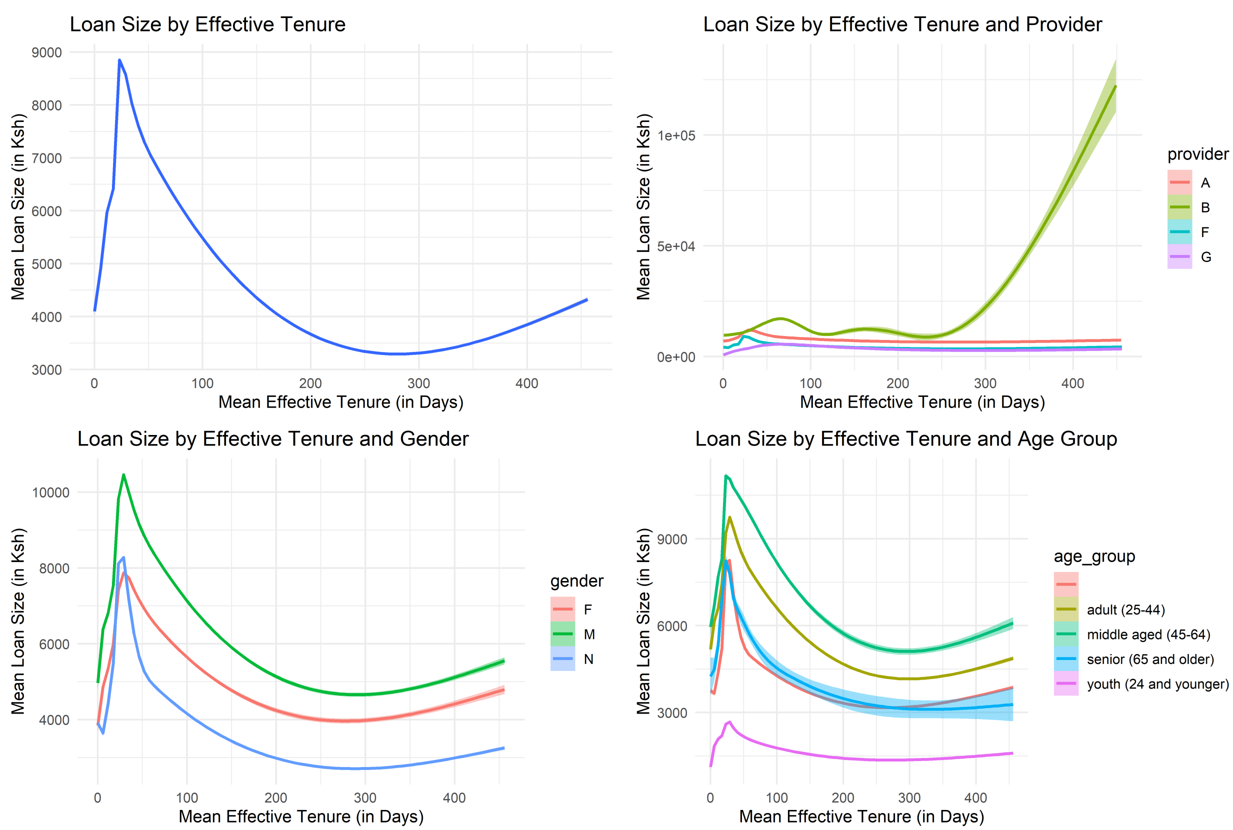

Figure A.8: Loan Size by Tenure, disaggregated by Provider, Age, and Gender