Financial Inclusion: Using a Randomized Control Trial to Assess the Impact of Loan Amounts and Tenors on Customers' Loan Take-Up and Repayment

A **Dissertation**

presented to

The **Development Finance Centre (DEFIC)**
Graduate School of Business
University of Cape Town

In partial fulfilment
of the requirements for the
Master of Commerce in Development Finance Degree

by

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29 December 2020

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Abstract

This study aims to contribute to the academic and business knowledge of how to enhance digital credit in Pakistan's unsecured lending sector, which is vital to the development of the country's financial ecosystem. A Randomized Control Trial (RCT) is conducted with a view to answering two questions: (1) What is the optimal amount to lend to a customer? (2) How long should the loan tenor be? The objectives of the RCT were to track product take-up and product repayment as both are crucial for the success of a lending institution as well as the credit history of the individual customer.

The study employs a linear probability model (LPM), estimated by an ordinary Least Squares (OLS) regression, to analyse take-up, and instrumental variables to analyse repayment sensitivity. The data used was obtained from a technology platform that partners with a Pakistani microfinance bank and was automatically collected via their USSD platform. The sample consisted of roughly 28,000 individuals.

Causal evidence of the impact of changes in loan amount and loan repayment tenor was found on both take-up and repayment. Loan take-up was most impacted by the loan amount offered with the highest take-up for the loan of the largest amount and having the longest tenor. Repayment rates were better for the longer tenor loans and this was particularly apparent at the larger loan amount level. Some additional characteristics were also causally relevant in loan take-up but not in repayment, such as whether a customer read through the terms and conditions. Although the starting sample was large (28,000 individuals), the limited take-up of the product significantly reduced the actual sample, as is common in other studies of this kind. Future studies might seek for an even larger starting sample, alter price as one of the variables for an RCT, or add qualitative surveys to better understand loan usage and reasons for repayment and non-repayment.

Acknowledgements

I would like to thank The University of Cape Town Graduate School of Business and in particular the professors and assistants who made the MCOM program possible. Special thanks go to my supervisor Prof Abdul Latif Alhassan, who continuously and consistently encouraged, guided and helped me through this thesis for many months.

Thank you to my fellow MCOM classmates. Listening to your experiences, stories, and opinions taught me more than any textbook could. In particular, thanks to Unathi and Mokete for keeping my spirits high during weeks and weeks of full-day classes.

Thanks also to my colleagues, friends and family who supported me during the last two years on my academic journey.

Finally, thanks you to the people of Pakistan, who made this work possible.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

CNIC	Computerised National Identification Card
eCIB	Electronic Credit Information Bureau
GDP	Gross Domestic Product
GPFI	Global Partnerships for Financial Inclusion
ICT	Information and Communication Technologies
KYC	Know Your Customer
MFB	Microfinance Banks
MFI	Microfinance Institution
MOMO	Mobile Money
NGO	Non-Government Organization
NPL	Non-Performing Loan
RCT	Randomized Control Trial
SBP	State Bank of Pakistan
SDG	Sustainable Development Goal
SMS	Short Message Service
UN	United Nations
USSD	Unstructured Supplementary Service Data

Chapter 1
Introduction

1.1 Background of the Study

Financial inclusion has been recognised as a key contributor to the reduction of poverty by the Global Partnership for Financial Inclusion (GPFI), which is a subsidiary organisation of the G20 created to focus on addressing financial inclusion. The *World Bank Global Financial Inclusion Database* finds that just under two billion adults globally have no access to formal financial services (World Bank, 2019), which includes saving, insurance and lending. Unfortunately, this issue is concentrated in developing countries that already face many barriers to reducing poverty and reaching other United Nations Sustainable Development Goals (SDGs). Some countries are particularly worrisome according to *The World Bank's 2017 Global Findex Report,* which finds that almost half of all unbanked people live in just seven countries: Bangladesh, China, India, Indonesia, Mexico, Nigeria, and Pakistan (Asli Demirgüç-Kunt, Leora Klapper, Dorothe Singer, Saniya Ansar, 2017). This is visualized in their report and shown below in Figure 1.

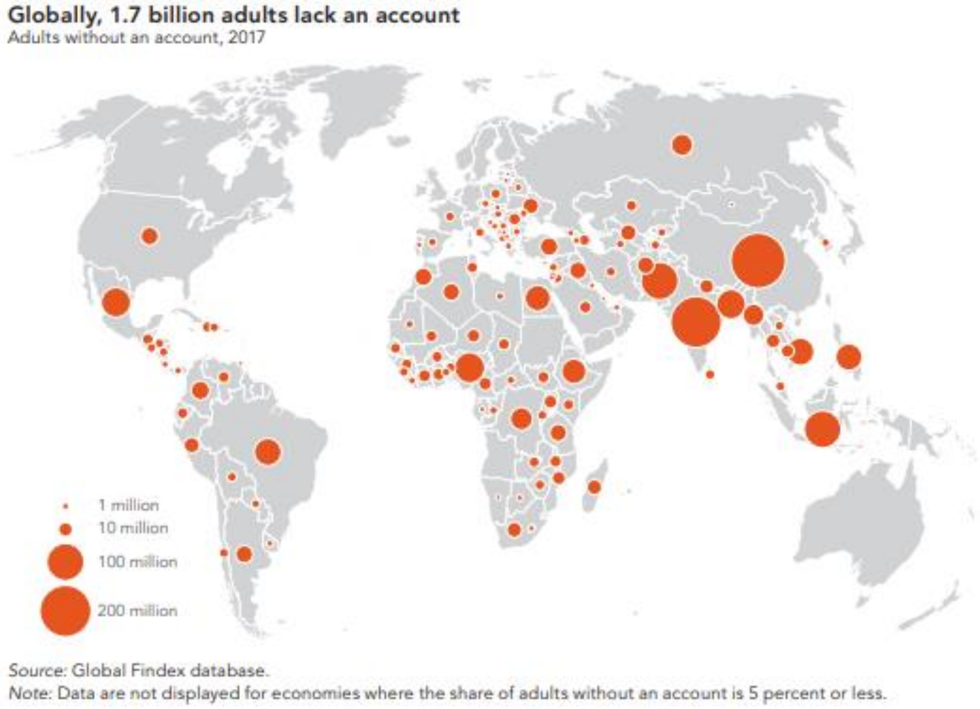


Figure 1: Unbanked Adults Globally

The country of focus for this study is Pakistan and the product of focus is unsecured lending via microfinance. Pakistan is the fifth most populous country in the world, with a population of 200 million. Findings from *Finclusion.org* corroborate what the World Bank has reported: Pakistan has one of the largest unbanked populations in the world with only 14% of the adult population having access to finance, which is 19% below the South Asian average of 33% (Financial Inclusion Insights, 2017). In terms of lending, the same report finds that only 3% of the population borrows money from formal financial institutions.

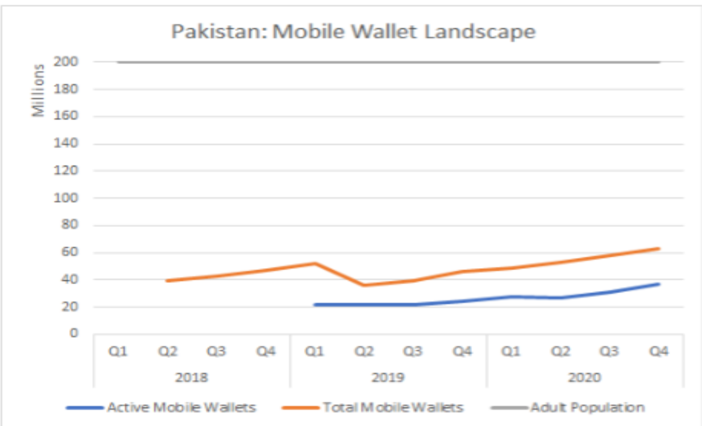
The State Bank of Pakistan (SBP) set up a National Financial Inclusion Strategy in 2015 to address these low levels of financial inclusion with the goal of having half of the country financially included by 2020, which has unfortunately not been achieved. The SBP identified several barriers to financial inclusion, which range from cultural to economic. Culturally, gender-based discrimination is a barrier to financial inclusion. While half of Pakistan's population is women, 86% of the banked population is men, according to the SBP. Economically, the country faces continual surging debt repayments and a shrinking GDP, resulting in a shrinking economy and reduced lines of credit in the private sector according the *Centre for Economic Research in Pakistan* and continued reliance on International Monetary Fund (IMF) bailouts (Tariq, 2019). Despite these bailouts, some progress has been made by the SBP: the country boasts strong regulatory frameworks for microfinance banks (MFBs) and the government has guaranteed their debts, allowing them lend to the underserved population. The country also has robust verification and know your customer (KYC) protocols in place and has over time built up an online credit information bureau (eCIB) of all citizens currently included in the financial sector in order to create financial footprints for them.

While these regulatory initiatives are required for a functioning financial system, it does create pressure on microfinance banks to be very strict about what types of customers they serve. While there may be hundreds of millions of excluded Pakistanis, these banks also need to give out financial products in a sustainable fashion and cannot simply open accounts for everyone. In particular, it is difficult for a bank to determine a customer's creditworthiness when that customer has no financial records or documentation other than their national identification card. Given that these unbanked customers do not have access to formal savings, they cannot post collateral for money borrowed, and this means the bank must lend unsecured to these unknown customers while adhering to strict regulations ensuring repayment ratios are met.

Unsecured lending thus comes with much higher risk of default. In Pakistan, non-performing loans are carefully monitored by the State Bank of Pakistan and microfinance banks have to report on how non-performing loans (NPLs) impact both their liquidity and their income statements (Badar & Yasmin Javid, 2013). The definition of a non-performing loan can vary from country to country, but universally it is understood to be a loan where the recipient has breached the expected repayment amount and date and where the lender has limited confidence the loan will be repaid. In an ideal world, non-performing loans would not exist. In reality, however, for financial service providers to compete in markets they must offer lending services and they must predict with some accuracy which customers will repay. Failure to do so could result in the banks losing their licenses.

While non-performing loans and default are often attributed to macroeconomic factors, such as the regulatory environment (Ranjan & Dhal, 2003), there is also a direct correlation of NPLs to each individual that receives a loan. Therefore, individuals must be assessed for their creditworthiness before receiving a loan. As discussed, this is difficult when individuals have never received a loan before, or even used a bank card. Firms must therefore be creative in the ways that they score these customers. Financial technology, or 'FinTech' companies as they are colloquially known, have started addressing this need by using alternative data sources to score financially excluded customers and offer them financial services (Jagtiani & Lemieux, 2017). This is particularly relevant in Pakistan, where the number of mobile wallets is growing and the information about an individual's mobile wallet usage can be used to assess their creditworthiness. Between 2008 and 2020, there has been a slow but gradual growth of mobile wallets in Pakistan as shown in Figure 2.

Figure 2: Growth of mobile wallets



Source: https://www.sbp.org.pk/publications/acd/branchless.htm

For the present study, mobile wallet users are pre-scored based on their mobile wallet usage, and a sample of customers that are considered high risk are offered a loan.

Given that these customers were already labelled as high risk and likely to default, the bank needed to ensure that customers were given the optimal loan amount and repayment period. However, the product was among the first of its kind in the market and there was as a result little precedent on what these parameters should be. A Randomized Control Trial (RCT) was therefore conducted, which in the FinTech world would normally be referred to as an A/B test, where customers are randomly divided into treatment groups and each group is offered a slightly different product or service in order to determine whether this difference has an impact on their behaviour. The present study follows such an approach, offering customers from the different treatment groups different loan options to assess the effectiveness of each loan option. The goal is for this study to contribute to the knowledge of unsecured lending using mobile money data and to provide recommendations to the firm supplying the loans so that the firm can operate in a sustainable way while reaching previously excluded Pakistanis and driving financial inclusion.

1.2 Research Problem and Research Question

The research problem is twofold: what loan amounts should be given and how long should the loan tenors be. In addition, the metrics of success that were being tracked by the bank offering the loans were also twofold: how could the bank maximize both the numbers of customers that would take a loan and the numbers of customers that would repay. While these were specific business model problems for the bank, the questions raised served as the research problems for this study. By working with a digital bank in Pakistan, the research and RCT could be conducted with accurate implementation and a large sample of real-time data.

The nano loan product targets traditionally unserved or underserved populations with limited access to financial services. The product is delivered to customers via their mobile wallet on their cell phone. Customers do not need a smartphone. Using the accessible technology of Unstructured Supplementary Service Data (USSD), customers can select a loan amount and loan tenor which they can pay back via their mobile wallet once the due date is reached. Since these are people who may have never had a credit card or bank account or even a payslip, the types of data points used in traditional credit-scoring algorithms are scarce. Additionally, national credit bureaus in these markets usually have no record of unserved customers. This creates a risk scenario for the firm offering the lending product; who should they lend to and what are the optimised levers (such as loan amount) to offer? The firm therefore uses alternative date points that it receives from partner Mobile Network Operators (MNOs) to create scorecards used to determine a customer's risk of default.

While these scorecards are useful in predicting default and, to a degree, customer affordability, they do not indicate what the optimal loan amount or tenor is for a customer group. To determine this, the study follows the concept of a randomised control trial (RCT) by splitting a qualifying base of customers into distinct groups and offering various iterations of loan amount and loan tenor. The results of this RCT are then fed back to decision makers at the firm, who can determine optimal offerings for customer groups in order to create product/market fit. The study therefore addresses the following research questions:

a) What is the impact of different loan amount and tenor have on loan take-up?
b) What is impact of different loan amount and tenor have on loan repayment?

1.3 Research Objectives

The purpose of this research is to examine the impact of offering different loan parameters to a randomised cohort of customers. The specific objectives include:

a) examining the effect of loan amount and tenor on loan take-up
b) examining the effect of loan amount and tenor on loan repayment

1.4 Scope and Justification of the Study

The study helps deliver insights on digital lending in developing markets. In this case, Pakistan is the country of focus, which is again helpful as it is estimated that Pakistan has some of the lowest financial penetration globally. From a research perspective, it is prudent to close this knowledge gap. While the scope of this study is very specific and focuses only on a sample of approximately 28,000 individuals, the methodology and insights can be applied in future RCTs for unsecured, digital lending programs. Additionally, the learnings can be generalised and applied to a wider subscriber base by the firm offering the product.

From a commercial perspective, it is important that firms offering these types of products can do so optimally. They need to adapt their product to drive customer acquisition, while ensuring that they balance their credit risk exposure to defaulters and non-performing loans. If banks are not able to limit their exposure, they will reach a liquidity crisis and their income statements will be negatively impacted by the required provisioning for loan losses. This can spiral them into insolvency, so it is in their best interest to conduct studies like this one in order to serve a wider audience while protecting the future of their business.

1.5 Organisation of the Study

This study is divided into five chapters. Chapter 1 introduces all necessary concepts and themes and describe the problem being addressed. Chapter 2 reviews prior research done on related topics and highlights knowledge that is useful for wider context. This section also points out potential flaws in existing literature or theories that are contradicted by this study. Chapter 3 outlines the quantitative methodology used in the study, that of an RCT, and describes in detail the various steps in ensuring that a rigorous scientific approach is followed. Chapter 4 summarises the results of the intervention and gives summary statistics for the regressions. Chapter 5 links theories to the results and explores insights from the study. Recommendations are made based on the results of the intervention and suggestions given for future studies that might add to this body of knowledge.

Chapter 2
Literature Review

2.1 Introduction

This chapter discusses in detail microfinance and associated technologies used for distributing microfinance and digital lending. Key terms are explained and described in the context of developing countries with a focus on Pakistan. Both theoretical and empirical literature is reviewed in assessing determinants of loan take-up and the associated loan repayment. The literature studied is focused on microlending, but some studies also extend to student loans, firm debt and sovereign debt. General human behaviour and biases are also discussed as part of the theoretical literature.

2.2 Defining Key Terms and Concepts

2.2.1 Financial Inclusion

There are many definitions of financial inclusion. Broadly it can be described as "initiatives that make formal financial services available, accessible and affordable to all segments of the population" (Demirgüç-Kunt & Klapper, 2012, p.25). Conversely, financial exclusion is defined as "a process that prevents poor and disadvantaged social groups from gaining access to the formal financial systems of their countries" (Conroy, 2015, p.1). More recently, Naceur et al. (2015) note that financial exclusion can be for one of two reasons: either because an individual wants access to institutions that offer financial services and cannot access them, or because an individual opts not to be included even if option exists. "Worldwide financial exclusion for religious reasons seems relatively small, but the share varies notably across countries and can be particularly high in certain Muslim countries" (Naceur, Barajas, & Massara, 2015, p.3). This distinction is important in the Pakistani context as it could be a key determinant in the low levels of financial inclusion. Franklin et al. (2012), however, argue that it is not the case for Muslim populations outside of Sub-Saharan countries and that Muslim individuals are not less likely to desire financial inclusion than their non-Muslim counterparts (Franklin, Demirguc-Kunt, Klapper, & Soledad Martínez Pería, 2012).

The definitions of financial exclusion and inclusion suggest that financial inclusion should be focused on marginalised groups that traditionally have been excluded from the personal or household financial system. Financial inclusion is a challenging but necessary task and must be addressed by government, multi-national development banks, and private firms.

2.2.2 Microfinance and Development

Microfinance has become a widely studied industry since its inception in the 1980s, attributed to Muhammad Yunus who created Grameen Bank (initially called Village Bank) to lend to the poor communities in his home country, Bangladesh. In his Nobel Prize acceptance lecture in 2006, he explained his rationale for creating microfinance,

"The creation of opportunities for the majority of people − the poor − is at the heart of the work that we have dedicated ourselves to during the past 30 years... I wanted to do something immediate to help people around me, even if it was just one human being, to get through another day with a little more ease. That brought me face to face with poor people's struggle to find the tiniest amounts of money to support their efforts to eke out a living…The first thing I did was to try to persuade the bank located in the campus to lend money to the poor. But that did not work. The bank said that the poor were not creditworthy. After all my efforts, over several months, failed I offered to become a guarantor for the loans to the poor. I was stunned by the result. The poor paid back their loans, on time, every time!" (Muhammad Yunus, 2006).

Further, Yunus went on to utilize technology and created Grameenphone, in partnership with Norwegian operator Telenor, to deliver cell phone banking to drive financial inclusion in Bangladesh at a larger scale.

Since then, microfinance has expanded in developing countries across Africa, Asia and South America as the solution to bringing financial services to the poorest of the poor, a segment that traditionally retail banks will not serve. Theoretically, with microfinance, the poor will be able to borrow money to expand their business and open savings accounts to better their future and the lives of their children. However, many studies reject this notion and argue that microfinance has very limited impact benefit for the poor and does not lift them out of poverty (Mossman, 2015). Some studies even refute the benefits of microfinance and show evidence that many microfinance lenders have instead become the exact predatory lenders than Yunus initially tried to supplant (Hulme & Maitrot, 2014).

Despite growing evidence that microfinance is not a miracle solution for the poor, there remain solid examples of microfinance programs that have positively contributed to development and financial inclusion. In their work tracking individual households, Collins et al. argue that although microfinance may not lift individuals out of poverty, but is useful just for smoothing of household cash flow and helps households deal with unexpected financial shocks like medical bills or seasonal variations like agricultural yields (Collins, Morduch, Rutherford, & Ruthven, 2009). Their book, *Portfolios of the Poor: How the World's Poor Live on $2 a Day,* goes into extensive detail of individual poor households in India, Bangladesh and South Africa, and they find that even borrowers of the famed Grameenbank may not use microfinance productively but for consumption because of an unexpected financial shock. The question then is whether access to microfinance for consumption is sufficiently helpful toward development and Gertler et al. argue that microfinance can be incredibly helpful for cases like accessing emergency life-saving healthcare, which would have otherwise been unavailable had an individual been unable to afford it (Gertler, Levine, & Moretti, 2009). In Pakistan specifically, microfinance has been shown to benefit the poor and help reach the UN SDGs (Niaz & Iqbal, 2019) and that women particularly trust microfinance and perceive it as a source of economic growth and empowerment (Bel Hadj Miled & Jalel-Eddine Ben, 2015). Even if microfinance is not the perfect solution that Yunus originally dreamed of, it remains useful in helping the poor and driving development.

2.2.3 Mobile Money

As noted above, microfinance bank Grameenbank now co-exists with technology provider Grameenphone, which offers mobile financial services. Mobile money is the term coined for this type of service. Perhaps the most synonymous brand associated with mobile money success is M-Pesa, which first introduced mobile banking for Kenyan Safaricom users over a decade ago and has now become a part of daily lives of Kenyans (Mutsune, 2015). However, mobile money success has not just been limited to Kenya; in Ghana MTN has found success in delivering a digital lending product through MTN's mobile money service (MoMo) called QWIKLOAN. Over two million Ghanaians have received loans via QWIKLOAN to date with over $300 million being disbursed ("AFB's Qwikloan hit 2million customers," 2019). Likewise, in Uganda, over seven million MTN customers have received a "Mokash" loan from NCBA Bank ("MTN micro loan users grow to seven million," 2020). While local press headlines show the impressive growth statistics of these platforms, more relevant are the impact studies done to assess how mobile money has changed people's lives. Studies show that access to M-Pesa has assisted with bringing 2% of Kenyan households out of poverty (Suri & Jack, 2016), which shows how mobile money can complement microfinance institutions with their goals of financial inclusion at scale.

Regions beyond Africa have, however, not had the same success in mobile money adoption. For example, in Pakistan, nine out of ten households have access to a mobile phone but only 5% of households use mobile wallets (Mirzoyants, 2013). Of the surveyed households, most could only access loans via family or employers, which highlights the issue of financial exclusion to formal lending markets. The *Financial Inclusion in the Middle East and North Africa* report by the World Bank also corroborates this finding, noting that "Mobile banking has been used primarily for payments and transactions so far, and not for loans or savings" (Pearce, 2011 p.16), which shows that the necessary infrastructure is already in place to facilitate digital transactions but that firms need now to provide lending and saving products with this infrastructure.

2.2.4 Unsecured Lending

Unsecured lending is the act of lending money without requiring any down-payment or collateral. Banks and financial institutions typically prefer secured lending, where a customer has given some deposit to indicate they can afford the future repayments. This became even more important after the 2008 Global Financial Crisis as banks face more regulatory scrutiny on who they lend to (Degryse, Karapetyan, & Karmakar, 2012). However, unsecured lending is necessary in order to address financial inclusion, since millions of people have no money or assets to post as collateral. There has been much scrutiny on these unsecured lending practices, particularly in countries with low levels of regulation where customers become overindebted because they cannot repay a loan or because they take out more loans to pay off existing ones. This can be crippling to the entire drive for financial inclusion and can leave individuals worse-off than if they had never received credit in the first place. Individuals can become further trapped in poverty (Schicks, 2010), face high stress or depression in dealing with over-indebtedness (Field, Pande, Papp, & Park, 2012), and in some cases resort to suicide (Sarkar, 2020). Therefore, banks and microfinance institutions must exercise some fiduciary duty in who they lend to and how much they lend.

2.2.5 Technology and Alternative Credit Scoring

The introduction of better Information and Communication Technologies (ICTs) in developing markets has reduced transaction costs for firms delivering communication and financial services (Kpodar & Andrianaivo, 2014). This is largely because the cost of running a physical retail store or bank branch is removed and customers are able to self-service or use MNO agents to assist them with transactions via their phones. Every transaction that is completed via a mobile phone also contributes to a digital database that can later be used to create financial identities for customers who were previously not recorded. “Therefore ICT and mobile phone in particular improve access to credit and deposit facilities, allow more efficient allocation of credit, facilitate financial transfers, and boost financial inclusion” (Kpodar & Andrianaivo, 2014, p.8)

Additionally, new technologies related to machine learning have contributed to the field of data science and allowed for new types of credit scoring on non-traditional datasets. For example, banks would ordinarily score customers using their transaction histories to assess their credit-worthiness (Baofeng, Xue, Bi, & Yizhe, 2020), but new technology players like Tala, a platform that partners with MNOs or ICTs for customer mobile phone usage data, have been successful in using other types of information, such as what time of day a customer charges their phone, to determine their creditworthiness. Researchers partnering with Tala note that “an individual whose calls to others are returned may have stronger social connections that allow them to better follow through on entrepreneurial opportunities” (Björkegren & Grissen, 2019, p.5) . They are able to use millions of data points like this to create a credit score for someone who owns a mobile phone but has never had a bank account. The present study leans on these types of data points to qualify a set of customers for a loan, although these data points are unfortunately not available for publication.

2.3 Theoretical Literature

Since this research paper focuses both on loan take-up and on loan repayment, the theoretical concepts of these behaviours are discussed separately. Microfinance research is largely supported by empirical literature but some theoretical literature pertaining to human behaviour is useful in understanding loan take-up and default.

2.3.1 Determinants of Loan Take-Up

Theoretical determinants of loan take-up are not widely studied, and most studies on credit tend to focus on repayment. However, theoretical research focusing on student loan take-up can be applied in this paper. Loan take-up of the Student Loan Scheme in the UK in the early 1990s was low, with less than 28% of eligible students taking a loan (Gayle, 1995). To understand why this was the case, researchers turned to surveys and found that one of the most common determinants of loan take-up was students who already had credit card debt. This was an alarming realisation and speaks to the theory of risk preferences, according to which an individual already in debt is more likely to take a loan. This theory could be useful for the present study when loan take-up is later analysed.

2.3.2 Determinants of Credit Default

Theories of credit default date as far back as the original practice of lending and borrowing. Given the risks of over indebtedness, it is critical that firms lend responsibly, disbursing amounts that are both useful and repayable. The loan tenor is a also crucial factor. Some theorists argue that shorter tenor loans encourage timely repayment and that longer tenors result in lower likelihood of repayment. These arguments are based on theories of human behaviour—for example that short deadlines discourage procrastination. In his book, *Predictably Irrational*, behavioural economist Dan Ariely argues that deadlines force humans to create action plans and keep them accountable. He also argues that deadline extensions do not result in better work, and rather just delay the start of the work (Ariely, 2018). Based on these theories, it may not be beneficial to the customer or the lender to grant longer loan terms or loan extensions. Other schools of thought argue that short, inflexible repayment plans are not beneficial, that customers need longer periods to repay, and that these extended periods do not increase the risk of default (Field et al., 2012). An alternative theory based on *present-bias* states that regardless of an activity's duration, humans will always overestimate their ability to complete a future task (such as repayment of a loan), and when the time comes they are unable to do so (O'Donoghue & Rabin, 1989). Based on this theory, risk of default may be more strongly correlated to the loan amount than the tenor.

Ghosh and Ray (1999) created a theoretical model to figure out what the optimal first loan size is for a new customer who has no collateral, no credit history, and has never taken a loan from the bank before. They find that offering a very small loan is most optimal because it filters out customers that cannot repay even the smallest loan without the bank losing too much capital and they base this on the concept of *adverse selection,* according to which there is a "critical minimum proportion of natural defaulters in the population" (Ghosh & Ray, 2016, p.80) and that this is hardest to predict for new customers. However, they theorise that as the lender learns more about the borrower, the *information asymmetry* starts to fall away, as they start to have a record of a borrower's previous loans and the repayment of previous loans signals good behaviour. The lender can then alter future loans, such as making them bigger and cheaper, and these incentives encourage the borrower to repay as there is more utility in repaying and receiving a larger loan than in defaulting on the current one.

2.4 Empirical Literature

As per the theoretical literature discussions, the empirical literature is discussed first for loan take-up and then for loan repayment.

2.4.1 Determinants of Loan Uptake

A report that summarises seminal work on low microfinance take-up rates combines the results of several field surveys conducted across South America and Asia and finds that the main determinants of low take-up are prices that are too high, loan amounts that are too low, or individuals who have a personal scepticism of the institution offering the loan or a scepticism of their own ability to repay (Karlan, Morduch, & Mullainathan, 2010). The researchers point out that take-up rates across their studies vary quite significantly, from a 4% credit take-up rate in a study with Compartamos Banco in Mexico to a 45% credit take-up in a study with BIDS in Bangladesh. They argue that the design of the loan product will heavily impact take-up, but caution that even a cheap, easy-to-understand loan product may still have low take-up due to the scepticism of the individual or their preference to stay out of debt.

Magill and Meyer (2005) conducted a baseline study of 17,000 microenterprise entrepreneurs in Equador and found similar results of low take-up for credit. They found that 85% of the respondents had not taken a loan in the last twelve months and this was proportional across male and female entrepreneurs. The reasons for the low take-up included distance from the lender and complicated paperwork to apply for a loan. These barriers and transaction costs can be removed with a digital loan that requires no paperwork and no travel because it can be disbursed directly to a mobile money account accessible via cell phone. The researchers also segmented the responses by income level and found that wealthier respondents were more likely to borrow than poorer respondents and cite reasons such as wealthier respondents having confidence in their ability to repay and being more comfortable with formal financial institutions.

In a similar study Navajas et al (2006) analysed household surveys from five countries in Central America (Ecuador, Guatemala, Panama, Nicaragua, and Dominican Republic) to understand the state of microfinance in these countries. The researchers also focused on why individuals did not take loans. The most common reason given was that the individuals simply did not need the credit. The next most common answer was that the available options were not desirable given their product design. In contrast to Magill and Meyer, distance from a lender was one of the least common answers. Based on this research, it is a combination of an individual need, and the offerings of the market, that contribute to low credit take-up.

Gine and Yang (2007) conducted a study in which they offered 800 farmers in Malawi a loan but offered half the group a standard loan and half the group a loan with required insurance. Consistent with other research, the take-up rates were low with only 33% of the standard loan group, and only 17.6% of the loan-with-insurance group, taking the product. The authors were surprised by the results and found that education level was highly correlated with take-up of the loan-with-insurance product, indicating that limited education may be a barrier to taking a product if the customer is not able to understand the dynamics of it. Although this study looked at insurance in addition to credit the findings are relevant to the study of microfinance as a whole and the problem of uneducated individuals opting out of a product due to confusion or scepticism.

To combat the issues of a lack of education Gine (2019) later conducted an experiment with a microfinance institution in rural Pakistan where clients of the institution were randomly assigned to receive an eight-day business training on financial management, marketing and budgeting. The group that received training was compared to a group that did not receive training. In addition, the groups were further segmented where some customers were randomly offered a loan size seven times larger than normal. The researchers found that the business training had no impact on loan take-up, but the larger loan offers had a significant impact on take-up. This somewhat contradicted with previous research that indicated that education or training may impact loan take-up and pointed towards loan size as the reason customers do or do not take a loan.

Gulesci et al. (2020) base their empirical research on the previously mentioned theory of *adverse selection* and hypothesise that loan take-up is dependent on the type of borrower. Responsible borrowers are attracted by low prices and large loans whereas riskier borrowers take-up loans due to advantageous selection. They studied small business owners in urban Uganda and found that hypothetically dropping loan price from 25% to 20% would increase the take-up of non-risky borrowers that have lower risk appetites and non-seasonal businesses. This indicates that pricing is an important parameter in enticing good repayers to take-up loans.

The overlap of technology and microfinance are important in this context and Bhardwaj et al. (2019) study this overlap in Kenya by accessing the loan data of Safaricom's M-Pesa customers who use their mobile phones to take a loan offered by Safaricom, called M-Shwari. Of the eligible base of M-Pesa subscribers, 34% took a M-Shwari loan over the two-year period. The study finds that only 6% of this population had a bank loan from elsewhere over the two-year period indicating that the bulk of the base only has the M-Shwari option as their only source of credit. The researchers conclude that the use of alternative credit scoring using mobile data improves likelihood of digital loan take-up for customers that have almost no other choice. Therefore, loan take-up is partially determined by supply in the market and may increase of there is no competition of other lenders.

In summary, the empirical literature across multiple continents and across nationwide surveys and other field experiments points to several factors that impact loan take-up. This can be broadly categorised into three themes: firstly, the characteristics of the individual borrower and their need for a loan, their risk preferences, their education level, and their income level; secondly, the design of the loan will impact loan take-up and these design parameters include loan amount, pricing, and repayment terms; lastly, the supply of credit to the market, and what available options a single customer has, will impact whether they take a specific lending product.

2.4.2 Determinants of Credit Default

Credit default has been studied at varying levels from national debt to firm debt to indebtedness at the household or individual level. A more recent group of Nobel Prize laureates (for Economics, not Peace) are Abhijit Banerjee, Esther Duflo, and Michael Kremer, who were recognized for their experimental work in studying and alleviating poverty. They assert that a key determinant for credit default is moral hazard, where "if the cost of default were lower than the interest payment, the borrower would always choose to default" (Banerjee & Duflo, 2010, p.4). This exact determinant is the reason so few retail banks lend to customers that are informally employed (no proof of income) or customers that have no savings (no ability to post collateral) and why these people end up financially excluded. If a customer is better off by keeping the principal amount, instead of repaying the principal and interest and receiving a higher second loan, they may choose to default. This ties in with the theory of adverse selection where there exists a group of customers that will not pay back.

Vogelgesang (2003) argues the default is actually due to two factors: clients that have multiple loans are most likely to default and clients with certain attributes have a higher likelihood of repayment when there is sufficient competition. The study focuses on 76,000 microentrepreneurs that take loans from Caja Los Andes, a Bolivian microfinance bank, over an eight-year period. It was found that customers with multiple active loans from different microfinance or consumer credit institutions struggle to repay and become overburdened with debt. This finding is particularly important from the perspective of regulation and national credit bureaux: if there is over-supply of credit, without regulatory restrictions on how many loans an individual or business can take, this can lead to default. Given this finding, it is clear that the process of helping customers transition to being financially included should be managed carefully to avoid over-indebtedness. However, the study also finds that increased supply of microfinance loans can have some positive aspects. When there is healthy competition in the market, microfinance and consumer credit institutions must offer well-priced products, which improved the likelihood of repayment. The key then is to have a healthy competition in the market, but also to have regulatory measures in place to prevent over-indebtedness.

Schreiner (1999) also studied a microlender in Bolivia. The researcher ran a logit model on 39,956 loans from 1998 in order to assess which variables best predict future default. The variables include demographic data, such as the gender of the borrower, as well as behavioural data, such as whether the borrower had a loan in arrears before. The researcher found that there was a 0.02 percentage point increase in likelihood of default for every extra $100 increase in loan size. While this is important, Schreiner cautions that other variables mentioned above play a factor in loan repayment.

Chaudhury and Matin (2002) found pockets of poverty stricken areas in Bangladesh where many households, despite claims that they were financially excluded, were trapped in debt cycles by having loans at multiple microfinance institutions. They analysed data for 240 households and categorized them into three groups: regular (good repayers), irregular (inconsistent repayers), and defaulters (poor payers). The defaulters became trapped into multiple debts by borrowing money for emergencies or economic shocks, which they call distress management. The researchers suggest that micro-lenders need to design products for the poor that build in an expectation that the poor deal with emergencies which can cause delays in repayment.

Alfaro and Galardo (2012) analyse data from *The Survey of Household Finances* in Chile, where they estimate specifications of a probit model to find determinants of household credit default. They find that there is a combination of personal characteristic determinants as well as financial determinants. Almost four million households were surveyed over a year and the researcher found that higher incomes led to lower likelihood of defaults and that the education level of the head of the household also correlated with lower likelihood of default. The defaults included mortgage debt and personal household debts of all individuals in the household combined. Given that education and income are closely linked, it makes intuitive sense that both positively contribute to repayment of debts. The researchers propose that the high levels of income inequality in Chile produce different risks in lending to the richest and poorest quintiles and that the poorest, owing to limited job security, cannot absorb macro-economic shocks. The researchers find that even in poorer households where multiple individuals have incomes, the risk of default is still higher compared to a wealthier household where a single person provides all the income. This provides further evidence that job security and lack of predictability in cash flow in poorer households drives uncertainty in loan repayment.

Costa and Farinha (2012) use a similar approach to study data from the *Household Finance and Consumption Survey* in Portugal from 2010. Their research again validates findings that lower income households have a higher likelihood of default even though their higher likelihood of rejection means they are less likely to enter the credit system in the first place. They also find that younger households have a higher likelihood of default. The researchers create an indebtedness ratio, with which they project how many years it would take for a household to pay off all their debts assuming all annual income over the period were used to pay off debt. They find that 60% of the poorest households have concerning indebtedness ratios. Mortgages are the main cause of higher indebtedness ratios in medium- and higher-wealth households, but for poorer households the debt is for general credit. This is concerning as it indicates that the debt itself may not even lead to a future asset and that the debt may be to smooth out household cashflow problems.

Outside of the household level, defaults among SMMEs are also correlated by ratio of the borrowed amount against revenue or assets which is a similar indicator of affordability. This appears to be a global trend as exhibited by several studies. McCann et al. (2012) analyse the loan histories of 6,000 SMMEs in Ireland and find that the profitability ratio and liquidity ratio are strong predictors of default. They also find that larger firms tend to have lower likelihood of default unless the ratios of loans to assets is large. In Slovakia, Fidrmuc (2009) analyses 700 SMMEs loan records and finds that liquidity and profitability are the strongest determinants of loan repayment. They also find that indebtedness only increases the likelihood of default for firms that are overly indebted, which is similar to the household finding of individuals defaulting when they take out too many loans. In South Africa, Eresia-Eke (2013) used a cross-sectional approach to surveying 160 small enterprises in the Durban area. Of the surveyed businesses, 60% had defaulted on a loan before and the researchers found no significant correlation on the factors that they assessed, which included age of the business head, education level, and size of the business (ranging from 1 employee to 100 employees). The researchers conclude that SMMEs broadly appear to struggle with loan repayments and more work must be done on an educational and regulatory level to reduce defaults.

From individuals to households to small businesses, the growing evidence suggests that loan default is predominantly an affordability issue, where the loan parameters are not appropriate for the individual, particularly if the individual or business is over-indebted. Default also occurs when the benefit of repayment does not outweigh the benefit of keeping the borrowed capital. Bulow and Rugoff (1989) prove this even at a sovereign level: governments default on debt when the burden of repayment outweighs the benefit of a potential future loan from the same provider. Loan size therefore needs to grow at a higher rate than the interest repaid on the prior loan. For the purpose of the present study, which only focused on the first loan take-up and repayment, these findings may not be as relevant, but they are important in the long-term tracking of these customers.

2.5 Chapter Summary

This chapter summarizes the existing literature on microfinance with a focus on microlending and household-level credit defaults. Key terms that are relevant to this study are explored deeply and conflicting schools of thought regarding microfinance practices are compared. Theoretical literature that centres on behaviour in the context of lending, deadlines and the human tendency to overestimate future abilities are all reviewed. Empirical literature ranging from other RCTs to massive nationwide surveys on microfinance are reviewed, and the findings from each are discussed in detail to better understand reasons for low loan take-up and repayment. All of these studies are useful in assessing some of the results that emerge in Chapter 4 and some of their methodologies are useful for the methodology in Chapter 3.

Chapter 3
Methodology

3.1 Introduction

This chapter outlines the business experiment that was conducted to determine which loan amounts and which loan durations would be appropriate for the customer base. The experiment conducted was a Randomized Control Trial (RCT) that split a sample of approximately 28,000 participants into four distinct groups. This chapter explains how the sampling was conducted, what the hypotheses were, how the experiment was implemented and what regressions were used to explore the results. This chapter also highlights some limitations of this experiment.

3.2 Research Approach

The research design approach is quantitative. The unit of analysis is individuals and their respective behaviour regarding two measurement points: firstly whether they take the lending product; secondly, for those that took the product, whether they repay on time. The research approach is that of an RCT in order to isolate the treatment effects of the four groups. The randomised control trial is used for its effectiveness as a method to isolate the impacts of changing the loan design on customer take-up and repayment behaviour.

At the time, the standard approach at the digital bank was to offer a Rs. 500 loan with a 14-day tenor. However, there was debate as to whether this should be increased to improve take-up and what the impact on repayment would be. The resulting hypotheses were raised to assess the impact of tenor and amount separately, according to the two research questions:

1. H_1: Offering a bigger loan amount (Rs. 1,000) will increase product take-up
2. H_2: Offering a longer loan tenor (30-day) will increase product take-up
3. H_3: Offering a bigger loan amount (Rs. 1,000) will result in poorer repayment and increases the risk of default
4. H_4: Offering a longer loan tenor (30-day) will result in improved repayment and decreases the risk of default

3.3 Research Design

3.3.1 Population and Sampling

Approximately 100,000 subscribers who had registered for the loan product via USSD were identified as the first sample. Thereafter, subscribers who had already been qualified for the product (72,000) were removed from the sample. This was done in order to target a group of customers who had never seen previous offers, tenors or prices. Even though the customers had registered for the product, since they had not yet been qualified, they would only ever see a USSD screen that told them that they were not eligible for the product at the time and to keep using their mobile wallet accounts to increase their chances of qualifying for a loan. Therefore, the loan offer that they would see during the experiment, once they were qualified, would be the first offer they were ever shown and they would not be anchored to previous offers.

The 28,000 customers were then randomly split into their four respective, mutually exclusive groups:

1. Control group: Offered Rs. 500 loan for 14-day tenor
2. Treatment group 1: T_1 – Offered Rs. 500 loan for 30-day tenor
3. Treatment group 2: T_2– Offered Rs. 1,00 loan for 14-day tenor
4. Treatment group 3: T_3 – Offered Rs. 1,00 loan for 30-day tenor

. The sizes of these groups are shown in Figure 2 below.

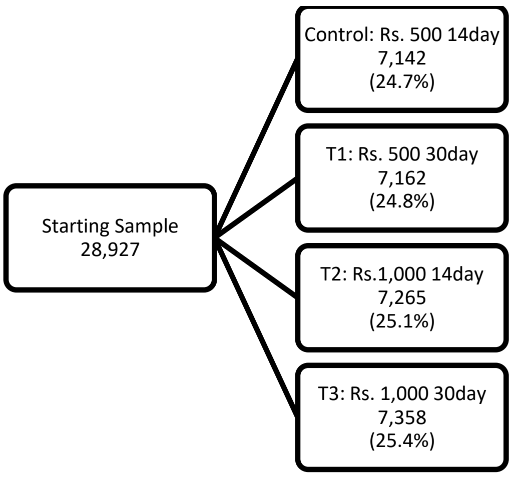


Figure 2: Split of the Four Groups

At the time, the bank was only offering 14-day loans and there was continual debate about whether opening a 30-day term was a good idea. Additionally, there was debate as to what loan amount should be given, with some executives arguing that a higher amount would drive acquisition, with other executives arguing that a high amount would result in poorer repayment rates. At the time, Rs. 500 was the standard amount given for a first loan. Therefore, the RCT was conducted to compare the four groups and determine which option was better.

3.3.2 Randomized Control Trial Implementation

The firm operating the technology behind the product, referred to henceforth as ‘the platform’, qualified the customers on their system. At the start of April 2019, they triggered an SMS from their system to each customer notifying them that they qualified for the product. The SMSs were sent at the same time on the same day to all of the 28,000 customers to control for time and day. The SMSs were also personalized to mention the exact offer that the customer was receiving. The observation window for product take-up started from 1 April and ended on 30 April, meaning that customers did not have to take the product straight away and had a full month to decide whether they wanted the loan. The observation window for repayment ran for ninety days past the repayment due dates. Figure 3 shows a timeline of the observation window.

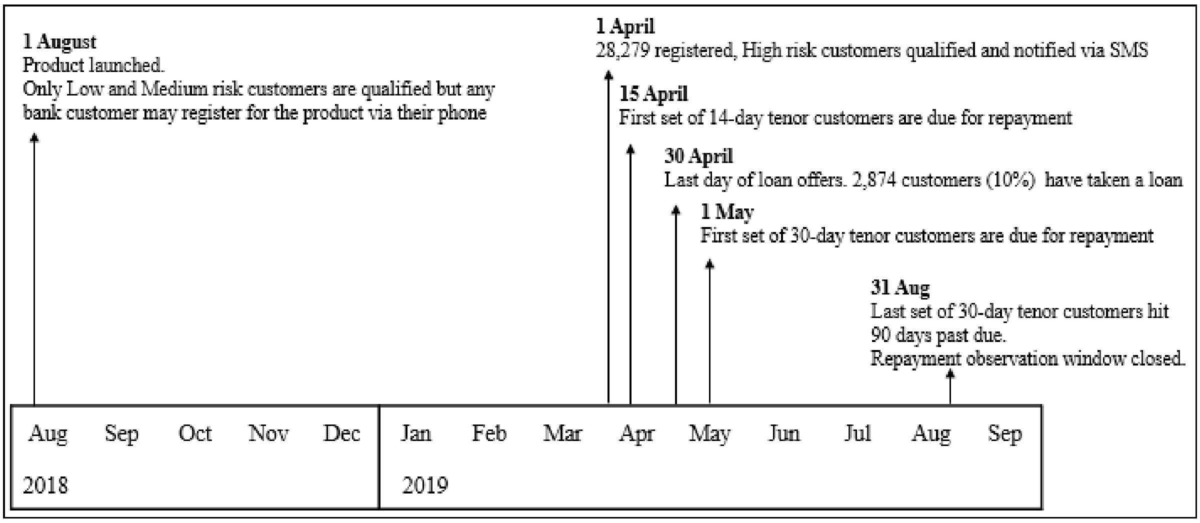


Figure 3: Timeline of Take-Up and Repayment Windows

There were 28,000 high risk customers that had registered for the product and all were subsequently qualified. There were additional customers that had registered that were classified as very high risk, and some as even higher high risk but these customers were not qualified.

Customers were pre-scored by the platform operating the loans. Their scores were based on a variety of previous behavioural factors such as airtime spend or time on the network. Customers were offered a loan linked to their individual SIM card and their Computerized National Identification card (CNIC), which ensured that customers could not swap out their SIM cards with others. Customers were also required to enter their own unique secret PIN number when registering for the product and again when accessing the loan, which helps ensure that the SIM card owner is the one taking the loan. Customers were also required to input the issuance date of their CNIC when applying for the loan. This input was sent in real-time to the Micro Finance Bureau to validate whether the date was correct. Loans were only disbursed when CNIC issuance dates were entered correctly, which again strengthens the confidence that the end-users were the correct individuals.

Other than their classification as high-risk by the technology provider, there is unfortunately not much known about the individual customers. For example, location, age, and gender are not known, as regulation in Pakistan does not allow for this type of identifying data to be shared outside of the country. Even the CNIC numbers and the SIM numbers were encrypted before leaving the country so there was no opportunity to conduct further qualitative research such as phoning the customers. While this may limit the viability of the study, the business experiment still holds value in tracking the treatment groups of randomly selected individuals. Additionally, it improves of the ethics of the study in that the participants' identities remained anonymous. RCTs in recent times have come under scrutiny for the approach of using humans as experiments subjects without their knowledge. The individuals in this case all opted in to the Terms and Conditions of the bank which included assessing their behaviour to improve the product offering. In addition, no individual was denied a service as part of the RCT; every individual was offered a loan and the price was kept identical for every user to create a fair experience.

3.3.3 Data Source and Collection

The advantage of a digital product is that the distribution is clean and simple. Once the SMSs had been sent, the observation window began, and the test was open from 1 April 2019 until 12 June 2019. Since the distribution mechanisms are automated and clean, the resulting data collection methods could be applied robustly and tracked daily. The platform's data tables were automatically updated when customers engaged with the USSD screens, and every time a customer proceeded to the next screen in the loan journey, the step was logged. If the customer chose to take the product, this was logged and the various repayments (or lack thereof) were also automatically logged. Other data points, such as whether customers read the Terms and Conditions screens, were also noted. The USSD information of every customer was analysed to understand how they engaged in the product. For example, a date and time stamp per individual was recorded every time they reached a certain USSD screen. This meant that additional variables could be created, such as how long customers took to read the various USSD screens and how long they took to access the USSD screen after the SMS was sent.

For the repayment measurement, customers were tracked from their due date and up until 90 days after their due date. All repayments were recorded automatically, and again additional variables could be created, such as whether the customer repaid their loan all at once or if they repaid in instalments. The method of collection was also noted. In some cases, customers opted to repay by topping up their account and selecting ‘Repayment’ on the USSD screen. In other cases, the customer’s account was automatically debited on the due date and whatever balance was in the account was taken for repayment up to the relevant level of the amount due.

The data was collected on the platform’s data tables and then extracted via SQL to be analysed in Stata. One data set specifically on product take-up tracked USSD behaviour, while a second data set on repayments tracked financial transactions that resulted in repayment. This was mapped back to the USSD data set to identify which customers repaid, repayment size and frequency.

3.4 Specification of Regression Equations

3.4.1 Take-Up

A linear probability model (LPM), estimated by an ordinary Least Squares (OLS) regression, was used to answer the first research question on the impact of loan amount and tenor on product take-up. Because the customers were randomly assigned to the groups, this is an appropriate methodology to calculate the impact of the treatment groups while controlling for other variables present across all the groups, like in which week the customers took the loan.

Similar studies that use RCTs to assess the impact of a treatment group also employ this method. Field used an RCT to randomly split Indian microfinance loan customers into two groups with one group repaying weekly and the other group repaying monthly. The results were then analysed using a LPM estimated by OLS to assess the impact of the weekly versus the monthly format (Field et al., 2012). Another example of an RCT using this analytical framework, also in microfinance in India, is the experiment by Aragon et al. that randomly split customers into either a flexible credit line (treatment) or a loan product (control) and used OLS to analyse the impact of the treatment versus the control (Aragón, Karaivanov, & Krishnaswamy, 2020). This method uses binary variables to indicate whether a customer belonged to the treatment or control group. In this experiment, there is one control group and three mutually exclusive treatment groups. This is represented by the equation:

$$Ltakeup_i = \beta_0 + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_i + \epsilon_i \qquad (1a)$$

Where $Ltakeup$ represents a binary variable measuring the outcome where 1 is the loan taken and 0 is the loan not taken; β_0 is the constant tenor; *T1 denotes the effect of* Treatment 1: Offered Rs. 500 loan for 30-day tenor and 0 if Offered Rs. 500 loan for 14-day tenor; *T2 denotes the effect of* Treatment 2: Offered Rs. 1000 loan for 14-day tenor and 0 if Offered Rs. 500 loan for 14-day tenor; *T3 denotes the effect of* Treatment 3: Offered Rs. 1000 loan for 30-day tenor, and 0 if Offered Rs. 500 loan for 14-day tenor.

A second equation is run including covariates. As discussed, there is limited information about the sample population and no demographic information that forms a baseline prior to the experiment start and the randomisation. There are, however, some variables that can be used that assess behaviour post-qualification but prior to taking the loan, such as how many attempts a customer makes and these are considered appropriate to use as covariates (Glennerster & Takavarasha, 2013) in order to reduce unexplained variance.

$$Ltakeup = \beta_0 + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_i + X_i + \epsilon \qquad (1b)$$

Where *T1*, *T2* and *T3* are defined as before; X denotes a vector control variables including Segment, Registered Week Before; Application Attempts, Week Loan, Terms and Conditions: Input Error; ϵ = Error term

3.4.2 Repayment

Similar to the uptake models (1a and 1b), the regression equation on the effect of loan amount and tenors on loan repayment is specified in equations 2a and 2b below;

$$Lrepay = \beta_0 + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_i + \varepsilon_i \quad (2a)$$

$$Lrepay = \beta_0 + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_i + X_i + \varepsilon_i \quad (2b)$$

where $Lrepay$represents a binary variable measuring the outcome where 1 is the loan repaid and 0 is the loan not repaid; *T1*, *T2* and *T3* are as defined before; X denotes a vector control variables including Segment, Registered Week Before; Application Attempts, Week Loan, Terms and Conditions: Input Error; $\epsilon =$ Error term

However, a problem arises in that the repayment rates are dependent on take-up, since a customer cannot repay a loan unless they have taken one. To solve this, a second set of regressions are run making use of instrumental variables. Instead of comparing all treatment groups against the control group simultaneously, each treatment group is compared separately to the control group. As discussed in *Running Randomized Control Trials* (Glennerster & Takavarasha, 2013), comparing each group directly against the control group adjusts average treatment effects by take-up rates.

The resulting equations are as follows: firstly, the effect of the control group (Offered Rs. 500 loan for 14-day tenor) compared only to treatment group 1 (Rs. 500 for 30-day tenor) of loan repayment is specified as;

$$Lrepay = \beta_0 + \beta_1 T1_i + X_i + \varepsilon_i \quad (3a)$$

Secondly, the effect of the control group (Offered Rs. 500 loan for 30-day tenor) compared only to treatment group two (Rs. 1000 14-days) of loan repayment is specified as;

$$Lrepay = \beta_0 + \beta_2 T2_i + X_i + \varepsilon_i \quad (3b)$$

Lastly, the effect of the control group (Offered Rs. 500 loan for 30-day tenor) compared to treatment group three (Rs. 1000 30-days) of loan repayment is specified as:

$$Lrepay = \beta_0 + \beta_3 T3_i + X_i + \varepsilon_i \quad (3c)$$

T1, *T2* and *T3* and X are as defined before.

3.5 Specification of Variables in the Regression Models

The variables were split by independent and dependent status. The independent variables included the four treatment groups as well as several other dummy variables. The dependent variables measure the hypothesis outcomes.

3.5.1 Dependent Variables in the Regression Models

The dependent variable, or outcomes and measures of success, are listed below:

Loan: this binary variable indicates whether a customer took a loan or not. The bulk of the 28,000 registered customers did not take the loan and only 6,000 customers took the loan.

Repay: this variable indicates how much of the loan was repaid at the due date. A customer with a 100 means that 100% of the loan was repaid at due date. A customer with 50 means that half the loan was repaid at due date. A customer with zero means that the customer repaid nothing at due date.

3.5.2 Independent Variables in the Regression Models

Control group

Rs500d14: this variable is an indicator of whether a customer was assigned to this group. This was the control group treatment where customers were offered Rs. 500 for a loan period of 14 days. If a customer was allocated to this group, they will have a 1 value. If a customer was not allocated to this group, they will have a 0 value.

Treatment groups

Rs1000d14): this variable is an indicator of whether a customer was assigned to this group. This was the treatment group where customers were offered Rs. 1000 for a loan period of 14 days. If a customer was allocated to this group, they will have a 1 value, otherwise they will be allocated to the control group described above.

Rs500d30: this variable is an indicator of whether a customer was assigned to this group. This was the treatment group where customers were offered Rs. 500 for a loan period of 30 days. If a customer was allocated to this group, they will have a 1 value, otherwise they will be allocated to the control group described above.

Rs1000d30: this variable is an indicator of whether a customer was assigned to this group. This was the treatment group where customers were offered Rs. 1000 for a loan period of 30 days. If a customer was allocated to this group, they will have a 1 value, otherwise they will be allocated to the control group described above.

3.5.3 Control Variables

Segment: this is a categorisation of the customers according to their wallet usage prior to being qualified for the loan. There are three classifications that a customer could have:

GSM: this customer has never had a wallet linked to their CNIC before
MMI: Mobile Money Inactive: this customer has a wallet linked to their CNIC but they had not recorded any activity on it in over 90 days
NW: New Wallet: this customer opened a wallet within the last 90 days

Registered Week Before: this variable counts how many weeks prior to the test date of 2 April the customer registered for the product. Customers needed to register via USSD before they could be solicited via SMS. Registration for the product was considered as the customer showing interest in the product and opting into direct marketing. If a customer registered from 27 March 2019 to 2 April 2019 (seven-day window) the customer was allocated a 1. If a customer registered from 20 March 2019 to 26 March 2019 (seven-day window) the customer will be allocated a 2. This continues until allocating a 35 to customers who registered when the product launched 35 weeks before in August 2018.

Application Attempts: this counts how many times a customer attempted to take a loan. For customers who did not attempt at all, a 0 (zero) is recorded. For customers who attempted only once, a 1 is recorded. Some customers attempt multiple times before getting a loan, which could be due to many reasons. The maximum attempts made in the observation window by a single customer is 129.

WeekLoan: this variable counts how many weeks after going live on 2 April 2019 the customer took the loan. If a customer took the loan from 2 April 2019 – 8 April 2019 (seven-day window) the customer will be allocated a 1. If a customer took the loan from 9 April 2019 – 16 April 2019 (seven-day window) the customer will be allocated a 2. This continues until allocating a 4 to the customers who waited the longest to take the loan. Customers who did not take a loan were allocated a 0 (zero).

Terms and Conditions (*TsCs*): this binary variable indicates whether a customer selected to read the terms and conditions on the USSD menu. During the loan application process, the customer acknowledges that they have read the Terms and Conditions, but some customers click to view all the Terms and Conditions as an extra step before accepting the loan offer. If a customer opted to read the extra Terms and Conditions they are allocated a 1. If the customer simply acknowledged that they had read them, without selecting to see the screens, they are allocated a 0.

Input Error: During the loan application process, the customers need to follow the prompts on the USSD screen to proceed. For example, they may have to press "1" to continue or "0" to go back. Any time a customer input is invalid (such as pressing "3" or "11" or "*" in this case), this is flagged, and the customer remains on the screen and must try again. If a customer had a USSD application session where they made a mistake or input the wrong value in the process, they are allocated a number for every session where they make an invalid entry. If a customer never made a mistake, they are allocated a 0. The maximum is a customer that had 119 attempts and in 17 of these made an input error.

3.6 Research Limitations

Unfortunately, although all 28,000 customers in the sample had registered for the product which indicated that they were interested in it, a very small portion of these customers actually ended up taking a loan. This does not impact the validity of the first research question pertaining to loan take up. However, it does impact the second research question pertaining to loan repayment since the base of customers that took a loan is no longer the full base of 28,000 and is only 2,870 customers, which greatly limits the sample. In addition, there is an element of selection bias in this sample that could impact the results of the repayment since customers have to select to take a loan before being categorised as repayers or non-repayers. Lastly, no demographic data was known about these customers. Therefore, no analysis could be done on gender, age groups, location (such as rural versus urban) and these demographic variables could not be used in the regressions. While the bank did have these details (as required by KYC) these details could not be shared with the researcher or technology platform as Pakistani regulation prohibits individual demographic data leaving the country. Again, this was also part of the ethical consideration to keep customers' identities anonymous.

3.7 Conclusion

This chapter provides a detailed overview of the business experiment conducted and how it was set up to answer two research questions: the impact of loan tenor (14 days or 30 days) and loan amount (Rs. 500 or Rs. 1000) on loan take-up and the impact of these controls on the subsequent repayment. The study used data provided by a technology platform company that conducted the sampling, the solicitation of customers, the randomisation of the treatment groups for the RCT and the data collection.

Chapter 4
Discussion of Findings

4.1 Introduction

This chapter summarizes the results of the experiment outlined in Chapter 3, in which 28,000 individuals were randomly assigned to four mutually exclusive treatment groups that differed on loan amount disbursed and the loan tenor allowed for repayment. Summary statistics for the experiment are discussed first with an overview of the take-up and repayment. The results of the loan take-up regressions from Chapter 3 are then discussed, followed by a discussion of the loan repayment regressions.

4.2 Summary Statistics

A summary of the number of customers who took a loan is shown in Table 1 below.

TABLE 1: Take-Up Overview

	Customers	
Did not take loan	26053	90.1%
Took a loan	2874	9.9%
N	28927	100.0%

Source: Researcher's estimates from research data

A summary of the number of customers that repaid a loan is shown in Table 2 below.

Table 1: Repayment Overview

TABLE 2: Repayment Overview

	Customers	
Repaid loan	1211	42.1%
Did not repay loan	1663	57.9%
N	2874	100.0%

Source: Researcher's estimates from research data

Aligned with literature discussed in Chapter 3, the take-up rates for this experiment were very low at just under 10%. Customers were given one month to take the loan and only 2874 customers did so. Likewise, the repayment rate was low with only 42.1% of customer repaying on time. The remaining 57.9% did not repay their loan on time by the due date.

The stages of treatment assignment and loan take-up and loan repayment are bifurcated and displayed in Table 3 below.

TABLE 3: Take-Up Overview by Treatment Group

Group	Sample	Took a loan		Did not take a loan	
rs500d14	7142	622	8.7%	6520	91.3%
rs500d30	7162	667	9.3%	6495	90.7%
rs1000d14	7265	745	10.3%	6520	89.7%
rs1000d30	7358	840	11.4%	6518	88.6%
N	28927	2874	9.9%	26053	90.1%

Source: Researcher's estimates from research data

In terms of take up, the group with the highest take-up was Rs. 1,000 30-day at 11.4%, followed by Rs. 1,000 14-day at 10.3%, then Rs. 500 30-day at 9.3% with the control group of Rs. 500 14-day coming in last at 8.7%. At first glance, it appeared that increasing the loan amount from Rs. 500 to Rs. 1,000 at 14-days would improve the take-up rate from 8.7% to 10.3% and increasing the loan tenor from 14 days to 30 days (at Rs. 500) would improve the take-up rate from 8.7% to 9.3%. Finally, increasing both the loan amount and the loan tenor to Rs. 10,000 at 30 days would make the biggest difference compared to the control group, from 8.7% to 11.4%. This will be further discussed using regression on the next section.

The stages of treatment assignment and loan repayment and loan repayment are bifurcated and displayed on Table 4 below.

TABLE 4: Repayment Overview by Treatment Group

Group	Sample	Took a loan		Did not take a loan	
rs500d14	622	258	41.5%	364	58.5%
rs500d30	667	301	45.1%	366	54.9%
rs1000d14	745	265	35.6%	480	64.4%
rs1000d30	840	387	46.1%	453	53.9%
N	2874	1211	42.1%	1663	57.9%

Source: Researcher's estimates from research data

In terms of repayment, the results are slightly different. The group with the strongest repayment was Rs. 1,000 30-day at 46.1% followed closely by the Rs. 500 30-day at 45.1%, which indicates that a longer tenor may be more helpful to customers in repaying. The third-best repayment was the control group (Rs. 500 14-day) at 41.5% and the poorest repayment was the Rs. 1,000 30-day group, trailing at 35.6%. The widest divergence for repayment was for the two groups offered Rs. 1,000, where the 30-day repaid the highest at 46.1% and the 14-day repaid the lowest at 35.6% indicating that as the loan amount increases the sensitivity to tenor is even greater. These results will be validated in the following sections.

4.3 Loan Take-Up Regression Results

The regression results to examine the impact of the different treatment groups and control group on loan take-up are shown below in table 5. The results are split in two columns: (1a) denotes the first regression where covariates were not used and (1b) includes the covariates.

TABLE 5: Loan Take-Up Regression Results

VARIABLES	(1a) takeup	(1b) takeup
rs500d30	0.00604	0.00765*
	(0.00479)	(0.00425)
rs1000d14	0.0155***	0.00994**
	(0.00488)	(0.00431)
rs1000d30	0.0271***	0.0159***
	(0.00499)	(0.00441)
applicationattempts		0.0335***
		(0.00259)
registeredweekbefore		-0.00110***
		(0.000189)
tscs		0.0627**
		(0.0295)
inputerror		-0.00354
		(0.0261)
Constant	0.0871***	0.0677***
	(0.00334)	(0.00438)
Observations	28,927	28,927
R-squared	0.001	0.206
F-Value	79.6***	70.3***

*Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*
Source: Researcher's estimates from research data

All three treatment groups have a higher probability of take-up than the control group (Rs. 500 for 14-days), which is shown from their positive correlations to take-up. The customers in the treatment group given a Rs. 1000 loan for 30 days had the highest likelihood for take-up (additional 2.71% likelihood), followed by the treatment group given Rs. 1000 for 14 days (additional 1.55% likelihood) and then trailed by the group offered Rs. 500 for 30 days (a mere 0.6% additional likelihood). These results lean towards the suggestion of offering higher loan amounts to increase product take-up and indicate that this is a more important lever to adjust than the loan tenor lever. This makes sense, and links back to some of the aforementioned literature in Chapter 2. For example, other research has shown that customers are less likely to take a loan when the loan amount is too small (Karlan, Morduch, & Mullainathan, 2010) and in the Pakistani context the work of Gine (2019) corroborates that loan amount is a crucial level for loan take-up. Other theoretical research found that customers assess their own affordability using their own *risk preferences* and a longer tenor may lead a customer to believe that they have a higher chance of paying it off (Gayle, 1995).

Additionally, the results for the treatment groups offered Rs. 1000 were significant at the 1% level which gives strong confidence that these results were owing to the treatment and not to chance.

To further extract the impact of the treatment groups, several additional dummy variables were added to assess their impact on the outcomes. The highest impact variable was Terms and Conditions (*tscsc)*, which indicated whether a customer read the Terms and Conditions and increased probability of loan take-up by 6% at the 5% level. Interestingly, this ties in with other research that shows that customers who are more informed and more educated are more likely to take a product (Magill and Meyer, 2005). The other variable with a positive correlation for the outcome is *applicationattempts*, which increased probability by 3.33% at the 1% level and makes sense, as customers may have needed to start the journey a few times to see the options and assess whether they needed and could repay the loan.

The two other dummy variables had negative correlations: the negative correlation of *registeredweeksbefore* means that the longer the time since the customer had registered (such as registering in August 2018, almost eight months before the start of the RCT) the less likely the customer was to take up the product once they were qualified in April 2019. This also makes sense, as a customer may have received loan from another provider since registering or may no longer need one. The negative correlation of *inputerror* means that for every additional input error a customer made on the USSD application, the lower the likelihood that they completed the application and received a loan. This may indicate that they did not understand the process or had difficulty following through with the process on the phone they were using. Network outages may have also caused a customer’s attempt to fail.

Overall, the regression shows that there is statistical evidence that increasing loan amount may have increased take-up and this supports the summary statistics in the prior section. There is also some weak evidence that increasing tenor may have increased loan take-up.

4.4 Loan Repayment Regression Results

The regression results presented in Table 6 examine the impact of the treatment groups and control group on repayment. The independent variable, and measures of success, is how much a customer repaid on their due date. An ideal customer settled the full amount by their due date, although this is rarely the case.

TABLE 6: Loan Repayment Regression Results

VARIABLES	(2a) RepayRate	(2b) RepayRate
rs500d30	0.00538	0.00627**
	(0.00331)	(0.00303)
rs1000d14	0.00113	-0.00210
	(0.00321)	(0.00294)
rs1000d30	0.0158***	0.00942***
	(0.00347)	(0.00318)
applicationattempts		0.0198***
		(0.00154)
registeredweekbefore		-0.000407***
		(0.000131)
tscs		0.0257
		(0.0214)
inputerror		-0.0140
		(0.0157)
Constant	0.0401***	0.0264***
	(0.00226)	(0.00286)
Observations	28,927	28,927
R-squared	0.001	0.143
Log likelihood	3857.34***	4019.22***

*Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*
Source: Researcher's estimates from research data

The treatment effects appeared to have a very low influence on the repayment rate in this view. Only the treatment of Rs. 1,000 disbursed for 30-days was statistically significant at the 1%

level and there was only a 1.58% additional increase in repayment of this treatment group versus the control group; when including dummy variables this changes to 0.9%. Likewise, the dummy variables themselves have low explainability and selection bias limits the results because the regression assess repayers against the original sample of 28,000 even though 26,053 customer did not take a loan.

Therefore, a second set of regressions were run as per the methodology in Chapter 3 and these make use of instrumental variables to rather compare the control group directly to each treatment group individually. Therefore, three regressions are run: control against treatment 1 (3a), control against treatment 2 (3b) and control against treatment 3 (3c).

TABLE 7: Loan Repayment Regression Results with Instrumental Variables

VARIABLES	(3a) Repayment Rate	(3b) Repayment Rate	(3c) Repayment Rate
rs500d30	0.571***		
	(0.159)		
rs1000d14		-0.220	
		(0.369)	
rs1000d30			0.828**
			(0.377)
applicationattempts	(0.369)	0.00197	-0.00838
	(0.0131)	(0.00480)	(0.0148)
registeredweekbefore	-0.000615	0.000366	0.000172
	(0.000399)	(0.000254)	(0.000284)
tscs	0.0346	-0.0182	-0.00205
	(0.0284)	(0.0181)	(0.0141)
inputerror	-0.0566***	-0.0159*	-0.0266
	(0.0202)	(0.00894)	(0.0275)
Constant	0.0415	-0.0148	-0.0252
	(0.0260)	(0.0126)	(0.0225)
Observations	14,407	14,500	14,304
R-squared	0.143	0.452	0.236
Log likelihood	1763.16***	3144.57***	480.37***

*Note: robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.*
Source: Researcher's estimates from research data

Here the effects of the treatment groups are isolated. For (3b), there is a 22% lower additional probability that a customer with Rs. 1,000 for 14 days will repay versus a customer with Rs. 500 for 14 days. This indicates that customers showed strain to repay taking the 14-day options particularly for the larger loan. For the 30-day options there was a 1% significance for both treatment groups. The group offered Rs. 500 (3a) had a 57% higher likelihood of repayment and the group offered Rs. 1,000 (3c) had an 82% higher likelihood of repayment compared with the control group. Therefore, it is clear that offering a 30-day option significantly increased the repayment likelihood and this was even more prominent when offering Rs. 1,000. It is not clear that increasing the loan from Rs. 500 to Rs. 1,000 decreased likelihood of repayment as originally hypothesised, since the Rs. 1,000 14-day customers had a lower likelihood of repayment than the control group but the Rs. 1,000 30-day customers had a higher likelihood of repayment.

Loan tenor therefore seems to be the most significant lever in terms of driving repayment and giving more time to repay increased probability of repayment. In some ways, this is consistent with the reviewed literature, which states the giving customers more time to repay will improve their likelihood of repayment. The theoretical work of Donahue (2019) states that humans run the risk of *present bias* and tend to overestimate their future ability to complete a task and this relates back to the customers who may have overestimated their ability to repay in 14 days. However, the results actually contradict the theoretical work of Ariely (2018), who states that longer deadlines do not improve the likelihood of some completing a task, in this case repaying a loan.

Regarding the covariates, *inputerror* was the only covariate that was significant at the 1% level in equation 3a with a negative 5.6% impact on repayment. It was significant at the 5% level in equation 3b with a negative 1.6% impact of repayment. For regression 3c it had a negative 2.66% impact although this is weak. Broadly speaking, the more errors a customer made on their application, the lower their likelihood of repayment. The other covariates had low weakness for all three regressions with the exception of application attempts in 3a which was significant at the 5% level and increase repayment by 2.8%.

4.5 Conclusion

It is clear that the treatment groups had some impact on loan take-up and on loan repayment. For loan take-up, there was a small increase in likelihood of take-up when customers were offered a larger loan. For repayment, when using instrumental variables, the analysis shows that it was actually loan tenor that was most significant in driving repayment. Both 30-day options outperformed the control group, which was offered 14 days. Additionally, the outperformance was most obvious when larger loans are given—that is, when disbursing Rs. 1,000 there was lower repayment in the 14-day group compared to the 30-day group.

Chapter 5
Conclusions and Recommendations

5.1 Introduction

This chapter summarises and concludes the key elements of this research. The findings in Chapter 4 are noted and suggestions and recommendations are based on these results. A broader view of microfinance in Pakistan is revisited and policy recommendations for legislative bodies and wider bodies of government are given. Recommendations for future research are also presented.

5.2 Summary of the Study

This study analyses the results of a 2x2 RCT that split customers into four groups, a control group that received Rs. 500 14-day loan, a treatment group that received Rs. 500 for a longer 30-day loan, a second treatment group that received double of Rs. 1 000 14-day loan, and a third group that received double of Rs. 1,000 and for a longer 30-day period. The RCT randomly assigned 28,000 customers that had previously registered for the loan and they all received an SMS alerting them that they qualified on the same day. The customer had a month to take a loan and any attempts they made were digitally tracked. Of those that took a loan, repayment was tracked at the due date.

For take-up, the two groups offered Rs. 1,000 had higher take-up than the two groups offered Rs. 500. The group offered Rs. 1,000 for 30 days had the highest take-up, the group offered Rs. 1,000 for 14 days ranked second, the group offered Rs. 500 for 30 days ranked third and the control group offered Rs. 500 for 14 days had the lowest take-up.

For repayment, the results were slightly different. The two groups offered 30 days had the best repayment, indicating that longer tenors are better for driving repayment. Additionally, the combination of amount offered and time to repay is important. The group offered Rs. 1,000 for 14 days had the worst repayment, performing worse than their Rs. 500 peers at 14 days, indicating that perhaps this was too much money borrowed for too short a time. However, both of the 30-day groups outperformed the control of Rs. 500 at 14 days, indicating borrowing Rs. 1,000 is reasonable as long as enough time is given to repay.

5.3 Policy Recommendations

The State Bank of Pakistan has done some groundwork on biometric verification and digital transformation as part of their financial inclusion initiative discussed in Chapter 1. However, they have not met their goals and this small study is a good example of this. Of the 28,000 customers that initially expressed interest in a loan, only 2,874 took a loan and of those only 1,211 paid the loan back on time. These low take-up and low repayment rate are not sustainable for the microfinance banks offering the product and they will be discouraged from targeting financial inclusion if the projects fail like this. Therefore the below recommendations are given as possible ways to improve microfinance lending.

5.3.1 Facilitating and Monitoring Private Lending

The SBP should assist private companies that offer financial services in two ways. First, they should offer financial assistance, such as grants, to private companies purely for the facilitation of lending to first-time borrowers. They should either directly fund these loans or they should offer collateral to microfinance banks that go out to these riskier customers. The SBP should lower their expectation of non-performing loans, particularly for first-time borrowers, so that companies are more willing to lend to first-time borrowers. Based on this research, the SBP should recommend longer tenor loans since this has the higher likelihood of repayment.

5.3.1 Set up a National Credit Bureau for Microlending

While it is important to drive first-time borrowing, the SBP must also ensure that over indebtedness does not occur. They can only do this if they have one central, national database of all individuals and their microlending history. Before banks can lend to customers, they should run the customer’s CNIC through a bureau check to see if the customer already has a loan somewhere else. This mechanism exists in Pakistan and the SBP should continue to focus resources on this initiative.

5.3.1 Drive Financial Literacy

With private firms supported by government to conduct lending, and a national database functioning to track microlending behaviour, the policies then need to focus on individuals and households. The SBP needs to work with other branches of government to implement policies that drive financial literacy in Pakistan. Although no qualitative surveys were done on defaulters in this study, based on surveys of other researchers, financial literacy is critical in getting customers to understand the importance of only borrowing what they need and being able to budget and grow their business.

5.3.1 Include Women

Even if the government of Pakistan successfully facilitates private lending and manages to drive a nation-wide financial literacy program, half of their country will remain financially excluded if they do not radically change their approach to including women. Educational programs addressing women's empowerment within the financial inclusion realm need to be set up and the government should work with think tanks and NGOs in this area to improve financial literacy and financial inclusion among women.

5.4 Recommendations for Further Research

While this study sought to understand the impact of loan amount and loan tenor on a customer's take-up and repayment, there was no differentiation in price, which is an important factor for financial services. A future study could replicate this method but alter the pricing between groups to see the price inelasticity of demand regarding credit in microfinance. Understanding pricing is a crucial part of the microfinance offering and it is important to assess individual levels off affordability.

While the selection of the treatment groups for this research was random, future research could use stratified sampling to better segment the individuals. Samples can be segmented by gender, age, geographic location, and education so that inferences can be made based on how these impact loan take-up and performance. These demographic breakdowns could be a reason why loan take-up is so low, particularly if they are segmented by gender as women are more likely excluded from financial services than men. It would be interesting to add some qualitative research alongside this demographic data and researchers could survey the customers to understand their needs, decisions and financial literacy.

Lastly, while most of the treatments within this study were significant at the 5% level, a larger sample would be more beneficial in separating treatment effects and random correlation. A future study should expect low take-up and start with a wider sample set. Given the availability of digital finance and real-time databases, such as the one used in this study, future researchers should look to partner with fintech providers that operate the same product in multiple countries and they could do a cross-country analysis. This would be particularly useful research to compare developing countries and understand the current state of financial inclusion of each one from a grassroots experiment.

5.5 Conclusion

There are in 2020 still two billion unbanked people, and this is a significant blocker in alleviating poverty. Delivering financial services, such lending products through microfinance, can be an effective way to drive financial inclusion. However, since so little is known about the unbanked, it is critical that we conduct business experiments and field research to explore what the best financial products would be for these segments. This study conducts such an experiment to determine the impacts of altering loan amounts and loan tenors on first-time borrowers. By sharing these learnings, future private institutions can improve their product offerings and governments can create legislation that encourages appropriate lending behaviour in unsecured markets. Future researchers can also build on this work and ultimately, the unbanked individual should theoretically get access to financial products that work for them, which will be a steppingstone on their way out of poverty.

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