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FINTECH LENDING CHARACTERISTICS AND LOAN REPAYMENT PERFORMANCE ANALYSES

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APPROVAL

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I, HAKKI DENİZ KARAMAN hereby declare

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In addition, I acknowledge that any claim of irregularity that may arise in relation to this work will result in a disciplinary action in accordance with the university legislation.

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22/12/2021

To my lovely wife Kübra and dear family...

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FINTECH LENDING CHARACTERISTICS AND LOAN REPAYMENT PERFORMANCE ANALYSIS

ABSTRACT

This thesis examines the differences in loan performance between traditional banking and financial technology borrowers in a developing market, Turkey. After the financial crisis of 2001, Turkey heavily regulated the overall lending activity through structural reforms. Unlike other emerging economies, peer-to-peer lending and marketplace for lending activities are not available for Turkish borrowers. Therefore, the development of fintech companies arises within traditional banking groups. This study relies on individual-level data on consumer loans from the fifth largest private bank in Turkey and its fintech subsidiary. Using over 5.5 million consumer loans, first of all an unprecedented increase in the share of fintech loans across all cities in Turkey between 2014-2020 is documented. Next, it is demonstrated that fintech borrowers are on average younger, better educated, have higher income, higher savings levels, pay less interest and have better credit history than traditional borrowers. In turn, we show that fintech borrowers are less likely to default even after controlling for personal characteristics such as income, savings, gender, age, education, occupation, and creditworthiness or loan characteristics such as interest rate, maturity, and loan size. Results have also been validated through analysis in subsamples of the data that have been created with propensity score matching. Results suggest that using better technology, fintech companies can identify and target higher-quality borrowers in emerging markets like Turkey. Findings also reveal that fintech firm can successfully identify creditworthy individuals even among the group of borrowers who are less educated and who have low-credit scores. These results are in contrast to the findings reported in the previous literature for developed markets where fintech firms target financially constrained borrowers with high default rates to gain market share.

Keywords: Digital lending, traditional banking, innovation, financial technology, credit markets

FİNANSAL TEKNOLOJİ ŞİRKETLERİ ARACILIĞIYLA KULLANDIRILAN KREDİLERİN KARAKTERİSTİK ÖZELLİKLERİ VE KREDİ GERİ ÖDEME PERFORMANS ANALİZLERİ

ÖZET

Bu tez, gelişmekte olan bir pazar olan Türkiye'de geleneksel bankacılık ve finansal teknoloji şirketlerinden kredi alan müşteriler arasındaki kredi performansı farklılıklarını incelemektedir. Çalışmada, Türkiye'nin en büyük beşinci özel bankasının geleneksel bankacılık kanalları ve yine ilgili bankanın finansal teknoloji iştirakinin online olarak verdiği tüketici kredilerine ilişkin bireysel düzeydeki verilerine dayanmaktadır. 5,5 milyonu aşkın ihtiyaç kredisi kullanılarak, öncelikle 2014-2020 yılları arasında Türkiye'nin tüm illerinde finansal teknoloji kredilerinin payındaki artış incelendi. Daha sonra, finansal teknoloji kredi müşterilerinin geleneksel bankacılık kredi müşterileri ile demografik ve kredi bazında karşılaştırmaları yapıldı. Bu yeni tip müşterilerin daha genç, daha iyi eğitimli, daha yüksek gelire, daha yüksek tasarruf seviyelerine sahip oldukları, daha az faiz ödedikleri ve geleneksel bankacılık müşterilerinden daha iyi kredi geçmişine sahip oldukları gösterildi. Buna ek olarak, finansal teknoloji kredi müşterilerinin gelir, tasarruf, cinsiyet, yaş, eğitim, meslek ve kredibilite gibi kişisel özellikleri veya faiz oranı, vade ve kredi büyüklüğü gibi kredi özelliklerini kontrol değişkeni olarak kullandıktan sonra bile temerrüde düşme olasılıklarının daha düşük olduğu gösterildi. Ayrıca bu sonuçların doğruluğu çeşitli alt örneklem metotları ile de teyit edildi. Sonuçlar, finansal teknoloji şirketlerinin daha iyi veri madenciliği teknikleri kullanarak Türkiye gibi gelişmekte olan pazarlarda daha yüksek kaliteli kredi müşterilerini tespit edip onları hedefleyebileceğini gösteriyor. Bulgular ayrıca, finansal teknoloji firmasının daha az eğitimli ve kredi notu düşük olan müşteriler grubunda bile kredibilitesi yüksek bireyleri başarılı bir şekilde belirleyebildiğini ortaya koymaktadır. Bu sonuçlar, gelişmiş ülke pazarlarında yapılan, finansal teknoloji firmalarının pazar payı kazanmak için yüksek temerrüt oranlarına sahip, finansal açıdan kısıtlı müşterileri hedef aldığını gösteren, önceki literatürde bildirilen bulgularla çelişmektedir.

Anahtar Sözcükler: Dijital kredi, geleneksel bankacılık, inovasyon, finansal teknoloji, kredi pazarları

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1. INTRODUCTION

Throughout history, business of banking has been simple from a customer's point of view; collect money from depositors and lend it to creditors. If we consider banks only for this core banking business, we can see them as simple merchants that buy the good (in this case money) for a price and sell them at a higher price (in this case these prices are interest rates) and the difference between these two prices, in this case spread, is the profit gathered by the bank. In reality, operation of a banking business is not that simple but it is the most essential one. Movement of funds from depositors to creditors via banking system is the keystone of the economic well-being of any country. In the past 30 years, core business has evolved and diversified with the effect of new financial tools such as derivatives, insurances, futures, forwards etc. This was not a change that is driven by customer needs; this was more of a profit-oriented transition that led to Mortgage Crisis of 2008.

Another big change in our lives is the rapid technological development. Nowadays online world governs our day-to-day lives and banking sector is not an exception to this. With technological development, banking systems evolve too. In the early days of modern banking, customers were obliged to use "physical branches" for their daily transactions or financial needs but nowadays any financial service is available through smartphones; perhaps in the upcoming future there will be no need for physical branches.

Banks try to adapt changing world dynamics via online banking. They are trying to digitalize all of their financial services. This is partly because of cost-cutting purposes but its main cause is the changing customer profile. As financial services become digitalized, in the future as big financial technology firms enter banking business as another step for becoming "super app" (super app is not an academic term, rather it is a term invented by technology firms which represents a mobile application that have all the features to run an individual's day-to-day lives), a bank's main competition will not be another bank but it is going to be technology firms. As stated before we can simplify banks' role in the society to merchants who sells money as commodity. So theoretically, with technological development, digital channels and the data gathered from these channels any technology firm can become a digital bank. In the top of that, Mortgage Crisis of 2008 shook customers' confidence to banks, so people started looking for alternative institutions for their financial transactions such as online payment methods via financial technology (fintech) firms.

Banks try to close the gap between the digital world and banking sector via online banking with no human touch or agents involved. This self-serving banking system created a new kind of banking customer profile with different financial behaviors. In the past, individuals who use banking services were only consumers in the eyes of the banks, nowadays they are customers and tomorrow they will be clients, in other words users of the digital banks or these "applications". Banks will be forced to adapt all its services to digital world and this new kind of "clients" are not only price seekers of classical banking era; they prefer user experience, convenience rather than dealing with banking agents in a branch. Technology firms have the upper hand in this context, they already help people to overcome day-to-day problems and they also have all the data and user preferences of a client.

In this process not only banks began to become digital, only-digital banking platforms that do not use physical branches as service channels emerged as well. These only-digital banking platforms do not use conventional banking channels, offers convenience, 100% commission free payment methods and advantageous deposit and loan rates. They do not have the cost of a physical branch so their offers can be more generous.

The evolution of financial systems is often called "disruption" to conventional banking sector. Without serious disruption, an ecosystem cannot change or evolve. Zalan and Toufaily studies the disruptive nature of fintech ecosystem in emerging markets and argue that fintech companies are not that disruptive to financial system as anticipated due to cultural, regulatory and structural reasons (Zalan and Toufaily 2017, 415-430). Their study focuses the financial markets in Middle Eastern and North Africa (MENA) region and cultural reasons especially stands the way of fintech adoption. Their claim is that in emerging countries, financial market leaders face future disruptions by bank-fintech collaborations and these mergers often speed up innovations in conventional banking sector. The study conducted by (Thakor 2019, 41) on the other hand, claims that the real disruptive force in the banking sector would be the online payments that will change the financial world as we know it. Similar to the findings by (Zalan and Toufaily 2017, 415-430), Thakor also suggests that peer-to-peer lending relies on market segmentation and is not disruptive one may think; it is argued that these new lending platforms will not replace conventional banks anytime soon. (Thakor 2019, 41)

In another study, Gupta and Xia focus on disruptive nature of fintech companies in emerging countries in Asia. They show that in Asia, fintech companies create a serious challenge and disruption to conventional banking system. According to their study, mobile wallets, online payment and lending platforms gain market share rapidly. This rapid increase in market share depends on values that serve customer better, transparency and reduction in risks as technology develops further. Government and central banks' policies regarding regulations will play the main role in evolution of financial ecosystems in near future. (Gupta and Xia 2018, 215-254)

Jaksic and Marinc in their study (Jaksic and Marinc 2017, 3) analyze the technological progress and the disruptive effects of financial technology companies from a different point of view. They argue that relationship banks that still rely on human touch via banking agents will still have an edge in the future and a strong relationship between the customer and the bank creates a competitive advantage. In their study, their argument is based on geographic and cultural proximity between the clients and the branches. They claim that human banking agents cannot be fully replaced with machine learning algorithms, especially in lending, at least not yet. This argument has valid points regarding the acceleration of process but I believe it is a bit shortsighted. Digitalization and development of technology is the next step in human evolution and fully rational consumer in all non-financial marketplaces knows and shows its behavioral patterns, financial world would have to adapt to this evolution. This argument maybe still valuable for generations that didn't surround by the globalization of technological development but in near future this debate would be futile for next generations.

This digital transition is mainly derived by social dynamics and has a rapid pace but in the financial system, transition from "real world" to digital world is not that seamless as one may think; as Jaksic and Marinc implied in their study. The first concern is the security of the financial information of the individuals for regulators. With improvements in cyber security, regulators have begun to loosen legal restrictions on online transactions and replace them with security restrictions that companies have to obey. On the other hand, from users' point of view, adoption to new technologies have challenges. Technology adoption is not one of the topics investigated in this thesis but nevertheless it is worth mentioning that prior studies tend to focus on this matter through innovation resistance theory (IRT) and technology acceptance models (TAM).

(Puneet et al. 2020, 55) discuss these challenges that mobile payment solutions face through an innovation resistance theory perspective. According to their article, without going into detail, IRT can be defined as the theoretical framework that defines the resistance, fully rational individual exhibits when he/she decides to alter his/her behaviors. So, in that context, IRT helps us understand and identify the key variables of the adoption or evolution process of consumers' behavioral patterns. Their findings suggest that usage and risk barriers have a high impact on using mobile payment solutions. Their findings also state that tradition and cultural elements do not have a high effect on user intentions. (Lee 2009, 130-141) studied the elements that effect adoption on online banking. The findings showed that security or privacy risks have a negative effect on the adoption of online banking and "perceived usefulness and perceived benefits" have a positive effect on the adoption, as expected. Theoretical framework and academic studies that focus on the adoption and evolution of consumer behaviors regarding innovative technologies yet exist, try to keep up with the rapid pace of innovations. I believe that as consumer behaviors dominate the decision-making process of banking sector, behavioral studies will have a high importance in near future.

As an emerging country, Turkey also got his share of digital banking conversion via fintech subsidiaries. According to official reports from The Banks Association of Turkey, as of September 2019 there are over 48 million retail customers who use digital channels when conducting banking transactions. Many big banks began to digitalize all of its financial services but there are struggles concerning business flows that are designed through conventional banking channels. Seeing these struggles, some banks didn't only improve its online banking channels, but they also began to establish its fintech subsidiaries. Especially because peer-to-peer lending market is not well established in Turkey due to legal restrictions. (Puneet et al. 2020, 55)

With this move, banks tried to aim new generation customer segment, white-collared, educated young professionals that prefers convenience, user experience and do not want to waste time in a physical branch. In their fintech subsidiaries, they created price advantages through cutting its operational, rental costs which is a main concern in conventional banking. With new generation clients, digital banks value quality over quantity; customer base growth can be slow but with more loyal customers, the revenue generated eventually catch up as economies of scale affect in a few years with high active customer base ratios. It is a business driven by customer needs and desires rather than bank profitability. One thing banking sector learn from these big technology and social media companies is that monetization of big customer data is more important than short term profit goals.

As stated, once technology firms enter into banking sector, they will have the upper hand. However, banks still have the advantage of their "know-how" information accumulation throughout years. They are capable of collect deposits and can evaluate the customers' loan credibility. In addition to that, banks also differentiated its loan credibility evaluation criteria with the big data they gather. In the modern world, with integrated data sharing mechanisms, automated credit scoring systems are used for evaluation process. However, many quantitative models used in evaluation process still consider conventional variables. (Jagtiani and Lemieux 2019, 18) shows that alternative data sources and machine learning models that is used by fintech lending platforms can have an effect on increasing financial inclusion and better assessment criteria for lenders. This has a positive effect to borrowers too; in their study they show that borrowers are assigned better loan ratings due to additional information and lower priced loans. In another study by Costello, Down and Mehta, inclusion of additional variables such as data from social medias improve risk assessment process of loan disbursement significantly. (Costello, Down and Mehta 2020, 3)

Usage of digital channels triggered transition from customers to clients but it also changed especially the repayment behavior of the customers with no banking agent involved in the loan disbursement process. Loan marketplace has begun to digitalize and it is changing with rest of the banking sector. Online intermediaries shape this new landscape of the marketplace for consumer loans. Online intermediation through peer-to-peer or marketplace lending by fintech firms is an essential funding source for individuals and small businesses (Bachmann et al. 2011, 16). Fintech companies, which use state-of-the-art data analysis tools to assess borrowers' creditworthiness, aim to

match lenders and borrowers without the high costs associated with traditional financial intermediation. According to (Michlitsch 2020, 4) the fintech industry reached a 40% market share in the consumer credit market in the U.S. by 2019. Fintech ecosystem and lending is a stronger tool in developed countries than in emerging markets where financial lending activity outside of the banking sector relies on peer-to-peer lending. Haddad and Hornuf's findings support this notion, the development level of the economy and corporate venture capital's availability in a country is positively correlated with the number of fintech start-up firms. (Haddad and Hornuf 2018, 81-105)
Di Maggio and Yao, in their study argue two potential channels for the fintech industry to grow. First, fintech companies can serve individuals underserved by banks (Tang 2019, 1900-1938) (Erel and Liebersohn 2020, 3) (Di Maggio and Yao 2020, 2). To that end, fintech companies may diminish credit frictions such as credit rationing or imperfect competition. They can provide funding to financially constrained households or lower financing costs for those who switch from banks due to their significant cost advantages. Second, due to their superior ability to assess individuals' creditworthiness, fintech companies may capture the most creditworthy borrowers, which reduces the average quality of individuals borrowing from banks.
Prior evidence indicates that the fintech industry grows in developed economies by serving individuals that the banks cannot serve. Jagtiani and Lemieux claim that fintech lending platforms penetrates areas that need additional credit supply where there is less competition created by conventional banks, where economic indicators are more challenging. (Jagtiani and Lemieux 2018, 43-54) Similarly, (Di Maggio and Yao 2020, 2) show that fintech firms generate market share by targeting risky borrowers where banks cannot operate. Specifically, they document that fintech lenders tend to lend risky individuals when they first enter the consumer loan market and increase the quality of their pool of borrowers over time. Their results indicate that fintech loans are significantly more likely to default as fintech borrowers are more likely to spend the additional funds rather than consolidating their debt. In turn, fintech lenders charge additional interest rates compared to banks. More specifically, fintech lenders are better at pricing their loans as the interest rates on their loans are more correlated with the delinquency rate. (Di Maggio and Yao 2020, 2)

Recent studies that examine the differences in loan performance between traditional and fintech borrowers mainly focus on developed economies. However, the fintech industry is essential for emerging economies where access to financing is limited due to low levels of financial literacy (Cole et al. 2011, 66), regulatory constraints (Philippon 2016, 5) (Zetzsche et al. 2017, 7), or even due to lack of physical infrastructure required for the fintech industry to grow (Yermack 2018, 3). (Tang 2019, 1900-1938) argues peer-to-peer lending as a potential substitute for banks where economic indicators are challenging. Some emerging countries have the required legal and technical infrastructure to establish digital peer-to-peer lending platforms, other emerging countries still rely on conventional banks and fintech lending platforms.

In this thesis, I investigate several aspects of fintech ecosystem and especially fintech lending platform repayment performances in an emerging country setup. My first aim is to show the different characteristics of fintech customers who prefers a fintech platform for its financial needs compared to conventional banking customers. Secondly, I analyze whether there are significant differences in the performance of consumer loans in fintech and traditional lending in an emerging market. Specifically, I rely on data on consumer loans from the fifth-largest private commercial bank (henceforth, the bank) that operates in Turkey and its fintech subsidiary (henceforth, the fintech firm). As stated before, peer-to-peer and marketplace for lending activities are strictly regulated in Turkey after the financial crisis of 2001. Unlike other developing economies, heavy regulations over the peer-to-peer and marketplace for lending activities (BRSA 2005, 1) resulted in the development of fintech firms under the banking groups. The fintech platform examined in this study is the only platform in Turkey where all transactions are conducted digitally without the intermediation of a bank with a physical branch. Even though the fintech firm is owned by the bank, both firms are separate entities with a different and separated customer base.

The bank is one the 5th biggest private bank in Turkey with 9% market share in loan market. The bank's active retail customer base consists around 5 million customers which can be considered a good benchmark for around 50 million digital bankable population in Turkey. The bank mainly focuses on retail banking but also has a corporate banking operation (this thesis focuses on retail banking customers and consumer loans). Besides the conventional physical branch as a service channel (around

600 physical branch all over Turkey) the bank also has its own fully operational mobile banking and internet banking channels. The customers can use its mobile and internet banking services for almost every financial need.

In 2012, the bank launched fintech subsidiary, which is designed as a fully digital bank. From a technical point of view, this fintech is not a separate bank from QNB Finansbank, rather a digital brand of the bank. But in practice, they are 2 separate entities and from a customer point of view, they are 2 "separate banks". This was a deliberate marketing move from the bank which was aiming to reach a new customer segment for the bank; young white collared professionals whom has no time to conduct financial transactions in a physical branch. Despite the fact that the organization of the fintech is under the bank's umbrella, all of its processes are designed for a fully digital bank. The bank has its own mobile and internet banking channels but still relies mostly on its physical branches for customer generation, sales, loan application, etc. whereas in the fintech subsidiary there are no physical branches that can be used. All of its operations, loan applications, financial transactions, even the communication with the customer uses digital channels (mobile and internet banking). In the fintech subsidiary customers can deposit a money to their account via ATM or transfer from another bank. Even their customer bases are separate; if you are a customer of the bank you need to apply for being a customer of fintech subsidiary and sign another banking contract with fintech officials. Actually, due to legislative reasons, signing a banking contract with the customer is the only occasion where the fintech customer get in touch with a banking agent (this has changed after the digital onboarding legislation in 2021 in Turkey). The same is true for a fintech customer who wants to be a customer of the bank as well. Thus, the Bank is a conventional bank with its own digital channels and fintech is a fully digital bank which only relies on its digital channels. In fact, it is the closest entity in Turkey that can be called as a fintech. As of September 2019, fintech subsidiary has over 1.7 million fully digital customers.

All banks in Turkey including the one that is examined in this study, conduct online banking services as a direct extension of their traditional banking services. In our case, fintech borrowers are not necessarily customers of the bank or vice versa.

The loan application process is significantly different for these two firms. Evaluations for the bank rely on information for which a banking agent plays an active role. In the loan application process, the borrower must visit a physical bank branch in order to complete application. Borrowers are required to fill an application form which is actually completed with the help of a banking agent. Banking agent can give advices to the applicant in this process regarding the size and maturity of the loan borrower is applying for. Motivation for these advices is driven by banking agent's key performance indicators set by the bank to evaluate agent's performance. The main motivation of the agent is to increase the sales of consumer loans; so, agents can give advices either to increase loan size to achieve his/her sales target or adjust the size of the loan application with the banking or loan evaluation know-how he/she possess so the possibility of a decline diminishes. The crucial aspect is that the sale of the loan happens right away but if the loan defaults, the effect on the agent's performance is lagged since the default cannot happen until borrower doesn't pay the debt for some time.

After the application form is submitted, an automated evaluation gives a decision: approval, decline or decline/refer. There are some grey areas in the decline answer and this is called decline/refer; for some borrowers automated system gives advice to decline the application but gives branch manager to approve the loan application on his/her discretion. In some cases, banks want to give limited authority to banking agents to use their own judgement with their know-how about the borrower.

In contrast, fintech loan evaluations rely mainly on information processed with state-of-the-art data analysis tools. Fintech banking experience is a self-service banking system, so is the loan application process. Without any direction from the bank, borrower logins to his/her mobile or internet banking channel and fills out an online loan application form on his/her own. This loan application form is similar to conventional bank's loan application form, with these inputs and the data Fintech gathered from multiple sources (such as credit bureau, borrower assets etc.) there is a fully automated state-of-the-art data modeling process which tries to estimate the probability of default of the borrower. With default probability and other inputs about the borrower, system decides whether to approve or decline the loan application. There are no grey areas in this system and the whole loan evaluation process is done within seconds. After the loan application is submitted, the borrower can learn its loan application result in the next page in the mobile application. If it is approved, borrower can transfer the loan value to his/her accounts.

One can assume that presence of a banking agent in the loan application process can diminish the default arising from opportunistic behavior of the borrowers. This can be true for small societies or neighborhoods but in today's world with big data and state-of-the-art data modeling tools, presence of an agent can cause a bias for the loan evaluation processes, an error for statistical models.

In this thesis, in a panel regression setting with city and year fixed effects, I first compare the borrower and loan characteristics of the bank and the fintech firm. I document that fintech borrowers are on average younger, better educated, have higher income and savings levels, have a better credit history, and pay less interest than the traditional borrowers. Next, I compare the performances of loans issued from the bank and the fintech firm. In that regard, I show that fintech borrowers are less likely to default even after controlling for borrower characteristics such as income, savings, gender, age, education, occupation, creditworthiness, or loan characteristics such as interest, maturity, and loan size. As a second step, I analyze my dataset using via logistic regression models; these model results validate my previous findings. In addition to these analyses, I again test the loan repayment behavior and compare loan performance of fintech loans compared to conventional bank loans using subsamples I created via propensity score matching and show that my baseline findings are in fact robust. At last, I conduct an interaction analysis to get more insight regarding fintech lending.

My results are in contrast to the findings of studies conducted in developed economies. Several studies document that fintech borrowers are more likely to default as fintech firms target risky individuals underserved by banks (Tang 2019, 1900-1938), (Erel and Liebersohn 2020, 3) (Di Maggio and Yao 2020, 2). My results suggest that fintech firms can identify and target higher-quality borrowers in emerging economies like Turkey. In addition to that, interaction analysis revealed that fintech firm can also successfully identify creditworthy individuals among the group of borrowers who are less educated and who have low-credit scores. Even though there are growing number of studies on the different aspects of the fintech industry in emerging economies like China (Lin et al. 2017, 3538-3545), (Chen et al. 2019, 112), (Chen et al. 2020, 4) to the best of my knowledge, my results are first in documenting that the growth in fintech market share can significantly differ in emerging markets compared to developed markets.

The thesis is organized as follows. In chapter two, I analyze fintech customer characteristics and try to emphasize the differences compared to conventional customers by showing several distributions, summary statistics and also in a panel regression setting. In chapter 3, using panel regression I compare the loan repayment or default behavior of fintech borrowers when compared to conventional banks. In this chapter I also analyze the loan performance via logistic regression analysis, through subsamples using propensity score matching, again panel regressions using interaction terms. At last, I analyze the effect of being a Fintech loan customer among bank loans. As of 2021, only consumer loans are available via online channels in Turkey; other loan types such as mortgages or auto loans cannot be disbursed via online banking channels. That is why in this thesis, only consumer loans are the focus of attention.

2. FINTECH LENDING GROWTH AND ITS CHARACTERISTICS

2.1 Introduction

When competing in the same financial ecosystem a financial technology (fintech) company and a conventional bank have the same motivation; reducing cost and maximizing their profit. Cost of any financial organization have many sub-elements and one of them is the fixed cost and operational costs. In that regard, commercial banks' costs of running a physical branch have a huge role on bank's expected profit and cost per customer served. Fintech firms on the other hand, have the advantage of having lower operational costs when compared to conventional banks with no physical branch network required.

In a competitive market, especially in the loan market, if fintech lending platforms and conventional banks as lenders have a similar level of expected profit per customer or per loan, one may expect that fintech lenders should anticipate a lower expected revenue from a loan compared to conventional banks since they have lower operational costs. Calculation of a loan's profitability for the lender is rather simple; gather interest revenue and record losses when the borrower is unable to repay. So, if a fintech firm can target high-quality borrowers, with the natural operational cost reduction of the fintech business, they can gain a competitive advantage against conventional banks in the loan market.

Prior evidence supports this notion by claiming that the fintech industry achieves growth in the market for consumer loans by targeting underserved individuals by the banking system (Tang 2019, 1900-1938) (Erel and Liebersohn 2020, 3) (Di Maggio and Yao 2020, 2) (Jagtiani and Lemieux 2018, 43-54). In their article (Di Maggio and Yao 2020, 2) suggest that fintech lenders, according to their original hypothesis, may be able to operate in areas where banks are unable to. This could be because they have significantly lower fixed costs, such as not having physical branches, or because they are less strictly regulated, allowing them to adopt more flexible lending standards. According to their claim, this could lead to increased loan availability for financially challenged households or cheaper financing prices for those who migrate from traditional lenders to new online lenders. On the contrary, by combining data and tools, fintech lenders may be able to target the most creditworthy customers, therefore lowering the average quality of the pool of people borrowing from banks. In the context of comparison of fintech and conventional bank borrowers' quality, they show that fintech lenders are more likely to lend to people who are less creditworthy, but that the quality of their pool of borrowers increases significantly with time. They also show that the terms offered by fintech lenders varied for similar borrowers. In particular, average loan sizes are greater and interest rates are higher.

In their study (Jagtiani and Lemieux 2018, 43-54) shows after studying one of the biggest online lending platforms' loan characteristics, online lending has reached places that could benefit from more credit from conventional banking system, such as highly concentrated banking markets and other places with fewer bank branches per capita, especially when fewer physical branches have to serve larger number of local potential borrowers. In their paper, they also showed that fintech firms had a greater market share in places where economic indicators represent a more difficult environment. (Jagtiani and Lemieux 2018).

Regarding quality of fintech borrower, findings of (Erel and Liebersohn 2020, 3) study states that fintech is disproportionately preferred in location with fewer bank branches, lower incomes and in industries with little ex-ante small business lending. Their claim is that fintech lending do not penetrate customer segments where conventional bank borrowers have already in, instead they aim low quality borrowers and in that way they increase financial inclusion and overall supply of financial services and funds.

In the study by (Tang 2019, 1900-1938), the focus of attention is not the fintech lenders, instead peer-to-peer lending has been investigated. In the paper, it is analyzed that whether peer-to-peer lending is a substitute for conventional banking system or it is simple a compliment for banks. The results in this paper contradict with the fintech lending evidence, suggesting that peer-to-peer lending is a complement to banks and the borrowers of peer-to-peer lending platforms have already access to credit from conventional banking system.

To the best of my knowledge, all the empirical studies regarding fintech lending have been done in developed countries; online lending in emerging countries has been studied with the perspective of peer-to-peer lending. My aim in this chapter is to test the prior evidence on the characteristics of fintech borrowers when compared to borrowers of a conventional bank. Especially my aim is to test these findings that has been found in developed countries in an emerging market setup where all financial dynamics are different.

2.2 Data

A proprietary dataset of over 5.5 million consumer loans offered by the bank and Fintech firm between 2014 and 2019 is obtained. All loans in the dataset are collateral-free. The sample is skewed towards loans provided by the bank, with approximately 4 million observations attributed to the bank loans and the remaining 1.5 million to Fintech loans. Sample consists 2,567,333 million unique individuals; 311,908 of which are obtained consumer loans only from Fintech firm, 54,689 of which obtained both traditional and fintech loans and the remaining 2.2 million obtained loans only from the bank. Therefore, the sample is skewed towards traditional banking channels in terms of number of borrowers, as well. Consumer loan application and disbursement via online banking channels and online lending platforms are regulated and became available to Turkish loan market after the year 2014, that is why the time of the data used in this study begins from 2014.

2.2.1 List of Variables

Each entry in the sample contains information regarding the loan, such as the date, loan size, maturity, interest rate, and information about the borrower, such as income, savings, age, gender, education, occupation, and credit performance.

Loan specific variables:

• Loan size† (Independent variable):

Loan size is the TL denominated amount borrowed from the bank or from the Fintech firm.

• Interest Rate (Independent variable):

Interest rate is the monthly interest rate on the loan.

• Maturity/Inst. Cnt: Independent Variable

Maturity of the loan.

Savings and Income Specific Variables:

• Income† (Independent variable):

Borrower's monthly income at the initiation of the loan.

• Deposit Amount† (Independent variable):

Borrower's deposit levels in the bank or in the Fintech firm.at the initiation of the loan.

• Nu. Accounts (Independent variable):

Number of accounts of the borrower (with positive balance) in the bank or in the Fintech firm at the time of loan initiation.

Past credit performance related variables:

• High credit score‡ (Independent variable):

A dichotomous variable that takes one if the borrower is in the high-credit score group.

• Mid credit score‡ (Independent variable):

A dichotomous variable that takes one if the borrower is in the mid-credit score group.

• Low credit score‡ (Independent variable):

A dichotomous variable that takes one if the borrower is in the low-credit score group.

Borrower's personal/demographic characteristics:

• Male (Independent variable):

A dichotomous variable that takes one if the borrower is male.

• Age (Independent variable):

Age of the borrower at the initiation of the loan.

• Young (Independent variable):

A dichotomous variable that takes one if the borrower's age is less than 45.

• Primary school (Independent variable):

A dichotomous variable that takes one if the borrower's education ends after obtaining a primary school degree.

• High school (Independent variable):

A dichotomous variable that takes one if the borrower's education ends after obtaining a high school degree.

• Undergraduate (Independent variable):

A dichotomous variable that takes one if the borrower's education ends after obtaining an undergraduate degree.

• Graduate (Independent variable):

A dichotomous variable that takes one if the borrower's education ends after obtaining a master's degree.

• Private sector (Independent variable):

A dichotomous variable that takes one if the borrower works in a private firm at the loan initiation.

• Public sector (Independent variable):

A dichotomous variable that takes one if the borrower works in public service at the loan initiation.

• Self Employed (Independent variable):

A dichotomous variable that takes one if the borrower is self-employed at the loan initiation.

• Retired (Independent variable):

A dichotomous variable that takes one if the borrower is retired at the loan initiation.

• Unemployed (Independent variable):

A dichotomous variable that takes one if the borrower is unemployed at the initiation of the loan.

Control Variables:

• City fixed effects:

It is a set of dummy variables that takes the value 1 if the borrower lives in that corresponding city, 0 otherwise. Since there are 81 cities in Turkey, there are 81 independent city fixed effect variables, each representing the corresponding city.

• Year fixed effects:

It is a set of dummy variables that takes the value 1 if the borrower gets the loan in the corresponding year, 0 otherwise. Since this study's time frame is between 2014 and 2020, there are 7 independent time fixed effect variables, each representing the corresponding loan disbursement year.

Dependent Variables:

• Default:

It is a dichotomous variable that takes the value 1 if the borrower defaults on his/her debt, 0 otherwise. It is a dependent variable in every default estimating regression model.

• Fintech: It is a dichotomous variable that takes the value 1 if the corresponding loan is borrowed from the fintech firm, 0 otherwise. In chapter 2, this variable is used as a dependent variable in the regression models estimating fintech loan characteristics. However, in chapter 3 it is used as an independent treatment variable as a focus of attention.

Other Independent Variables:

• FintechLoanCust (Independent variable):

A dichotomous variable that takes one if the borrower is a mutual borrower, in other words if the borrower disbursed a loan from both fintech and the bank, 0 otherwise. This independent variable used as a treatment variable at part 3.7 when analyzing the default behaviors of the bank borrowers.

Using logarithmic transformation, variables that are indicated by † standardized and since the sample I used cover a 5 year time period in a country with high inflation rates, to diminish the effect of devaluations these variables' values are discounted to their 2014 present values using compounding inflation rates.

Variables that are indicated by ‡ capture the past credit performance of the borrower. I label a borrower as high credit score if the probability of default for that borrower (delinquency rate) at the loan initiation is less than 1%. Any borrower who has a probability of default between 1% and 3% is labeled a mid-credit score. Finally, I label a borrower as low credit score if the probability of default is greater than 3% at the loan initiation. Each observation in the sample has information about the probability of default of the borrower at the loan initiation. The bank and the Fintech firm have proprietary techniques to assess the probability of default of an individual and these probabilities of defaults are calculated using bank's credit scorecard model.

2.2.2 Descriptive Statistics

I provide the descriptive statistics about the loan and borrower characteristics of both the bank and Fintech firm in Table 2.1. Fintech borrowers are younger compared to borrowers of the bank. Specifically, the average age of a bank borrower is around 40, whereas fintech borrower's average age is around 33. People under the age of 45 use 93% of the fintech loans in the sample.

Fintech borrowers, on average, have higher savings levels compared to bank borrowers. The number of accounts with a positive balance is also higher for fintech borrowers. I also observe that an average fintech borrower has a larger income than an average bank borrower. 24% (12%) of the fintech (bank) borrowers had a high credit score at the loan initiation. 11% of fintech borrowers in the sample had a low credit score at loan initiation, whereas 21% of the bank borrowers had a low credit score. It can be observed that 72% (64%) of the fintech (bank) borrowers work in the private sector. The difference in terms of borrowers' employment status is most significant.

	Panel A: The Bank					
Variable	Observations	Mean	Std. Dev.	Min.	Median	Max.
Age	4,059,986	39.95	11.55	18.00	38.00	96.00
Loan Size†	4,059,986	8.60	0.99	3.60	8.70	15.88
Maturity	4,059,986	26.80	13.55	1.00	24.00	120.00
Male	4,059,986	0.76	0.43	0.00	1.00	1.00
Young	4,059,986	0.68	0.47	0.00	1.00	1.00
Private Sector	4,059,986	0.64	0.48	0.00	1.00	1.00
Public Sector	4,059,986	0.11	0.31	0.00	0.00	1.00
Self Employed	4,059,986	0.06	0.23	0.00	0.00	1.00
Retired	4,059,986	0.18	0.38	0.00	0.00	1.00
Unemployed	4,059,986	0.00	0.06	0.00	0.00	1.00
Primary School	4,059,986	0.26	0.44	0.00	0.00	1.00
High School	4,059,986	0.43	0.50	0.00	0.00	1.00
Undergraduate	4,059,986	0.24	0.43	0.00	0.00	1.00
Graduate	4,059,986	0.02	0.15	0.00	0.00	1.00
High Credit Score	4,059,986	0.12	0.32	0.00	0.00	1.00
Mid Credit Score	4,059,986	0.67	0.47	0.00	1.00	1.00
Low Credit Score	4,059,986	0.21	0.41	0.00	0.00	1.00
Default	4,059,986	0.04	0.20	0.00	0.00	1.00
Nu. of Account	4,059,986	0.81	1.00	0.00	1.00	56.00
Deposit Amount†	4,059,986	2.26	3.00	-5.26	0.35	18.12
Interest Rate	4,059,986	1.64	0.44	1.00	1.54	3.60
Income†	4,059,986	7.04	2.23	-5.26	7.55	25.36
	Panel B: Fintech					
Variable	Observations	Mean	Std. Dev.	Min.	Median	Max.
Age	1,520,576	32.88	7.41	18.00	31.00	74.00
Loan Size†	1,520,576	8.38	1.01	2.57	8.44	10.90
Maturity	1,520,576	22.17	15.87	1.00	18.00	72.00
Male	1,520,576	0.79	0.41	0.00	1.00	1.00
Young	1,520,576	0.93	0.26	0.00	1.00	1.00
Private Sector	1,520,576	0.72	0.45	0.00	1.00	1.00
Public Sector	1,520,576	0.18	0.38	0.00	0.00	1.00
Self Employed	1,520,576	0.05	0.23	0.00	0.00	1.00
Retired	1,520,576	0.03	0.17	0.00	0.00	1.00
Unemployed	1,520,576	0.00	0.05	0.00	0.00	1.00
Primary School	1,520,576	0.05	0.23	0.00	0.00	1.00
High School	1,520,576	0.24	0.42	0.00	0.00	1.00
Undergraduate	1,520,576	0.60	0.49	0.00	1.00	1.00
Graduate	1,520,576	0.11	0.31	0.00	0.00	1.00
High Credit Score	1,520,576	0.24	0.43	0.00	0.00	1.00
Mid Credit Score	1,520,576	0.65	0.48	0.00	1.00	1.00
Low Credit Score	1,520,576	0.11	0.31	0.00	0.00	1.00
Default	1,520,576	0.01	0.11	0.00	0.00	1.00
Nu. of Account	1,520,576	1.62	1.70	0.00	1.00	133.00
Deposit Amount†	1,520,576	4.53	3.42	-5.26	4.98	15.46
Interest Rate	1,520,576	1.59	0.45	1.01	1.44	2.93
Income†	1,520,576	7.92	0.60	-0.36	7.86	21.54

Table 2.1: Descriptive Statistics

In table 2.1, Panel A provides the descriptive statistics for the bank. Panel B provides the descriptive statistics for the Fintech firm. The first column in each panel corresponds to variable names. The second column presents the number of observations. The third and fourth columns respectively show the sample mean and standard deviation. Columns five, six, and seven presents the minimum, median and maximum values for a given variable, respectively. I adjust the variables that are denoted by † to changes in the inflation and use logarithmic transformations.

2.2.3 Insightful Characteristics of Fintech Borrowers and Online Lending

After the regulation became available for online lending, it began to take market share in Turkey loan market. Figure 2.1 shows the total consumer loan disbursement growth in terms of number of loans disbursed and Figure 2.2 shows the growth in terms of volume in Turkish Lira between 2014 and 2019 for the bank and the Fintech firm. In terms of number of loans disbursed, the bank's growth is negative up until 2018-2019 period. After that, in 2019-2020 period number of consumer loans disbursed increases again. When we analyze the trend for the Fintech, since it starts from scratch in 2014, its number of consumer loan disbursement figures have a monotonically increasing trend.

When we investigated the consumer loan volume in Figure 2.1, it can be seen that as time passes the bank's loan disbursement volume neither increases nor decreases up until 2019-2020 period. On the other hand, Fintech's loan disbursement volume is increasing rapidly. Figure 2.3 shows the growth of Fintech's share in consumer loan volume. As a result of Fintech's growth rate, its loan volume takes share and is near to 50% in a 5 year period.

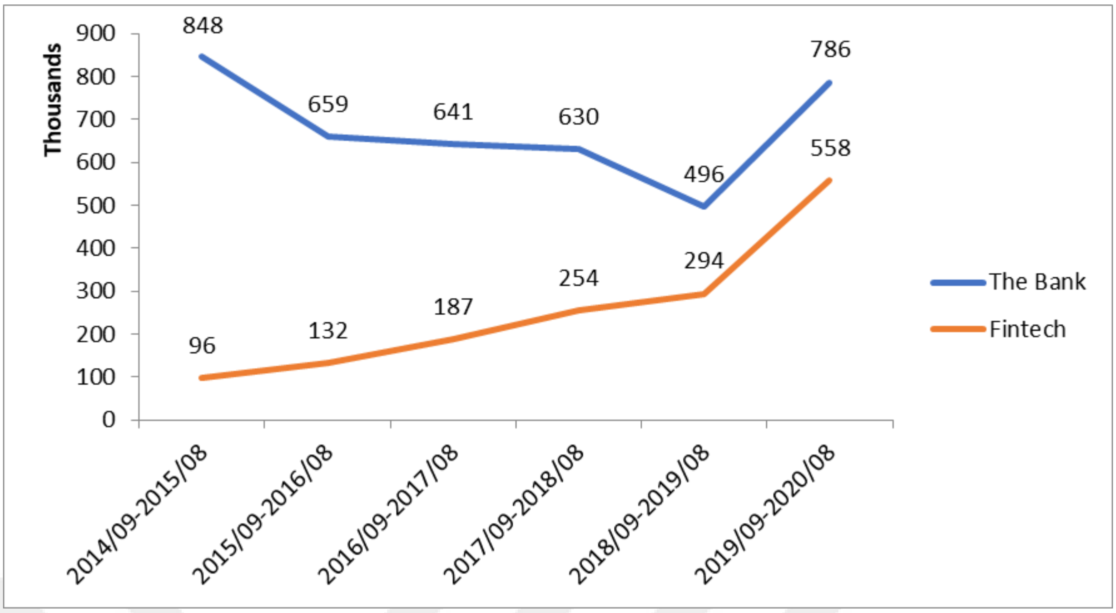

Figure 2.1 Consumer Loan Growth of The Bank and Fintech (number of loan disbursement)

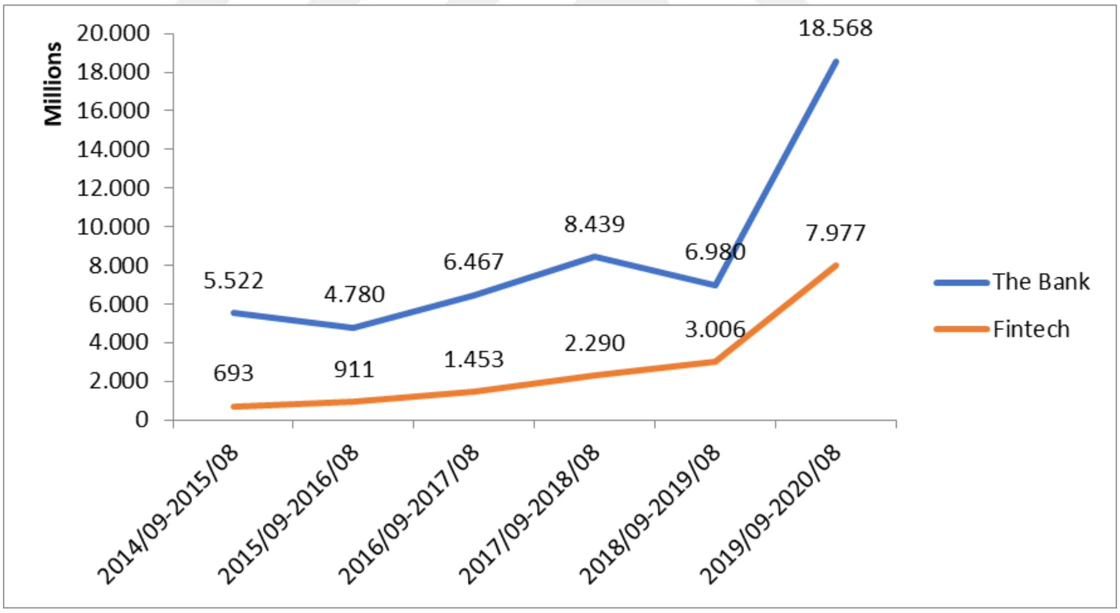

Figure 2.2 Consumer Loan Growth of The Bank and Fintech (volume of loan disbursement)

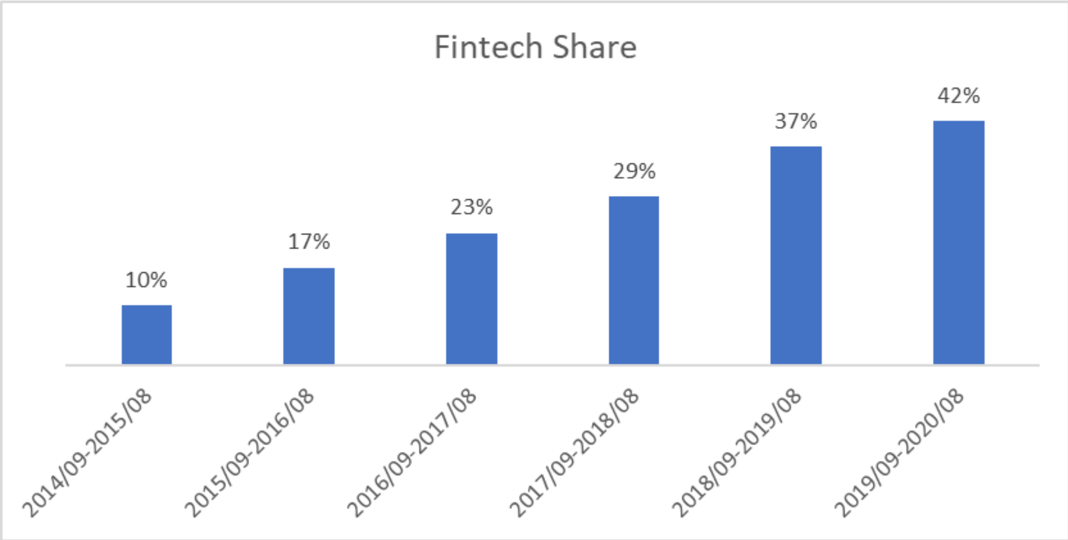

Figure 2.3 Market Share Growth of Fintech

In table 2.2 we can see the average age depending on loan initiation period. The bank loans' average age fluctuates between 39 and 40, Fintech's average age fluctuates between 32 and 34; does not vary a lot as time passes. However, it can be seen that, independent from loan initiation period, fintech borrowers are younger compared to the bank's borrowers.

Initiation Period	The Bank	Fintech
2014/09-2015/08	39,7	33,2
2015/09-2016/08	40,0	33,3
2016/09-2017/08	39,1	32,9
2017/09-2018/08	39,2	32,5
2018/09-2019/08	40,6	32,4
2019/09-2020/08	41,0	33,1

Table 2.2 Average age depending on loan initiation

In table 2.3 average loan size (ticket size) depending on loan initiation period can be found. All figures are in Turkish lira. It can be seen that as time passes, ticket sizes increase for both the bank and Fintech but the bank's figures are higher compared to Fintech's except for the first time period (2014/09-2015/08). After that, ticket sizes increase rapidly but the bank's growth rate is higher. Since loan disbursement from online channels is rather new for financial organizations, Fintech might behave in a cautious manner when approving consumer loans or the bank might launch an aggressive marketing campaign. We do not have the sufficient information to give judgement on the matter.

Initiation Period	The Bank	Fintech
2014/09-2015/08	6.514	7.180
2015/09-2016/08	7.252	6.919
2016/09-2017/08	10.084	7.786
2017/09-2018/08	13.400	9.009
2018/09-2019/08	14.072	10.230
2019/09-2020/08	23.617	14.302

Table 2.3 Average loan size (in TL) depending on loan initiation

In table 2.4 average maturity of consumer loans depending on loan initiation period can be found. Up until 2019-2020 period the bank loans' maturity is higher compared to Fintech loans. However, in the last time period average maturity for The Bank jumps from 24,1 to 31,3 and the gap between the average maturity widens. We do not see a similar increase in the Fintech loans. When we put together this increase with the ticket size increase that is shown in Table 2.3, we can say that there is a paradigm change in The Bank's loan disbursement policy. This conclusion is made without empirical evidence or any other insider information; this can just be called as an educated guess. Loan disbursement policy or marketing decisions of the banks are not included in the research areas of this thesis.

Initiation Period	The Bank	Fintech
2014/09-2015/08	25,3	23,3
2015/09-2016/08	24,3	21,8
2016/09-2017/08	26,9	23,7
2017/09-2018/08	27,8	22,6
2018/09-2019/08	24,1	20,3
2019/09-2020/08	31,3	22,3

Table 2.4 Average maturity depending on loan initiation

In table 2.5, average monthly interest rates depending on loan initiation period can be found. It can be seen that after 2015-2016 period Fintech loans are cheaper compared to the bank loans. The price movements of the loans are similar, probably depending on market conditions and risk-free interest rates. In addition to that, in table 2.6 we can see the weighted average monthly interest rates with respect to loan size. When analyzing those prices, we can see that when combining the effect of loan size and interest rates Fintech loans are cheaper in every loan initiation period. Another interesting aspect is that up until 2017-2018 period, Fintech average interest rates and weighted average interest rate with respect to loan size are exactly same. This implies that until that period, Fintech does not change its interest rates depending on loan size but after that point, pricing policy changes for Fintech. It seems that the bank always uses a pricing policy that depends on the loan size. The change of loan pricing of the Fintech can be a subject for future studies.

Initiation Period	The Bank	Fintech
2014/09-2015/08	0,95	1,15
2015/09-2016/08	1,19	1,39
2016/09-2017/08	1,41	1,38
2017/09-2018/08	1,76	1,69
2018/09-2019/08	2,46	2,28
2019/09-2020/08	1,35	1,20

Table 2.5 Average monthly interest rate depending on loan initiation

Initiation Period	The Bank	Fintech
2014/09-2015/08	1,24	1,15
2015/09-2016/08	1,39	1,39
2016/09-2017/08	1,44	1,38
2017/09-2018/08	1,70	1,70
2018/09-2019/08	2,32	2,22
2019/09-2020/08	1,22	1,19

Table 2.6 Weighted average monthly interest rate with respect to loan size depending on loan initiation

In table 2.7 city distribution of loan disbursements depending on loan initiation year; in the table the distribution includes top 10 cities. Figures in *Panel A* represents the distribution of the bank loans and in *Panel B* Fintech loan distribution can be found. It can be observed that the bank and Fintech loans' city distribution does not fluctuate by a big margin as loan initiation period change; except between first and second time period for Fintech loans. The key takeaway from these distributions is that Fintech loans are concentrated in big 3 cities in Turkey, namely Istanbul, Ankara and Izmir, compared to the bank's loans. This is actually another perspective that gives hints about socioeconomic and demographic characteristics of loan customers of Fintech.

	Panel A: The Bank					
City	**2014/09-2015/08**	**2015/09-2016/08**	**2016/09-2017/08**	**2017/09-2018/08**	**2018/09-2019/08**	**2019/09-2020/08**
Istanbul	30%	30%	30%	30%	31%	31%
Ankara	9%	9%	9%	9%	8%	8%
Izmir	6%	7%	7%	7%	8%	8%
Bursa	5%	5%	5%	5%	5%	5%
Antalya	4%	4%	4%	4%	4%	4%
Kocaeli	3%	3%	3%	3%	3%	3%
Kayseri	2%	2%	2%	2%	2%	2%
Mersin	2%	2%	2%	2%	2%	2%
Muğla	1%	2%	2%	2%	2%	2%
Konya	2%	2%	2%	2%	2%	2%

	Panel B: Fintech					
City	**2014/09-2015/08**	**2015/09-2016/08**	**2016/09-2017/08**	**2017/09-2018/08**	**2018/09-2019/08**	**2019/09-2020/08**
Istanbul	36%	41%	41%	41%	42%	41%
Ankara	11%	11%	10%	10%	11%	11%
Izmir	7%	7%	7%	7%	8%	8%
Antalya	3%	3%	3%	3%	3%	4%
Bursa	4%	4%	4%	4%	4%	4%
Kocaeli	3%	3%	3%	3%	3%	3%
Mersin	1%	2%	1%	2%	2%	2%
Kayseri	1%	1%	1%	1%	1%	2%
Tekirdağ	1%	2%	2%	1%	1%	1%
Samsun	1%	1%	1%	1%	1%	1%

Table 2.7 City distribution of loan disbursements depending on loan initiation

In table 2.8 distribution of employment status depending on loan initiation can be found; as before, figures in *Panel A* represents the bank and Panel B represents the Fintech firm. It can be seen that percentage of borrowers who work private and public sector are higher for Fintech firm. When considering time as another element, the biggest difference for The bank loans is the high share of retired borrowers compared to Fintech which is expected. However, as time passes private sector and public sector percentage in the bank loans increase and they take share from retired and self-employed segments.

Panel A: The Bank						
Employment Status	**2014/09-2015/08**	**2015/09-2016/08**	**2016/09-2017/08**	**2017/09-2018/08**	**2018/09-2019/08**	**2019/09-2020/08**
Private Sector	61.74%	63.20%	66.52%	67.20%	66.32%	66.43%
Public Sector	9.53%	10.57%	10.61%	10.73%	10.72%	13.55%
Retired	20.63%	19.34%	16.52%	15.58%	17.60%	16.20%
Self Employed	7.27%	6.31%	6.01%	6.27%	5.18%	3.70%
Unemployed	0.84%	0.59%	0.34%	0.22%	0.17%	0.12%

Panel B: Fintech						
Employment Status	**2014/09-2015/08**	**2015/09-2016/08**	**2016/09-2017/08**	**2017/09-2018/08**	**2018/09-2019/08**	**2019/09-2020/08**
Private Sector	62.64%	66.07%	69.60%	71.77%	76.52%	76.77%
Public Sector	25.49%	22.36%	19.76%	18.36%	15.46%	16.49%
Retired	5.35%	4.68%	3.60%	2.71%	2.22%	2.36%
Self Employed	6.02%	6.45%	6.66%	6.87%	5.64%	4.29%
Unemployed	0.49%	0.44%	0.38%	0.29%	0.16%	0.09%

Table 2.8 Employment status distribution of loan disbursements depending on loan initiation

In table 2.9 education level distribution depending on loan initiation period can be found; again, *Panel A* represents the bank and *Panel B* represents the Fintech firm. It can be seen that Fintech borrowers have higher education levels compared to The Bank borrowers. As time passes Fintech borrowers' education level increases by a smaller margin but education level of the bank loan customers increase by a high margin as undergraduate share increases from 18.82% to 32.58%. If we combine employment status and education level shift of the bank loan customer base in a 5 year period, we can see that the demographic attributes of the conventional bank borrowers started to look like Fintech loan customer base. This can be understood as an evolution of customer base of conventional customers or as a consequence of technology adoption.

Panel A: The Bank						
Education	2014/09-2015/08	2015/09-2016/08	2016/09-2017/08	2017/09-2018/08	2018/09-2019/08	2019/09-2020/08
Primary School	31.68%	28.76%	26.85%	26.42%	25.33%	22.76%
High School	47.98%	47.66%	46.58%	44.73%	42.88%	41.37%
Undergraduate	18.82%	21.78%	24.56%	26.57%	29.09%	32.58%
Graduate	1.52%	1.80%	2.01%	2.28%	2.70%	3.29%

Panel B: Fintech						
Education	2014/09-2015/08	2015/09-2016/08	2016/09-2017/08	2017/09-2018/08	2018/09-2019/08	2019/09-2020/08
Primary School	5.49%	6.28%	6.09%	5.78%	5.04%	4.98%
High School	23.20%	24.90%	25.25%	25.10%	23.16%	22.46%
Undergraduate	59.24%	57.53%	57.83%	58.76%	61.26%	62.16%
Graduate	12.07%	11.30%	10.83%	10.36%	10.54%	10.40%

Table 2.9 Distribution of educational status of individuals at the time of loan disbursements depending on loan initiation

In table 2.10 distribution of gender depending on loan initiation period can be found; as before *Panel A* represents the bank and *Panel B* represents the Fintech firm. Percentage of male borrowers are constantly higher for Fintech; but as time passes female percentage begins to take share for both entities.

Panel A: The Bank						
Gender	2014/09-2015/08	2015/09-2016/08	2016/09-2017/08	2017/09-2018/08	2018/09-2019/08	2019/09-2020/08
Male	76.91%	76.03%	75.87%	75.54%	74.17%	74.57%
Female	23.09%	23.97%	24.13%	24.46%	25.83%	25.43%

Panel B: Fintech						
Gender	2014/09-2015/08	2015/09-2016/08	2016/09-2017/08	2017/09-2018/08	2018/09-2019/08	2019/09-2020/08
Male	80.96%	79.81%	79.24%	78.76%	78.13%	78.61%
Female	19.04%	20.19%	20.76%	21.24%	21.87%	21.39%

Table 2.10 Distribution of gender of individuals at the time of loan disbursements depending on loan initiation

In figure 2.4 the credit score distribution depending on loan initiation can be found. Between 2014 and 2019 Fintech borrowers constantly have higher credit scores compared to the bank's borrowers with respect to loan initiation.

Figure 2.4 Credit Score Distribution with respect to loan initiation

2.3 Methodology and Results

In the part 2.2.2 the summary statistics have been given for the variables used in the model. In addition to that, in the previous part the key statistics and distributions of the variables that include the time effect have been given. These statistics yet give an idea regarding some characteristic differences between a fintech borrower and a conventional bank's loan customer, is not adequate to give a statistically significant or economically interpretable results; especially not when controlling other key variables. Thus, in this part my aim is try to achieve these results and get a better understanding on fintech borrowers' characteristics.

To examine the ex-ante heterogeneity among the bank and fintech borrowers, I run the following linear regression model. In the model, *Fintech* is the dichotomous dependent variable; independent variables are depicted in part 2.2.1. There are also city and year fixed effects as control variables. The model representation is rather similar to (Di Maggio and Yao 2020, 2) but the variables are different. The model I used can be represented as:

$$Fintech_{i,\,c,\,t} = \beta X_{i,\,t} + \mu_c + \varphi_t + \varepsilon_{i,c,t} \qquad (1)$$

The dependent variable is a dichotomous variable that takes the value 1 if the borrower i, in city c, obtains a fintech loan in year t and otherwise 0. The independent variables are loan and borrower characteristics, $Xi,\_t$. The impact of year and city-specific characteristics on getting a fintech loan is controlled using year and city-fixed effects. This enables us to compare the neighboring individuals that borrow from the bank and the fintech firm around the same time.

The tables 2.11 and 2.12 reports the linear probability regression results of the model described in equation (1) with credit attributes as independent variables in 2.11 and demographic attributes as independent variables in 2.12. Fintech is a dummy variable that takes one if the individual i in city c at time t borrows from the Fintech firm and 0 otherwise. As mentioned before in all of the models, including univariate regression, it is controlled for city and year effects on fintech via corresponding fixed effects.

In Table 2.11, except for the last column, each pair of values in the diagonal represents the output of the corresponding univariate linear regression. In each univariate regression, the dependent variable is the dichotomous Fintech variable, independent variable is the corresponding variable in the first column along with the city and year fixed effect used as control variables. Each pair of output represents the coefficient of the corresponding variable and beneath it their respective t-values in parentheses. The variables marked with * are statistically significant at 1% level. At the bottom of the table the R^2 value of the linear regression model, intercept value of the regression equation and the number of observations can be found. The last column depicts the results of the multivariate linear regression model. Again, all the pair of values represent the coefficient and the t-values of corresponding independent variable. In Table 2.12 along with other linear regression results in this study presented in the same table format for consistency.

In Table 2.11, it can be observed that fintech borrowers have accounts with higher deposit levels and have more accounts with a positive balance. Fintech loans are smaller in size and have shorter maturities. We document that fintech borrowers are more likely to obtain higher credit scores, resulting in lower interest rates. Even after controlling for other factors, we show that one basis point (bps) increase in the borrowing costs reduces the likelihood of obtaining loans from the fintech firm by almost 2%.

In Table 2.12, the univariate regressions indicate that fintech borrowers on average have higher income levels. In terms of education, we observe that having an undergraduate (graduate) degree increases the probability of obtaining a fintech loan by 28% (33%). Fintech borrowers are more likely to be young. An increase in age is associated with a 1% decrease in obtaining a fintech loan. In terms of employment statuses, we observe that being a retiree reduces the probability of getting a fintech loan by 22%. Fintech borrowers are less likely to be unemployed.

The R^2 values represent the proportion of variation between the dependent variable and the predicted values by the regression model. R^2 values represent the measurement of the goodness of the fitness, in other words the prediction power of the model. In this study R^2 values of linear regressions are low but the aim of these models and this study is not to estimate possible future outcomes, the probability of being a fintech loan or probability of default; models are used to examine the statistical relationships between the dependent variable and independent variables to interpret economic results. Thus, low R^2 values are accepted in this study.

Credit Attributes									
Dep. Var	Digital Dummy Variable								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit Amount†	0.0347*								0.0315*
	(630.22)								(563.64)
No. of positive account		0.08*							-
		(568.37)							-
Loan Size†			-0.0659*						-0.0606*
			(-363.06)						(-304.36)
Inst. Cnt				-0.00467*					-0.00187*
				(-372.95)					(-137.6)
Low Credit Score					-0.0662*				-0.0242*
					(-138.09)				(-51.69)
Mid Credit Score						-0.0585*			-
						(-151.00)			-
High Credit Score							0.1711*		0.1044*
							(343.45)		(207.72)
Interest Rate								-0.0405*	-0.0148*
								(-103.71)	(-39.18)
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	14.5%	13.4%	10.5%	10.7%	8.7%	8.8%	10.3%	8.6%	18.1%
Constant Term	0.5487	0.5721	1.2737	0.8211	0.7016	0.7401	0.6594	0.7488	1.1373

Table 2.11: Individual Characteristics of Fintech Borrowers – Credit Attributes

Demographic Attributes														
Dep. Var	Digital Dummy Variable													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income†	0.0284*													0.0156*
	(287.58)													(167.96)
Primary School		-0.2206*												-
		(-498.00)												-
High School			-0.1495*											0.0444*
			(-406.52)											(100.09)
Undergraduate				0.2748*										0.2889*
				(742.70)										(590.12)
Graduate					0.3413*									0.4373*
					(395.43)									(499.9)
Private Sector						0.6744*								-0.0595*
						(104.62)								(-46.82)
Public Sector							0.1382*							-0.0125*
							(250.35)							(-9.31)
Self Employed								0.0185*						-0.041*
								(23.70)						(-28.69)
Retired									-0.2152*					-0.0103*
									(-0.2152)					(-7.47)
Unemployed										-0.0248*				-
										(-8.09)				-
Male											0.0483*			0.0837*
											(112.89)			(214.72)
Age												-0.0108*		-0.00853*
												(-685.79)		(-414.45)
Young													0.2405*	-
													(594.92)	-
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	9.8%	12.3%	11.1%	16.7%	10.9%	8.6%	9.4%	8.4%	11.1%	8.4%	8.6%	15.5%	13.9%	26.0%
Constant Term	0.4602	0.7084	0.7435	0.5303	0.6656	0.3256	0.6703	0.6977	0.7365	0.6981	0.6621	1.1031	0.5175	0.632

Table 2.12: Individual Characteristics of Fintech Borrowers – Demographic Attributes

2.4 Concluding Remarks

In this chapter, I analyzed characteristics associated with fintech borrower and compared to borrowers of the conventional bank. Prior empirical evidence suggests that for developed economies, the fintech industry achieves growth in the market for consumer loans by targeting underserved individuals by the banking system (Tang 2019, 1900-1938) (Erel and Liebersohn 2020, 3) (Di Maggio and Yao 2020, 2) (Jagtiani and Lemieux 2018, 43-54). Using a data on consumer loans from the fifth-largest private commercial bank in Turkey and its fintech subsidiary, my results indicate that fintech borrowers are on average younger, better educated, have higher income and savings, pay less interest, and have better credit scores than the borrowers of the bank.
This is new evidence for market equilibrium whereby fintech companies grow their market share by identifying high-quality borrowers in an emerging market. These results contrast to the findings for developed markets where fintech firms are shown to target borrowers with high default rates to obtain market share in the consumer loan market. These results indicate that conventional banks in emerging markets can either establish its own fintech subsidiary or make collaboration with an existing fintech lending platform to target high-quality borrowers for even better credit pricing for the high-quality borrowers. In addition to that, conventional banks have the advantage of reducing its fixed and operational costs by replacing its loan application/disbursement process with online channels.

3. FINTECH LOAN PERFORMANCE ANALYSES

3.1 Introduction

In this chapter, loan repayment performance of the loans lent by Fintech firm and the bank are analyzed and compared. Prior evidence suggests that fintech firms generate market share by targeting risky borrowers where banks cannot operate (Di Maggio and Yao 2020, 2). Specifically, they document that fintech lenders tend to lend risky individuals when they first enter the consumer loan market and increase the quality of their pool of borrowers over time. Their results indicate that fintech loans are significantly more likely to default as fintech borrowers are more likely to spend the additional funds rather than consolidating their debt. In turn, fintech lenders charge additional interest rates compared to banks. Prior studies mentioned have conducted in a developed country setup.

After conducting analyses and interpreting the results from the previous chapter, my claim is to have a different outcome to prior studies when replicating them in an emerging country financial ecosystem. In this chapter after replicating previous studies by analyzing the default behavior of fintech borrowers and compare them to conventional bank borrowers, further studies have been conducted. Robustness have been checked through subsampling using propensity score matching, logistic regressions have been implemented to get a different perspective and interaction analyses have been made.

3.2 Data

The same dataset in the chapter 2, with 5.5 million consumer loans offered by the bank and fintech firm between 2014 and 2019 has been used. Approximately 4 million observations attributed to the bank loans and the remaining 1.5 million to the Fintech loans. Sample consists 2,567,333 million unique individuals; 366,975 of which are obtained consumer loans only from fintech firm, 55,589 of which obtained both traditional and fintech loans and the remaining 2.2 million obtained loans only from the bank. Therefore, the sample is skewed towards traditional banking channels in terms of number of borrowers, as well.

The variables used for analyses and their descriptive statistics of these variables are already thoroughly discussed in the previous chapter. Before getting into the methodology and results, the descriptive statistics of the default behavior is analyzed. Without controlling any other variables, 1% of the Fintech loans have become NPL or defaulted, on the other hand 4% of the bank’s loans defaulted.

In the figures beginning from Figure 3.1, 3.2, 3.3, 3.4, 3.5, 3.6 and 3.7 default rates depending on financial and demographic variables is presented with the comparison between Fintech firm and the bank. These distributions should be considered as descriptive statistics and without controlling any other variables one should be cautious to make deeper interpretations

In Figure 3.1 it can be seen that as age increases, with higher age brackets, the bank’s default rates begin to decrease whereas Fintech loans’ default rates stays at a similar level.

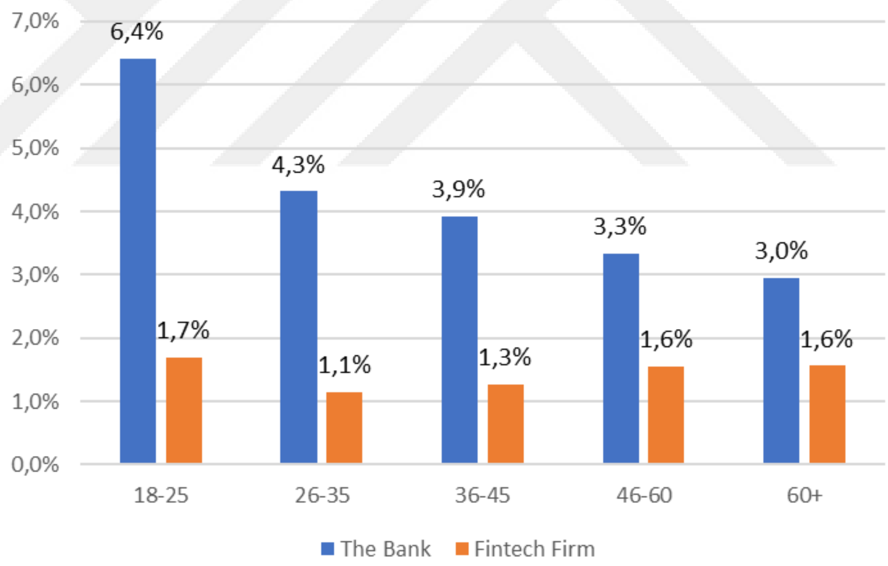

Figure 3.1 Default rates with respect to age brackets

In the Figure 3.2 it can be seen that without controlling any other variables Fintech borrowers have a lower default rate compared to the bank borrowers.

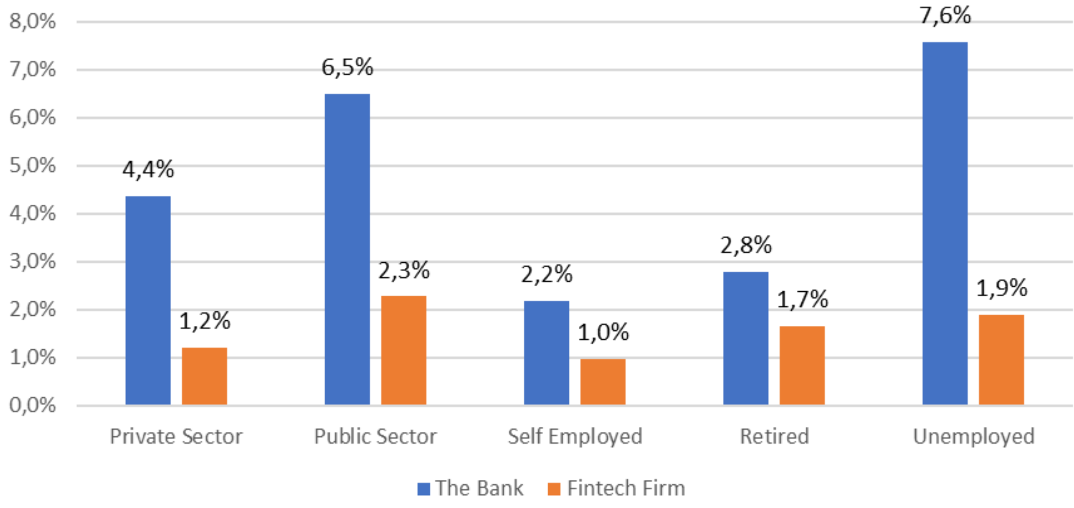

Figure 3.2 Default rates with respect to working status

In the Figure 3.3, it can be seen that as education level increase, the default rates decrease as anticipated, this correlation seems true for both Fintech and the bank borrowers. For all different education level segments, fintech borrowers' default rates tend to be lower.

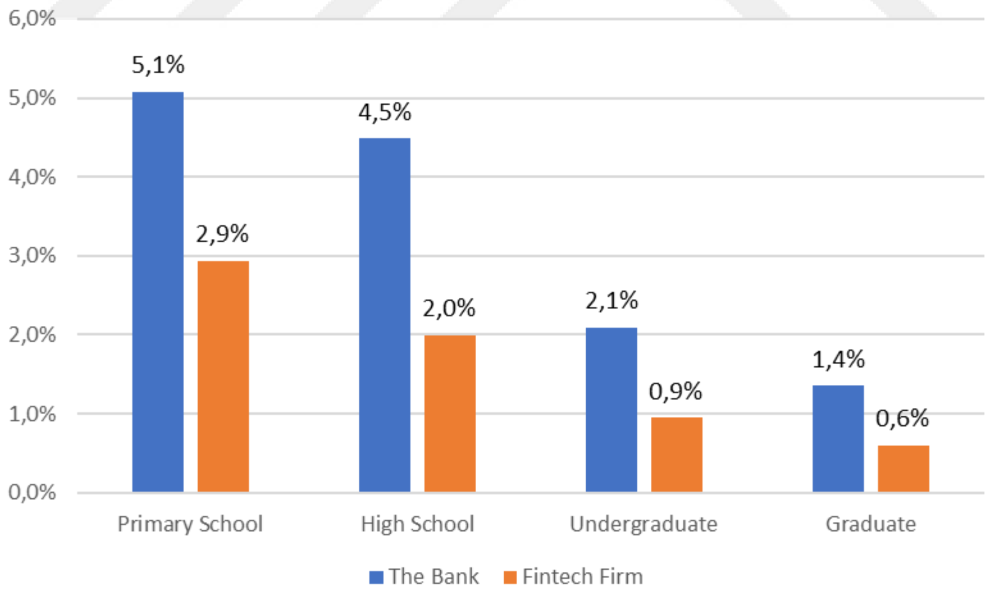

Figure 3.3 Default rates with respect to educational status

In the Figure 3.4 it can be seen that as yearly income increases the default rates decrease until a certain point as anticipated, but after reaching higher income brackets this negative correlation is distorted. My interpretation to this phenomenon is that; the variable, yearly income in a loan application is gathered via customers' declaration. A customer with opportunistic behavior and therefore an expected higher default rate can distort it with abnormally high income levels. Therefore, when using in my statistical models (as in the previous chapter) the income variable is standardized.

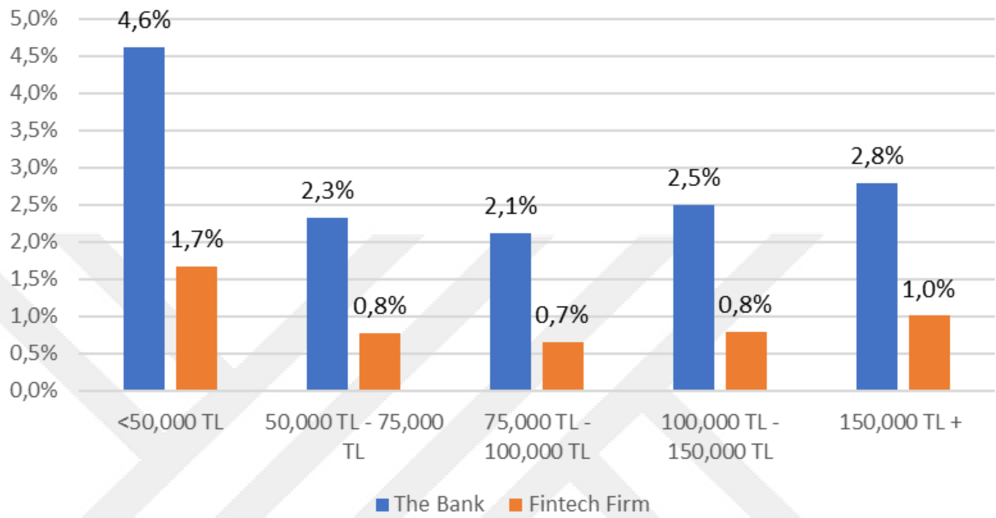

Figure 3.4 Default rates with respect to yearly income (in TL)

In the Figure 3.5 it can be seen that as credit score increases the default rates decrease. This result is expected and actually validates the credit scorecard model used by the bank and Fintech firm.

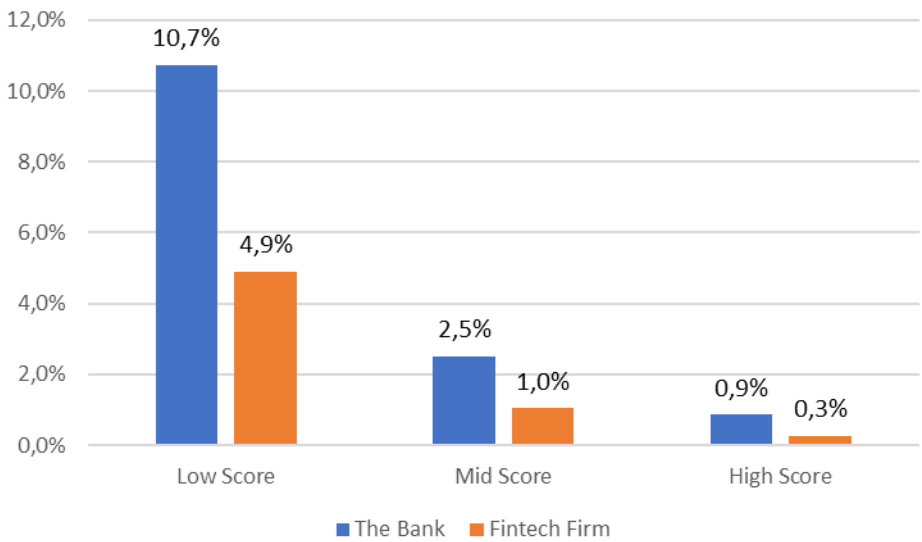

Figure 3.5 Default rates with respect to credit score

In the Figure 3.6 it can be seen that as loan size increases the default rates tend to increase until 15,000 TL level, after that threshold is reached, default rates begin to decrease. This correlation has the same behavior both in Fintech and the bank borrowers. It can be interpreted that after a certain point, loan size variable indicates that the quality of the borrower is high enough for the financial entity to approve a higher level of loan.

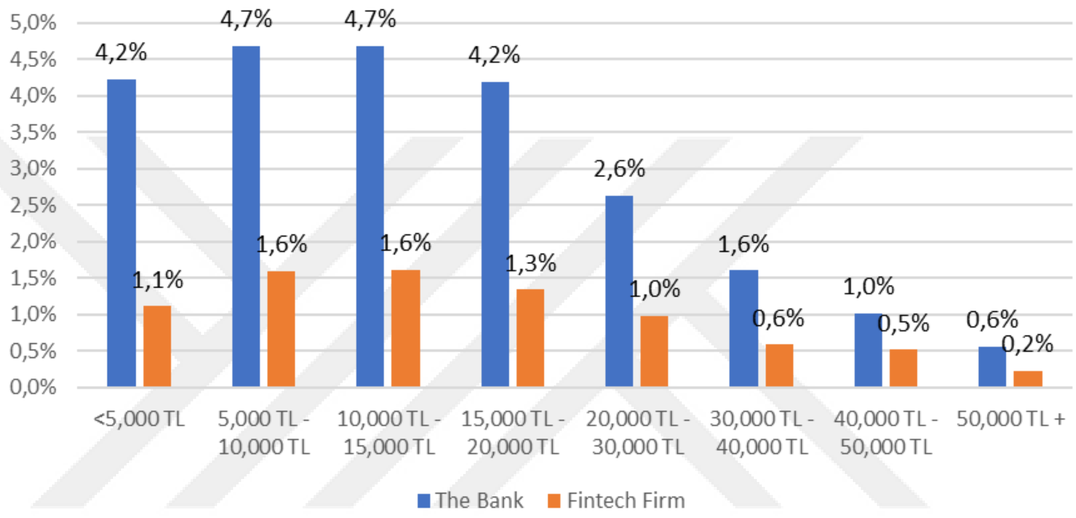

Figure 3.6 Default rates with respect to loan size

In the Figure 3.7 it can be seen that as deposit amount at the moment of loan initiation increases the default rates tend to decrease. The same correlation applies for both Fintech and the bank borrowers. Also, for all the deposit amount brackets, Fintech borrowers have a lower default rate compared to the Bank borrowers.

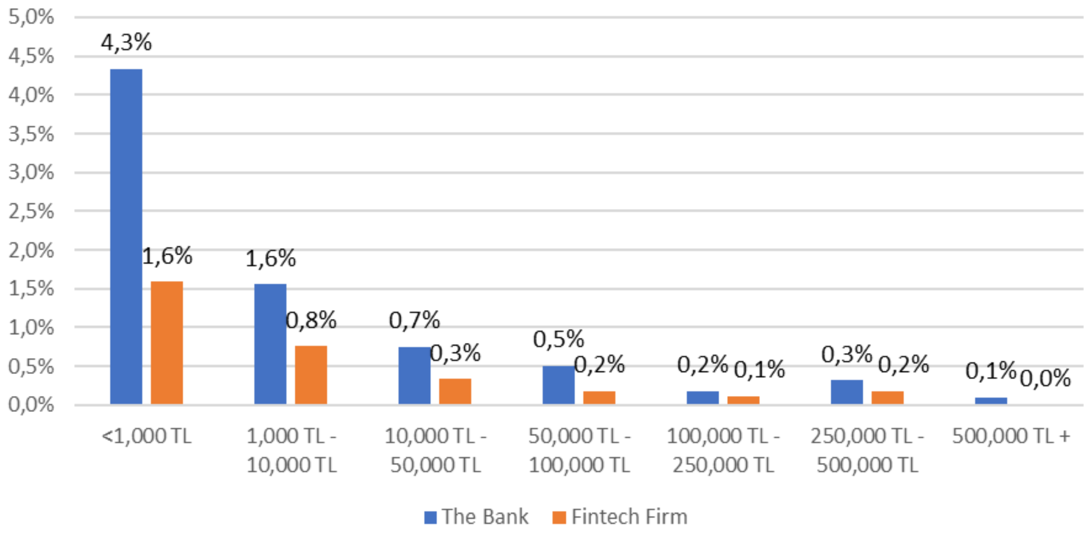

Figure 3.7 Default rates with respect to individuals' deposit amount

3.3 Methodology and Results of Linear Regression Models

Similar to part 2.3, again after analyzing general statistics and distributions to get an idea regarding the default and loan repayment behavior of fintech borrowers, in this part we analyze the default characteristics of Fintech's and the bank's borrowers in a controlled setup using linear regression models.

To examine and compare the loan performance of the bank and the fintech firm, I run the following linear regression model. In the model, *Default* is the dichotomous dependent variable; independent variables are depicted in part 2.2.1. In addition to previous linear regression in part 2.3, this time *Fintech* is an independent variable. There are also city and year fixed effects as control variables. The model representation is rather similar to (Di Maggio and Yao 2020, 2) but the variables are different. The model I used can be represented as:

$$Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t} \qquad (2)$$

The dependent variable is a dummy that takes the value one if the borrower i, in city c who obtain a loan in year t, defaults on his/her debt. Tables 3.1 and 3.2 provide the estimates of the model presented in (2) with credit and demographic attributes as independent variables, respectively. The tables report the linear probability regression results of the model (2) with credit attributes as independent variables in 3.1 and demographic variables as independent variables in 3.2. The regressions control for city and year effects on fintech via corresponding fixed effects. Fintech is a dummy variable that takes 1 if the individual i, in city c, at time t borrows from the fintech firm and 0 otherwise. Detailed descriptions of the dependent and independent variables are provided in the part 2.2.1.

In Table 3.1, except for the last column, each pair of values in the diagonal represents the output of the corresponding univariate linear regression. In each univariate regression, the dependent variable is the dichotomous Default variable, independent variables are the corresponding variable in the first column along with the Fintech dichotomous variable and the city and year fixed effect used as control variables. Each pair of output represents the coefficient of the corresponding variable and beneath it their respective t-values in parentheses. The variables marked with * are statistically significant at 1% level. At the bottom of the table the R^2 value of the linear regression model, intercept value of the regression equation and the number of observations can be found. The last column depicts the results of the multivariate linear regression model. Again, all the pair of values represent the coefficient and the t-values of corresponding independent variable. In Table 3.2, along with other linear regression models with dependent variable Default in this chapter, results are in the same table format for consistency.

In Table 3.1, it is observed that borrowers with high deposit levels are less likely to default. Similarly, as the number of accounts with a positive balance increase, default probability decreases. We show that the borrowers are more likely to default as the loan size gets bigger and the maturity gets longer. Borrowers in mid-and high-credit score groups are less likely to default than borrowers in low-credit score groups, as expected. Finally, I show that a 1% increase in the interest rate on the loan is associated with a 1.3% increase in default probability. One can argue that including interest rate as an independent variable can cause endogeneity when using default as a dependent variable. However, these banks do not use risk-based pricing, meaning that they do not alter their interest rates according to borrowers’ probability of default. Therefore, including interest rate in the model do not cause endogeneity. Risk-based pricing is not common in Turkey’s banking sector.

Unlike their counterparts in developed markets, I document that fintech borrowers are less likely to default on their debt even after controlling for all credit attributes. The coefficient that measures the effect of being a fintech borrower on default probability varies between -160 bps and -90 bps. The results indicate that being a fintech borrower reduces default probability by 10 bps even after controlling for all credit attributes.

As previous linear regressions, in this chapter R^2 values of linear regressions are low but the aim of these models and this study is not to estimate probability of default and build a new scorecard for these loans; rather statistical models are used to examine the statistical relationships between the dependent variable default and independent variables to interpret economic results. Thus, low R^2 values are accepted in this study.

Credit Attributes									
Dep. Var	Default Indicator								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit Amount†	-0.00302 *								-0.00168*
	(-124.07)								(-68.08)
No. of positive account		-0.00631*							-
		(-102.54)							-
Loan Size†			0.00435 *						0.00188*
			(56.71)						(21.77)
Inst. Cnt				0.000973*					0.000836*
				(183.72)					(142.39)
Low Credit Score					0.0669*				0.0637*
					(339.49)				(315.1)
Mid Credit Score						-0.028*			-
						(-174.29)			-
High Credit Score							-0.0269*		-0.00771*
							(-128.09)		(-35.43)
Interest Rate								0.0122*	0.0126*
								(75.52)	(77.08)
Fintech	-0.0156*	-0.0099*	-0.0127*	-0.00915*	-0.0108*	-0.0162*	-0.011*	-0.0136*	-0.00118*
	(-46.59)	(-55.04)	(-71.68)	(-51.81)	(-62.09)	(-92.38)	(-62.05)	(-77.86)	(-6.45)
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	2.2%	2.1%	2.0%	2.5%	3.9%	2.5%	2.2%	2.1%	4.7%
Constant Term	-0.0146	-0.0177	-0.0637	-0.0537	-0.0306	-0.00311	-0.0208	-0.0403	-0.0824

Table 3.1: Default characteristics of Fintech Borrowers - Credit Attributes

In Table 3.2, I control for demographic attributes when examining the relationship between fintech lending and default probability. Univariate results indicate a negative relationship between income levels and default probability. [1]

Results show that borrowers with undergraduate and graduate degrees are less likely to default than borrowers with primary-school and high-school degrees. Univariate regressions indicate that borrowers who work in the public sector or are retirees are less likely to default on their debt than those who work in the private sector or are self-employed. These findings may be attributable to the uncertainties associated with working in the private sector or running a business in an emerging economy, affecting debt repayment.

In Table 3.2, results show that being a male increases the probability of default by five bps. Moreover, it is documented that older people are less likely to default and an increase in age is associated with a one bps decrease in default probability. Similar to our findings in Table 3.1, we show that fintech borrowers are less likely to default even after controlling for all other demographic attributes. Our results indicate that being a fintech reduces the probability of default by one percentage point in a multivariate setting. Since our sample's average probability of default is around 3%, I argue that the results are both statistically and economically significant.

[1] The coefficient for income switches sign under multivariate setting. Borrowers declare their income levels at the initiation of the loan. The declared numbers can significantly differ from the individual's real income. One potential mechanism for positive relationship between income and the probability of default may arise from borrowers' tendency to overstate their income as they believe higher income would result in obtaining the loan. This tendency may increase when borrowers are financially constrained, leading a positive correlation between income values and default probability.

Demographic Attributes														
Dep. Var	Default Indicator													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income†	-0.0004*													0.000462*
	(-9.75)													(10.81)
Primary School		0.0123*												-
		(64.16)												-
High School			0.00745*											-0.00698*
			(47.56)											(-34.26)
Undergraduate				-0.0154*										-0.0237*
				(-91.79)										(-102.57)
Graduate					-0.0127*									-0.0272*
					(-34.66)									(-66.29)
Private Sector						0.0103*								-0.0268*
						(64.02)								(-46.03)
Public Sector							-0.0163*							-0.0387*
							(-70.68)							(-62.93)
Self Employed								0.0166*						-0.0145*
								(51.32)						(-22.18)
Retired									-0.017*					-0.0376*
									(-75.96)					(-59.14)
Unemployed										0.00669*				-
										(5.27)				-
Male											0.00487*			0.00219*
											(27.46)			(12.21)
Age												-0.00053*		-0.00048*
												(-74.34)		(-50.55)
Young													0.00998*	-
													(56.16)	-
Fintech	-0.014*	-0.0118*	-0.0128*	-0.00917*	-0.0132*	-0.0147*	-0.0129*	-0.0143*	-0.0165*	-0.0142*	-0.0144*	-0.018*	-0.0167*	-0.0101*
	(-79.44)	(-66.26)	(-71.98)	(-50)	(-74.38)	(-83.99)	(-73.34)	(-81.74)	(-93.06)	(-81.19)	(-82.43)	(-98.75)	(-92.49)	(-51.86)
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	2.0%	2.0%	2.0%	2.1%	2.0%	2.0%	2.0%	2.0%	2.1%	2.0%	2.0%	2.1%	2.0%	2.5%
Constant Term	-0.0214	-0.0268	-0.0279	-0.0187	-0.0241	-0.0303	-0.0222	-0.0248	-0.02	-0.0246	-0.0281	-0.00229	-0.0304	0.0346

Table 3.2: Default characteristics of Fintech Borrowers - Demographic Attributes

3.4 Methodology and Results of Logistic Regression Models

The main concern of this thesis is to understand the behavior of fintech borrowers that emerged as a new segment as a result of online lending. The differences in loan repayment behavior, default tendency, demographic and credit attributes has been thoroughly analyzed via mostly linear regression models because the aim is to analyze borrowers' characteristics and linear models are easier to interpret. However, the dependent variable, whether the fintech dummy variable or the default variable -*described in part 2.2.1*-, they are binary variables. Thus, in this part I also implemented a logistic regression model on the same dataset to have a different point of view and validate the outcomes through different perspective.

To that aim, the same dataset used in part 3.3 have been used. The following logistic regression model with dependent variable as *Default* is used. The independent variables in the logit function are depicted in part 2.2.1. The *Fintech* binary variable is again used as an independent variable in addition to independent variables used before. The model specification is similar to (Gebizlioglu and Ozturkkal 2018, 14) but the variables, interpretation and the results are different. In their study regarding mortgage defaults, the predictive powers of their models are strong because their aim is to predict future outcomes, compare different statistical models and show the dynamic structure of the stepwise estimation procedures. However, in this study the aim is not to estimate the probability of default of the loans, rather the aim is to examine the statistical relationships between the independent variables and the probability of default. In that way economic interpretations are made. The logistic regression model can be described as:

$$Pr(Default) = (1 + e^{-L})^{-1}$$

$$\text{where } L = \alpha + \beta X_{i,t} + \varphi_t + \gamma Fintech_{i,t} + \varepsilon_{i,t} \qquad (3)$$

Default is the binary variable that takes the value 1 if the corresponding loan *i* defaults, which was obtained a loan in year *t*, defaults and 0 otherwise, $Fintech_{i,t}$ is the binary variable that represents whether the loan is disbursed through the fintech firm in year *t* or the conventional bank (if fintech then takes the value 1, 0 otherwise), $X_{i,t}$ represents all the credit and demographic variables described in part 2.2.1 and used in the analyses in part 3.3. The fixed year effect as φ_t are also included in the model which represents the year loan was initiated to include time effect into the model. Unlike in the linear model deployed in part 3.3, city fixed effect wasn't involved due to performance issues. In this part one of the aims is to analyze and include interaction between variables, therefore stepwise iterative method was used when running logistic regression models and with close to 5.5 million observations and fixed city effect variables, getting results was impractical. Actually, with this part's goal in mind, exclusion of city fixed effect does not create a big downside in the analysis. On the other hand, more importantly, fixed time effect was included which carries more statistical significance when analyzing default behavior.

The method in this part is as follows; I implemented logistic regression models to the dataset as *Default* as the binary dependent variable. Unlike in part 3.3 I did not estimate univariate regression models for each different variable; I only ran multivariate logistic regressions for credit and demographic attributes separately, similar to part 3.3. In addition to that, the variance inflation factors and correlation matrices of the independent variables are showed to investigate possible multicollinearity issues.

In table 3.3 the results of the logistic regression model using demographic attributes can be seen. Panel A represents the variable estimation results and Panel B shows the model statistics.

Results show that as age and education level increase, probability of default tend to decrease, validating our results in part 3.3. According to variable estimation results, all the employment statuses tend to decrease probability of default but this can be explained through some multicollinearity problems which will be discussed later on. High income levels again tend to increase probability of default, similar to part 3.3 but as discussed before this is due to customers with opportunistic behavior, that are more likely to default overstating their income levels; which distort the results. Again, being a male borrower tend to increase probability of default. The most important result is that it can be seen that with the logistic regression model implemented and even after controlling for demographic variables, the coefficient of the Fintech variable's sign is again negative. We cannot interpret a direct economic impact factor from this result but this implies that being a Fintech borrower reduces the probability of default as a validation to prior results.

Panel A: Variable Estimation				
Variable	**Coefficient**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	-1.6587	0.028	3514.17	<0.0001
Age	-0.0176	0.000417	1786.2	<0.0001
Primary School	0.1857	0.0144	167.06	<0.0001
Graduate	-1.0804	0.0265	1668.4	<0.0001
Undergraduate	-0.6297	0.0153	1685.15	<0.0001
High School	0.0298	0.0141	4.44	0.035
Retired	-0.9698	0.0169	3277.49	<0.0001
Unemployed	-0.3551	0.0355	100.15	<0.0001
Self Employed	-0.2927	0.0163	321.97	<0.0001
Private Sector	-0.6051	0.0144	1768.26	<0.0001
Public Sector	-1.0438	0.0169	3800.67	<0.0001
Income†	0.00821	0.00137	35.92	<0.0001
Male	0.0652	0.00614	112.62	<0.0001
Young	-0.1582	0.0099	255.4	<0.0001
Fintech	-0.4882	0.00844	3349.65	<0.0001
Fixed Year Effect of 2014	0.4653	0.00938	2458.38	<0.0001
Fixed Year Effect of 2015	0.4622	0.0073	4002.89	<0.0001
Fixed Year Effect of 2016	0.1932	0.00772	626.32	<0.0001
Fixed Year Effect of 2018	-0.3259	0.00879	1375.92	<0.0001
Fixed Year Effect of 2019	-1.6117	0.0133	14683.46	<0.0001
Fixed Year Effect of 2020	-3.8231	0.0412	8591.88	<0.0001
Panel B: Model Statistics				
Misclassification Rate			0.03	
Mean Square Error			0.03	
Likelihood Ratio Test for Global Null Hypothesis: BETA=0				
Likelihood Ratio Chi-square			160688.176	
Pr > ChiSq			<0.0001	

Table 3.3: Logistic Regression Model Results- Demographic Attributes

In table 3.4, the summary of stepwise selection results that was used in logistic regression can be seen. As new variables enter the model, Chi-square score changes according to their statistical significance. In stepwise selection, no variable beside the fixed year effect of 2017 has been eliminated from the independent variable set which can be seen a positive result when selecting the model variables.

Step	Effect Entered	Score Chi-Square	Pr > ChiSq
1	Fixed Year Effect of 2015	35958.084	<0.0001
2	Fixed Year Effect of 2020	26039.9422	<0.0001
3	Fixed Year Effect of 2019	28537.8785	<0.0001
4	Undergraduate	15709.4884	<0.0001
5	Fintech	5596.8925	<0.0001
6	Age	6411.4423	<0.0001
7	Fixed Year Effect of 2018	4150.787	<0.0001
8	Graduate	3351.7233	<0.0001
9	Public Sector	2345.067	<0.0001
10	Fixed Year Effect of 2014	2014.2798	<0.0001
11	Retired	1742.612	<0.0001
12	Private Sector	2588.265	<0.0001
13	Primary School	899.4555	<0.0001
14	Fixed Year Effect of 2016	590.3047	<0.0001
15	Young	257.9115	<0.0001
16	Self Employed	169.9831	<0.0001
17	Male	158.636	<0.0001
18	Unemployed	109.7162	<0.0001
19	Income†	91.7083	<0.0001
20	High School	4.4444	0.035

Table 3.4 Summary of Stepwise Selection – Log. Reg. with Demographic Attributes

In table 3.5 the variance inflation factors of the demographic variables can be seen. The most problematic variables that can cause a multicollinearity problem in the model are the ones that represent employment status. This looks like the reason for the negative coefficients in the logistic regression, contrary to expectation.

Variable	Variance Inflation Factor
Age	3.75
Primary School	3.71
Graduate	14.40
Undergraduate	14.20
High School	10.66
Retired	1.24
Unemployed	5.07
Self Employed	17.70
Private Sector	9.67
Public Sector	2.02
Income†	1.04
Male	3.34
Young	1.34
Fintech	1.33

Table 3.5 Variance Inflation Factor– Log. Reg. with Demographic Attributes

In table 3.6, the correlation matrix of the variables can be seen. Employment statuses have a high correlation with age and gender besides the correlation with each other. Fintech binary variable has a low variance inflation factor in table 3.5 which implies a low correlation with other independent variables that can be seen in table 3.6.

Label	Age	Primary School	Graduate	Undergraduate	High School	Retired	Unemployed	Self Employed	Private Sector	Public Sector	Income†	Male	Young	Fintech
Age	100%	24%	-7%	-25%	6%	67%	0%	-1%	-43%	-5%	-2%	3%	-83%	-28%
Primary School	24%	100%	-11%	-36%	-39%	16%	0%	3%	-4%	-13%	1%	9%	-21%	-23%
Graduate	-7%	-11%	100%	-16%	-17%	-6%	-1%	0%	-1%	8%	9%	-2%	7%	18%
Undergraduate	-25%	-36%	-16%	100%	-56%	-17%	-1%	-3%	2%	16%	16%	-10%	21%	34%
High School	6%	-39%	-17%	-56%	100%	5%	-1%	0%	4%	-10%	4%	4%	-4%	-18%
Retired	67%	16%	-6%	-17%	5%	100%	-2%	-9%	-55%	-15%	-3%	-1%	-64%	-19%
Unemployed	0%	0%	-1%	-1%	-1%	-2%	100%	-1%	-8%	-2%	-7%	-10%	0%	-1%
Self Employed	-1%	3%	0%	-3%	0%	-9%	-1%	100%	-34%	-9%	5%	5%	3%	0%
Private Sector	-43%	-4%	-1%	2%	4%	-55%	-8%	-34%	100%	-54%	1%	0%	40%	7%
Public Sector	-5%	-13%	8%	16%	-10%	-15%	-2%	-9%	-54%	100%	1%	0%	6%	9%
Income†	-2%	1%	9%	16%	4%	-3%	-7%	5%	1%	1%	100%	5%	5%	21%
Male	3%	9%	-2%	-10%	4%	-1%	-10%	5%	0%	0%	5%	100%	-1%	3%
Young	-83%	-21%	7%	21%	-4%	-64%	0%	3%	40%	6%	5%	-1%	100%	25%
Fintech	-28%	-23%	18%	34%	-18%	-19%	-1%	0%	7%	9%	21%	3%	25%	100%

Table 3.6 Correlation Matrix– Log. Reg. with Demographic Attributes

In table 3.7 the results of the logistic regression model using credit attributes can be seen. Panel A represents the variable estimation results and Panel B shows the model statistics.

Results show that as credit score and deposit amount increases, probability of default tend to decrease, validating our results in part 3.3. According to variable estimation results, interest rate, maturity and loan size have a positive impact on probability of default which is in line with prior results. Again, the most important result is that it can be seen that even controlling for credit variables, the coefficient of the Fintech variable's sign is again negative. This implies that being a Fintech borrower reduces the probability of default as a validation to prior results.

In table 3.8, the summary of stepwise selection results that was used in logistic regression can be seen. In stepwise selection, *mid credit score* variable with the fixed year effect of 2017 variable has been eliminated from the dataset. *Mid credit score* variable was already eliminated for to avoid multicollinearity in part 3.3's multivariate regression, this result validates the elimination decision.

Panel A: Variable Estimation				
Variable	**Coefficient**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	-5.34	0.0273	38148.82	<0.0001
Fintech	-0.33	0.00816	1596.4	<0.0001
Low Credit Score	1.20	0.00526	52140.37	<0.0001
High Credit Score	-1.05	0.0149	4992.18	<0.0001
Maturity	0.04	0.00023	27467.86	<0.0001
Interest Rate	0.29	0.00543	2755.47	<0.0001
Deposit Amount†	-0.04	0.00149	702.24	<0.0001
Loan Size†	0.05	0.00348	246.67	<0.0001
Nu. Accounts	-0.24	0.00502	2240.09	<0.0001
Fixed Year Effect of 2014	0.61	0.0097	3905.25	<0.0001
Fixed Year Effect of 2015	0.66	0.00772	7295.03	<0.0001
Fixed Year Effect of 2016	0.40	0.00799	2458.43	<0.0001
Fixed Year Effect of 2018	-0.27	0.00942	826.48	<0.0001
Fixed Year Effect of 2019	-1.46	0.0136	11506.89	<0.0001
Fixed Year Effect of 2020	-3.77	0.0413	8301.99	<0.0001
Panel B: Model Statistics				
Misclassification Rate			0.03	
Mean Square Error			0.03	
Likelihood Ratio Test for Global Null Hypothesis: BETA=0				
Likelihood Ratio Chi-square			272207.297	
Pr > ChiSq			<0.0001	

Table 3.7: Logistic Regression Model Results- Credit Attributes

Step	Effect Entered	Score Chi-Square	Pr > ChiSq
1	Low Credit Score	163519.792	<0.0001
2	Maturity	29927.968	<0.0001
3	Fixed Year Effect of 2020	27995.2611	<0.0001
4	Fixed Year Effect of 2019	22978.1541	<0.0001
5	Deposit Amount†	14120.7332	<0.0001
6	High Credit Score	5475.0316	<0.0001
7	Fixed Year Effect of 2015	5522.2087	<0.0001
8	Fintech	3176.3132	<0.0001
9	Fixed Year Effect of 2014	2593.6412	<0.0001
10	Fixed Year Effect of 2016	3398.2275	<0.0001
11	Interest Rate	3039.3753	<0.0001
12	Nu. Accounts	2161.5172	<0.0001
13	Fixed Year Effect of 2018	926.7435	<0.0001
14	Loan Size†	246.7123	<0.0001

Table 3.8 Summary of Stepwise Selection – Log. Reg. with Credit Attributes

In table 3.9 the variance inflation factors of the credit variables can be seen. All the variables' variance inflation factors are small –*smaller than 2*- which implies there are no multicollinearity problems in the regression. The highest values belong to *Nu. Accounts* and *Deposit Amount*† variables that have a high correlation with each other. The correlations can be seen in table 3.10.

Variable	Variance Inflation Factor
Fintech	1.23
High Credit Score	1.14
Maturity	1.30
Interest Rate	1.83
Deposit Amount†	1.92
Loan Size†	1.38
Low Credit Score	1.14
Nu. Accounts	1.84
Fixed Year Effect of 2014	1.34
Fixed Year Effect of 2015	1.90
Fixed Year Effect of 2016	1.68
Fixed Year Effect of 2018	1.93
Fixed Year Effect of 2019	1.93
Fixed Year Effect of 2020	1.78

Table 3.9 Variance Inflation Factors – Log. Reg. with Credit Attributes

Variable	Fintech	High Credit Score	Maturity	Interest Rate	Deposit Amount†	Loan Size†	Low Credit Score	Nu. Accounts
Fintech	100%	16%	-14%	5%	33%	-9%	-12%	30%
High Credit Score	16%	100%	-10%	-7%	24%	7%	-20%	21%
Maturity	-14%	-10%	100%	-2%	-9%	44%	3%	-8%
Interest Rate	5%	-7%	-2%	100%	9%	18%	-10%	10%
Deposit Amount†	33%	24%	-9%	9%	100%	6%	-19%	67%
Loan Size†	-9%	7%	44%	18%	6%	100%	-14%	3%
Low Credit Score	-12%	-20%	3%	-10%	-19%	-14%	100%	-16%
Nu. Accounts	30%	21%	-8%	10%	67%	3%	-16%	100%

Table 3.10 Correlation Matrix– Log. Reg. with Credit Attributes

3.5 Subsampling Using Propensity Score Matching & Testing Prior Results

In part 3.3 and 3.4, it has been analyzed whether there are statistically significant differences in the performance of consumer loans between a fintech and a conventional bank. Even after controlling with several demographic and loan based independent variables, it has been showed that fintech borrowers are less likely to default.

My results yet statistically significant, may contain some unobserved selection bias. To test these prior results' robustness and check whether my result contain any bias due to unobserved heterogeneity in Fintech and the bank loans, in this part I apply propensity score matching approach (PSM) to make Fintech and the bank loans more comparable.

The methodology is rather straightforward; first I ran a logistic regression model using some borrower and loan characteristics using default dummy variable as dependent variable and calculated default propensity scores for all of the observations. Next, I matched observations through propensity scores to create subsamples. These subsamples are expected to have similar default probabilities since they have similar default propensity scores. At last, I analyzed these subsamples with the similar methodology implemented in part 3.3 to test robustness of my prior results.

To be able to analyze from both angles, I ran propensity score matching approach for both borrower and loan characteristics and analyzed them through different matched subsamples.

3.5.1 Matching Observations with Respect to Loan Characteristics

As first run, I use propensity score matching approach for loan characteristics. Specifically, I match the loans in three dimensions: loan size, maturity and month of loan initiation. To that end, I estimate the logistic propensity score model again with the similar specification in part 3.4 with different independent variables. For all loans in the sample the propensity scores are estimated using following model:

$$Pr(Default) = (1 + e^{-X})^{-1}$$

$$\text{where } X = \alpha + \beta_1 LoanSize_i + \beta_2 Maturity_i + \beta_3 MonthOfInitiation_i + \varepsilon_i \qquad (4)$$

The independent variables, loan size and maturity are defined in 2.2.1. I provide the results of logistic propensity-score model described in (4) along with the sample mean and standard deviation of estimated propensity scores in Table 3.11. Panel A provides the Chi-square statistics of logistic regression results. In Table 3.11, we observe that the probability of default is higher on average for loans that are smaller in size and that have longer maturities. I control for the month of initiation to capture any seasonal effect in loan characteristics for both Fintech and The Bank loans. Table 3.11 Panel B shows that the mean and standard deviations of the estimated propensity scores are 3.30% and 1.47%, respectively.

Panel A: Logistic Propensity Score Model Results				
Variable	**Coefficient**	**Standard Error**	**Wald Chi-Square**	**Pr> ChiSq**
Intercept	-2.88	0.022	17555.72	<0.0001
Maturity	0.03	0.000	33490.32	<0.0001
Loan Size	-0.16	0.003	3496.31	<0.0001
Month of initiation	-0.01	0.001	55.46	<0.0001
Panel B: Propensity Score Characteristics				
Average Propensity Score of Data			3.30%	
Standard Deviation of Propensity Score of Data			1.47%	

Table 3.11: Logistic Propensity Score Model Results – Loan Characteristics

Instead of examining the exactly matched propensity score subsamples, I round the propensity scores to second digit after the decimal to obtain subsamples where there are enough observations for statistical inference. It can be observed that even after aggregating subsamples by rounding the propensity scores, some subsamples have a limited number (if any) of fintech loans. This indicates that fintech loans may have specific characteristics that can lead to selection bias in the initial analysis explained in part 3.3.

After analyzing the subsamples with at least one Fintech loan, I chose the subsample with the highest default rate and number of observations for statistical inference. So for the first propensity score matching analysis, I use a subsample that has over 1.1 million loans, 16% of which are fintech loans and the percentage of defaults is around 6%. The descriptive statistics for the variables are described in Table 3.12. In this table, I present the descriptive statistics for loan and borrower characteristics of the matched subsample where the observations are matched with respect to loan characteristics. Second and third columns present the mean and standard deviation of a given variable for the Fintech loans, respectively. Fourth and fifth columns respectively present the mean and standard deviation of a given variable for the the bank loans. The last 2 columns correspond to the t-statistic of a test that has a null hypothesis that the bank and Fintech loans have the same mean for a given variable. The variables that are denoted by † are adjusted to changes in the inflation by discounting to 2014 values and use logarithmic transformations for normalization purposes.

Variable	Fintech		The Bank		t statistics	
	Mean	Standard Deviation	Mean	Standard Deviation	t value	p-value
Age	33.81	7.82	40.83	11.34	257.59	<0.0001
Loan Size†	8.64	0.85	8.58	0.99	-14.64	<0.0001
Income†	7.84	0.59	6.54	2.67	-211.88	<0.0001
Maturity	34.33	4.30	33.59	5.03	-39.43	<0.0001
Deposit Amount†	3.83	3.38	1.70	2.59	-310.09	<0.0001
Male	0.78	0.41	0.77	0.42	-15.77	<0.0001
Private Sector	0.69	0.46	0.63	0.48	-55.42	<0.0001
Public Sector	0.19	0.39	0.10	0.30	-110.24	<0.0001
Self Employed	0.06	0.23	0.05	0.22	-8.31	<0.0001
Retired	0.04	0.20	0.20	0.40	164.95	<0.0001
Unemployed	0.00	0.06	0.01	0.07	11.42	<0.0001
Primary School	0.07	0.26	0.29	0.45	203.77	<0.0001
High School	0.28	0.45	0.44	0.50	132.93	<0.0001
Undergraduate	0.57	0.50	0.18	0.39	-375.83	<0.0001
Graduate	0.09	0.28	0.01	0.12	-189.98	<0.0001
High Credit Score	0.17	0.37	0.09	0.29	-97.82	<0.0001
Mid Credit Score	0.69	0.46	0.65	0.48	-28.46	<0.0001
Low Credit Score	0.14	0.35	0.25	0.44	102.80	<0.0001
Interest Rate	1.51	0.45	1.31	0.71	-122.18	<0.0001
Young	0.90	0.29	0.65	0.48	-223.85	<0.0001
Nu. Accounts	1.36	1.47	0.63	0.81	-303.01	<0.0001
Default	0.03	0.18	0.06	0.24	53.23	<0.0001

Table 3.12: Descriptive Statistics of Matched Subsample– Loan Characteristics

It can be seen that difference in the loan size and the maturity of the bank and Fintech loans are smaller compared to the original sample, as expected from the matching procedure. In the full sample, the bank loans are larger in size. However, in the matched subsample, the average Fintech loan is larger in size compared to the average bank loan. Even though statistically significant, the difference in loan size between Fintech and the bank loans in this new subsample corresponds to 330 Turkish Lira (TL) which is economically insignificant. The difference in the full sample is more than 1000 TL which is approximately the 20% of the average loan in the sample. Similarly, the difference in maturities between the bank and Fintech loans are less than 1 month in the matched subsample whereas in the original sample the difference is around 4.5 months. Thus, the propensity matching procedure yields satisfactory matched results in that the matched set of loans are more similar in terms of loan size, maturity and initiation date characteristics as compared to the original full sample.

After creating the matched subsample, I repeat the analysis in the part 3.3 with the matched subsample. Specifically, the model described in (2) has been implemented to compare loan performance of The Bank and the Fintech.

Tables 3.13 and 3.14 provide the estimates of the model with the credit and demographic attributes as independent variables from the matched subsample. In the tables, values in parentheses are t-statistics of the coefficients. * indicates statistical significance at 1% level.

It is observed that the baseline results in part 3.3 are robust when a subsample used where Fintech and the bank loan characteristics are similar. Specifically, in table 3.13, it is documented that borrowers with high deposit levels are less likely to default. Similarly, as the number of accounts with a positive balance increase, the default probability decreases. In line with the baseline results, it is shown that the borrowers are more likely to default as the loan size gets bigger and the maturity gets longer. Borrowers with mid and high credit scores are less likely to default than borrowers with low credit score which is expected and again gives a validation to bank's credit scorecard. In the matched subsample, it is observed that a 1% increase in the interest rate on the loan is associated with 2.1% increase in the default probability. Finally, similar to the baseline findings in part 3.3, it is documented that in the subsample where the characteristics of Fintech and the bank loans are similar, Fintech loans are less likely to default even after controlling for all borrower and loan characteristics. The coefficient that measures the effect of being a Fintech borrower on default probability varies between -156 basis points (bps) and -80 bps. We show that being a Fintech borrower reduces default probability by almost 37 bps, after controlling for all credit attributes.

Finally, in Table 3.14, demographic attributes are controlled when examining the relationship between Fintech lending and default probability. In line with the baseline multivariate analysis, it is documented a positive relationship between income and default probability, which is unexpected. This relationship is possibly due to borrowers' tendency to overstate their income. In this subsample, an educated individual is less likely to default, in line with the baseline findings. Similarly, again it is documented that individuals who work in the public sector or retirees are less likely to default compared to individuals who work in the private sector or are self-employed. Furthermore, a negative correlation between age and default probability can be deducted, which again is in line with the original findings even though the coefficient is much smaller. Similarly, it is observed that being a male increases the probability of default, even though the statistical significance disappears in multivariate setting. Finally, it is documented that Fintech borrowers are less likely to default even after controlling for all other demographic attributes. Consistent with the baseline results, being a Fintech borrower reduces the probability of default by 109 bps. Therefore, the baseline results are robust to potential unobserved heterogeneity across Fintech and The Bank loans.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Credit Attributes								
Deposit Amount†	-0.00378*								-0.0025*
	(-47.36)								(-31.04)
No. of positive account		-0.0105*							-
		(-45.51)							-
Loan Size†			0.00792*						0.0122*
			(34.30)						(23.48)
Inst. Cnt				0.00154*					-0.00129*
				(33.97)					(-11.95)
Low Credit Score					0.0821*				0.0804*
					(160.62)				(153.15)
Mid Credit Score						-0.0443*			-
						(-96.82)			-
High Credit Score							-0.0475*		-0.0229*
							(-68.29)		(-32.14)
Interest Rate								0.0237*	0.0216*
								(59.63)	(40.81)
Fintech	-0.00796*	-0.00845*	-0.0141*	-0.0148*	-0.0100*	-0.0156*	-0.0111*	-0.0156*	-0.00368*
	(-12.97)	(-13.79)	(-23.55)	(-24.80)	(-16.89)	(-26.13)	(-18.48)	(-26.21)	(-6.04)
Intercept	-0.0319	-0.0322	-0.1143	-0.0973	-0.0494	-0.00693	-0.0361	-0.0733	-0.1336
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	2.0%	2.0%	1.9%	1.9%	4.0%	2.6%	2.2%	2.1%	4.6%

Table 3.13: Default characteristics of borrowers (matched subsample using loan characteristics) - Credit Attributes

	Demographic Attributes													
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income†	0.00209*													0.00316*
	(22.55)													(32.88)
Primary School		0.0136*												-
		(27.20)												-
High School			0.0103*											-0.00759*
			(23.44)											(-14.34)
Undergraduate				-0.0224*										-0.0328*
				(-42.38)										(-49.55)
Graduate					-0.0225*									-0.0408*
					(-16.36)									(-28.15)
Private Sector						0.0175*								-0.0364*
						(38.79)								(-24.18)
Public Sector							-0.0276*							-0.0573*
							(-40.26)							(-35.38)
Self Employed								0.0288*						-0.0149*
								(29.95)						(-8.5)
Retired									-0.0251*					-0.048*
									(-43.85)					(-29.19)
Unemployed										0.0126*				-
										(4.10)				-
Male											0.00305*			-0.00018
											(5.98)			(-0.35)
Age												-0.00101*		-0.00095*
												(-51.16)		(-34.93)
Young													0.0174*	-
													(36.71)	-
Fintech	-0.0165*	-0.0118*	-0.0130*	-0.00676*	-0.0131*	-0.0153*	-0.0120*	-0.0150*	-0.0184*	-0.0147*	-0.0148*	-0.0219*	-0.0192*	-0.0109*
	(-27.39)	(-19.53)	-21.58	(-10.79)	(-21.68)	(-25.67)	(-19.98)	(-25.14)	(-30.49)	(-24.60)	(-24.76)	(-35.76)	(-31.42)	(-16.73)
Intercept	-0.0586	-0.0449	-0.0464	-0.0335	-0.0412	-0.0509	-0.0386	-0.0425	-0.0337	-0.0419	-0.0441	0.00179	-0.0511	0.0319
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	1.9%	1.9%	1.9%	2.0%	1.9%	2.0%	2.0%	1.9%	2.0%	1.9%	1.9%	2.1%	2.0%	2.6%

Table 3.14: Default characteristics of borrowers (matched subsample using loan characteristics) - Demographic Attributes

3.5.2 Matching Observations with Respect to Borrower Characteristics

Next, with a similar approach but this time from a different point of view, the observations with respect to three borrower characteristics are matched; the borrower characteristics that is used are namely, income, age and credit score. To that end, the following logistic propensity-score model is estimated for all loans in the original sample again with the similar specification in the previous part with different independent variables used in the logit function:

$$Pr(Default) = (1 + e^{-X})^{-1} \qquad (5)$$

$$where\ X = \alpha + \beta_1 Income_i + \beta_2 Age_i + \beta_3 HighCreditScore_i + \beta_4 MidCreditScore + \varepsilon_i$$

The independent variables, income, age, mid credit score and high credit score, are defined in part 2.2.1. The results of the logistic propensity-score model described in (5) along with the sample mean and standard deviation of estimated propensity scores are presented in Table 3.15.

In Table 3.15, it is observed that the probability of default decreases with the increases in the income and credit score and decreases with age; which is in line with previous results. Table 3.15 Panel B shows that the mean and standard deviations of the estimated propensity scores are 3.29% and 3.18%, respectively.

Panel A: Logistic Propensity Score Model Results				
Variable	**Coefficient**	**Standard Error**	**Wald Chi-Square**	**Pr> ChiSq**
Intercept	-2.11	0.011	37777.89	<.0001
Age	0.01	0.000	587.66	<.0001
Income	-0.05	0.001	2362.45	<.0001
High Credit Score	-2.88	0.015	38097.09	<.0001
Mid Credit Score	-1.59	0.005	97957.9	<.0001
Panel B: Propensity Score Characteristics				
Average Propensity Score of Data			3.29%	
Standard Deviation of Propensity Score of Data			3.18%	

Table 3.15: Logistic Propensity Score Model Results – Borrower Characteristics

For proper statistical inference, again the propensity scores are rounded to second digit after the decimal to obtain subsamples with sufficient observations of default rates and Fintech loans. Our matched subsample, this time has 603,813 observations. 24% of the loans in our matched subsample are Fintech loans and the overall default rate is around 9%. The descriptive statistics for the variables in the matched subsample in Table 3.9.

	Fintech		The Bank		t statistics	
Variable	Mean	Standard Deviation	Mean	Standard Deviation	t value	p-value
Age	29.52	4.97	29.96	5.89	25.91	<0.0001
Loan Size†	8.10	0.88	8.38	0.84	108.92	<0.0001
Income†	7.64	0.50	7.55	0.56	-92.29	<0.0001
Maturity	25.28	15.26	26.24	13.03	23.26	<0.0001
Deposit Amount†	2.77	3.07	1.66	2.44	-141.48	<0.0001
Male	0.82	0.38	0.79	0.41	-30.34	<0.0001
Private Sector	0.73	0.44	0.81	0.39	64.19	<0.0001
Public Sector	0.17	0.38	0.08	0.28	-94.30	<0.0001
Self Employed	0.08	0.27	0.08	0.27	5.03	<0.0001
Retired	0.00	0.05	0.01	0.07	14.60	<0.0001
Unemployed	0.00	0.06	0.00	0.06	-2.82	0
Primary School	0.07	0.26	0.23	0.42	135.24	<0.0001
High School	0.32	0.47	0.52	0.50	128.26	<0.0001
Undergraduate	0.53	0.50	0.24	0.43	-219.70	<0.0001
Graduate	0.07	0.26	0.02	0.12	-110.03	<0.0001
High Credit Score	0.00	-	0.00	-	-	-
Mid Credit Score	0.00	-	0.00	-	-	-
Low Credit Score	1.00	-	1.00	-	-	-
Interest Rate	1.50	0.31	1.52	0.46	19.58	<0.0001
Young	0.99	0.08	0.98	0.12	-27.22	<0.0001
Nu. Accounts	1.05	1.19	0.63	0.76	-160.17	<0.0001
Default	0.05	0.21	0.10	0.30	61.93	<0.0001

Table 3.16: Descriptive Statistics of Matched Subsample – Borrower Characteristics

In Table 3.16, it is observed that all borrowers in the matched subsample are coming from low credit score groups as expected from subsample selection described in the previous part. As observations are being matched across age, the difference between the age of Fintech and the bank borrowers (less than six months) is significantly lower than the full sample where the age difference between Fintech borrowers and the bank borrowers is around 7 years. Similarly, the average monthly income between the bank and Fintech borrowers is around 180 TL which is 10% of the minimum wage in 2019 (according to www.tuik.gov.tr). To that end, it is argued that in the matched subsamples, Fintech borrowers are similar in terms of their age and income and most importantly identical in terms of their credit history.

Once again, the baseline analysis with the matched subsample is repeated. Specifically, I run the model presented in equation (2) to compare loan performance of the bank and the Fintech firm over similar borrowers. Tables 3.17 and 3.18 provide the estimates of the model with the credit and demographic attributes as independent variables from the matched subsample; as before both univariate and multivariate regressions have been implemented. It is again observed that the baseline results in part 3.3 are robust using the subsample where Fintech and the bank borrower characteristics are similar. Specifically, in Table 3.17, it is documented that as the borrowers' deposit amount and the number of accounts with a positive balance increase, the probability of default decreases. Similar to the previous findings, it is observed that loans that are larger in size, loans with longer maturities and loans with higher interest rates are more likely to default. Since all of the borrowers in the matched subsample are low credit borrowers, there is no need to control for credit score.

In line with the baseline findings, it is observed that in the subsample where the characteristics of Fintech and the bank borrowers are similar, Fintech borrowers are less likely to default even after controlling for all credit attributes. The coefficient that measures the effect of being a Fintech borrower on default probability varies between -3.6 and -2.7 percentage points (pp). It is also documented that being a fintech borrower reduces the default probability by almost 1.8 pp, even after controlling for all credit attributes.

In Table 3.18, I control for the demographic attributes of borrowers when examining the relationship between fintech lending and the default probability. Similar to the baseline results, it is observed a positive relationship between borrowers' income and the default probability. The results imply that more educated borrowers are less likely to default. The coefficients for some borrower employment statuses are different from the baseline analysis in part 3.3. Specifically, under the matched subsample, it is observed that borrowers who work in the private sector are less likely to default and the coefficient of being a retiree turns to positive even though it is statistically insignificant. The coefficient of age also switches sign. Therefore, after addressing the unobserved heterogeneity in fintech and bank borrowers, it can be derived that default rate increases with age.

More importantly, it is observed that fintech borrowers are less likely to default even after controlling for all demographic attributes. In line with the baseline results, it has been shown that being a fintech borrower reduces the probability of default by almost 2 pp. Therefore, the baseline results are robust to potential unobserved heterogeneity across fintech and bank borrowers.

Variable	Credit Attributes (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit Amount†	-0.00856*								-0.00768*
	(-61.59)								(-55.5)
No. of positive account		-0.0239*							-
		(-58.28)							-
Loan Size†			0.0233*						0.00159*
			(54.68)						(3.28)
Inst. Cnt				0.00253*					0.00235*
				(95.45)					(78.97)
Low Credit Score					0				0
					-				-
Mid Credit Score						0			-
						-			-
High Credit Score							0		0
							-		-
Interest Rate								0.0416*	0.0385*
								(41.14)	(37.79)
Fintech	-0.0277*	-0.0273*	-0.0289*	-0.0331*	-0.0365*	-0.0365*	-0.0365*	-0.0300*	-0.0188*
	(-31.42)	(-30.95)	(-32.89)	(-38.28)	(-41.94)	(-41.94)	(-41.94)	(-33.87)	(-21.03)
Intercept	-0.0382	-0.0315	-0.2395	-0.1163	-0.0388	-0.0388	-0.0388	-0.1014	-0.1821
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	2.6%	2.6%	2.5%	3.5%	2.0%	2.0%	2.0%	2.3%	4.2%

Table 3.17: Default characteristics of borrowers (matched subsample using borrower characteristics) - Credit Attributes

	Demographic Attributes													
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income†	0.00740*													0.00591*
	(11.07)													(6.96)
Primary School		0.0341*												-
		(36.95)												-
High School			0.0157*											-0.0174*
			(21.54)											(-17.82)
Undergraduate				-0.0407*										-0.0543*
				(-50.33)										(-48.47)
Graduate					-0.0351*									-0.0668*
					(-16.24)									(-28.62)
Private Sector						-0.00319*								-0.058*
						(-3.58)								(-23.97)
Public Sector							-0.0357*							-0.0816*
							(-29.63)							(-30.76)
Self Employed								0.0321*						-0.0359*
								(24.20)						(-13.11)
Retired									0.00826					-0.0598*
									(1.52)					(-10.09)
Unemployed										0.00229				-
										(0.37)				-
Male											0.00862*			0.000499
											(9.65)			(0.55)
Age												0.00118*		0.000476*
												(18.54)		(6.19)
Young													-0.0268*	-
													(-8.49)	-
Fintech	-0.0375*	-0.0314*	-0.0336*	-0.0251*	-0.0346*	-0.0368*	-0.0333*	-0.0365*	-0.0365*	-0.0365*	-0.0369*	-0.0358*	-0.0362*	-0.0194*
	(-42.81)	(-35.63)	(-38.20)	(-27.97)	(-39.42)	(-42.09)	(-37.91)	(-41.89)	(-41.91)	(-41.94)	(-42.34)	(-41.12)	(-41.56)	(-21.11)
Intercept	-0.0951	-0.0452	-0.0457	-0.0253	-0.0374	-0.0364	-0.0327	-0.0397	-0.0389	-0.0388	-0.0453	-0.0758	-0.0129	-0.0111
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	2.1%	2.3%	2.1%	2.4%	2.1%	2.0%	2.2%	2.1%	2.0%	2.0%	2.0%	2.1%	2.0%	2.9%

Table 3.18: Default characteristics of borrowers (matched subsample using borrower characteristics) - Demographic Attributes

3.6 Interaction Analysis

In this part, I explore the interactions between being a fintech borrower and all borrower and loan characteristics.

For the baseline regressions, interaction terms are added and present the results in Tables 3.19 and 3.20. Specifically, I run the model presented in equation (2) to compare loan performance of the bank and the Fintech firm with the inclusion of interaction terms. Table 3.19 represent the multivariate regression results including credit variable and interaction terms, table 3.20 represent the multivariate regression results of including demographic variables and the interaction terms. Similar to the methodology in part 3.3, the fixed year and city effects are included in each model.

In Table 3.19, all of the interaction terms are statistically significant at 1% level. Similar to the baseline results, it can be observed that among fintech borrowers, as the deposit amount of the borrower increases, the default rate decreases. Similarly, as the maturity and the size of a fintech loan increases, the default probability increases. Fintech borrowers who have higher credit scores are less likely to default compared to borrowers with low and mid credit scores. Similar to the PSM analysis, the interaction between credit score and fintech signals a potential mechanism for the superior performance of the fintech firm. Specifically, we observe that low credit individuals who borrow from the fintech firm have significantly lower default rates compared to bank borrowers with comparable credit score. The coefficient for the interaction term “Low-credit score * Fintech" is around -4pp and statistically significant at 1% level.

Thus, the results suggest that Fintech firm has a significant competitive advantage compared to the bank in identifying creditworthy individuals among borrowers who have low credit score. On the other hand, high credit score individuals who borrow from the fintech firm perform worse compared to high credit score bank borrowers. The coefficient for the interaction term “High-credit score * Fintech" is around 70bps, indicating that the difference between the default rate of bank loans and fintech loans in that subsegment is small in magnitude. That is, the competitive advantage of the Fintech firm over low-credit score individuals are much larger compared to its disadvantage over high-credit score individuals.

Moreover, the relationship between the default rate and the demographic attributes of the fintech borrowers is in line with the baseline results. Specifically, in Table 3.20, we observe that fintech borrowers with higher incomes are less likely to default. In addition, fintech borrowers with graduate degrees are less likely to default compared to individuals with lower education levels. Among the fintech borrowers, individuals that are working in the private sector or are self-employed are more likely to default compared to individuals that work in public sector or are retirees. Regression results imply that as fintech borrowers gets older, the default rate decreases. Finally, it can be observed that among the fintech borrowers, male borrowers are more likely to default compared to female borrowers. In terms of demographic attributes, we observe that all of the interaction terms for the occupations are positive. This would further imply that the loans that are offered to unemployed borrowers by the fintech firm have significantly lower default rate. Similarly, it is observed that for the fintech firm, borrowers with high school degrees have significantly less default rates compared to bank borrowers who only have high school degree.

Credit Attributes										
Dep. Var	Default Indicator									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Deposit Amount†	-0.00302 *								-0.00168*	-0.007*
	(-124.07)								(-68.08)	(-71.4)
No. of positive account		-0.00631*							-	-
		(-102.54)							-	-
Loan Size†			0.00435 *						0.00188*	0.001*
			(56.71)						(21.77)	(12.6)
Inst. Cnt				0.000973*					0.000836*	0.015*
				(183.72)					(142.39)	(150.5)
Low Credit Score					0.0669*				0.0637*	0.072*
					(339.49)				(315.1)	(319.7)
Mid Credit Score						-0.028*			-	-
						(-174.29)			-	-
High Credit Score							-0.0269*		-0.00771*	-0.012*
							(-128.09)		(-35.43)	(-43.4)
Interest Rate								0.0122*	0.0126*	0.006*
								(75.52)	(77.08)	(77.3)
Fintech	-0.0156*	-0.0099*	-0.0127*	-0.00915*	-0.0108*	-0.0162*	-0.011*	-0.0136*	-0.00118*	-0.006*
	(-46.59)	(-55.04)	(-71.68)	(-51.81)	(-62.09)	(-92.38)	(-62.05)	(-77.86)	(-6.45)	(-29.4)
Deposit Amount† * Fintech										0.005*
										(26.0)
Loan Size† * Fintech										0.001*
										(6.7)
Maturity * Fintech										-0.009*
										(-49.8)
Low Credit Score * Fintech										-0.044*
										(-83.8)
High Credit Score * Fintech										0.007*
										(16.0)
Interest Rate * Fintech										-0.004*
										(-24.1)
s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	2.2%	2.1%	2.0%	2.5%	3.9%	2.5%	2.2%	2.1%	4.7%	5.0%
Constant Term	-0.0146	-0.0177	-0.0637	-0.0537	-0.0306	-0.00311	-0.0208	-0.0403	-0.0824	-0.0277

Table 3.19: Default characteristics of borrowers (full sample with interaction variables) - Credit Attributes

Demographic Attributes															
Dep. Var	Default Indicator														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Income†	-0.0004*													0.000462*	0.0013*
	(-9.75)													(10.81)	(13.5)
Primary School		0.0123*												-	-
		(64.16)												-	-
High School			0.00745*											-0.00698*	-0.006*
			(47.56)											(-34.26)	(-27.9)
Undergraduate				-0.0154*										-0.0237*	-0.025*
				(-91.79)										(-102.57)	(-97.2)
Graduate					-0.0127*									-0.0272*	-0.030*
					(-34.66)									(-66.29)	(-47.1)
Private Sector						0.0103*								-0.0268*	-0.041*
						(64.02)								(-46.03)	(-57.0)
Public Sector							-0.0163*							-0.0387*	-0.056*
							(-70.68)							(-62.93)	(-74.0)
Self Employed								0.0166*						-0.0145*	-0.025*
								(51.32)						(-22.18)	(-31.0)
Retired									-0.017*					-0.0376*	-0.051*
									(-75.96)					(-59.14)	(-67.0)
Unemployed										0.00669*				-	-
										(5.27)				-	-
Male											0.00487*			0.00219*	0.003*
											(27.46)			(12.21)	(13.0)
Age												-0.00053*		-0.00048*	-0.006*
												(-74.34)		(-50.55)	(-50.5)
Young													0.00998*	-	-
													(56.16)	-	-
Fintech	-0.014*	-0.0118*	-0.0128*	-0.00917*	-0.0132*	-0.0147*	-0.0129*	-0.0143*	-0.0165*	-0.0142*	-0.0144*	-0.018*	-0.0167*	-0.0101*	-0.042*
	(-79.44)	(-66.26)	(-71.98)	(-50)	(-74.38)	(-83.99)	(-73.34)	(-81.74)	(-93.06)	(-81.19)	(-82.43)	(-98.75)	(-92.49)	(-51.86)	(-27.8)
Income† * Fintech															-0.001*
															(-6.8)
High School * Fintech															-0.003*
															(-4.1)
Undergraduate * Fintech															0.007*
															(9.9)
Private Sector * Fintech															0.035*
															(25.1)
Public Sector * Fintech															0.044*
															(30.5)
Self Employed * Fintech															0.025*
															(16.0)
Retired * Fintech															0.040*
															(23.8)
Male * Fintech															-0.003*
															(-8.0)
Age * Fintech															0.005*
															(16.6)
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	2.0%	2.0%	2.0%	2.1%	2.0%	2.0%	2.0%	2.0%	2.1%	2.0%	2.0%	2.1%	2.0%	2.5%	2.6%
Constant Term	-0.0214	-0.0268	-0.0279	-0.0187	-0.0241	-0.0303	-0.0222	-0.0248	-0.02	-0.0246	-0.0281	-0.00229	-0.0304	0.0346	0.033

Table 3.20: Default characteristics of borrowers (full sample with interaction variables) - Demographic Attributes

3.7 Default Characteristics of Mutual Borrowers

As mentioned in chapter 2, full sample exploited in previous parts includes 2,567,333 million unique individuals; 311,908 of which are obtained consumer loans only from Fintech firm, 54,689 of which obtained both traditional and fintech loans and the remaining 2,200,736 individuals obtained loans only from the bank. In previous chapters, it has been shown that Fintech borrowers' loan default performance is significantly better compared to conventional bank borrowers'; analyses were conducted in a panel regression setting and through subsamples using propensity score matching to eliminate selection bias. It has also been shown via interaction analyses that Fintech can identify creditworthy customers among those who were labeled as low credit score segment. All these analyses show an inferior loan performance on the conventional bank's side, so in this part, the focus of attention is on conventional bank loans. The aim is to show that the difference in loan repayment performance is due to the characteristics of the fintech borrowers and not as a result of an inferior loan collection strategy imposed by the conventional bank. To that end, I ignore the loan setting and evaluation criteria of Fintech firm and only used conventional bank loans. However, these bank loans have been divided into two, but this time on customer level.

There are over 4 million bank loans in the dataset used by 2,225,425 individuals. 54,689 of these individuals also used a consumer loan from the Fintech firm. These "mutual borrowers" used 110,098 consumer loans from the conventional bank. I separated these 110,098 loans from the rest of conventional loans; so I have 2 separate sets of consumer loans, one consist of mutual borrowers who also used a consumer loan from the Fintech firm and the other one consists borrowers whom used consumer loans only from the bank. My aim is to show whether there are any significant differences between these bank loans when separated as fintech affiliated customers and only bank customers.

Table 3.21 shows the descriptive statistics of these 2 separate consumer loans. Panel A represents the bank loans used by only bank borrowers and Panel B represents the bank loans used by mutual borrowers. It can be seen that mutual borrowers have higher deposit levels on average compared to only bank borrowers. Loan size and maturity of consumer loans used by mutual borrowers are smaller but the interest rates on these loans are higher than only bank borrowers' consumer loans. The descriptive statistics implies that on average, mutual borrowers are younger, have a higher level of educational degree, a lower level of income. A higher proportion of mutual borrowers are working in private sector and only bank borrowers' retiree percentage is higher than mutual borrowers. Many of borrower characteristics of mutual borrowers are similar to fintech loans analyzed in previous chapters in comparison with the bank loans. The one difference is that these mutual borrowers have similar credit scores with only bank borrowers where fintech loans had a higher margin on that borrower characteristic. In that regard, 2 subsamples have similar credit scores.

Borrower characteristics of fintech loans and the conventional loans used by mutual borrowers can be expected to be similar since these mutual borrowers are also in the dataset of Fintech loans but it should be noted that credit attributes of conventional loans used by mutual borrowers are similar to fintech loans on average in comparison with only bank borrowers.

Variable	Observations	Mean	Std. Dev.	Min.	Median	Max.
	Panel A: Only Bank Borrowers					
Deposit Amount†	3,949,888	2.21	2.98	-5.26	0.16	18.12
Nu. of Account	3,949,888	0.79	0.97	0.00	1.00	56.00
Loan Size†	3,949,888	8.60	0.99	3.60	8.71	15.88
Maturity	3,949,888	26.83	13.51	1.00	24.00	120.00
Low Credit Score	3,949,888	0.21	0.41	0.00	0.00	1.00
Mid Credit Score	3,949,888	0.67	0.47	0.00	1.00	1.00
High Credit Score	3,949,888	0.12	0.32	0.00	0.00	1.00
Interest Rate	3,949,888	1.45	0.65	0.00	1.49	3.60
Income†	3,949,888	7.03	2.24	-5.26	7.54	25.36
Private Sector	3,949,888	0.64	0.48	0.00	1.00	1.00
Public Sector	3,949,888	0.11	0.31	0.00	0.00	1.00
Self Employed	3,949,888	0.06	0.23	0.00	0.00	1.00
Retired	3,949,888	0.18	0.38	0.00	0.00	1.00
Unemployed	3,949,888	0.00	0.06	0.00	0.00	1.00
Primary School	3,949,888	0.26	0.44	0.00	0.00	1.00
High School	3,949,888	0.44	0.50	0.00	0.00	1.00
Undergraduate	3,949,888	0.24	0.43	0.00	0.00	1.00
Graduate	3,949,888	0.02	0.14	0.00	0.00	1.00
Male	3,949,888	0.76	0.43	0.00	1.00	1.00
Age	3,949,888	40.14	11.57	18.00	38.00	96.00
Young	3,949,888	0.67	0.47	0.00	1.00	1.00
Default	3,949,888	0.04	0.20	0.00	0.00	1.00

Variable	Observations	Mean	Std. Dev.	Min.	Median	Max.
	Panel B: Mutual Borrowers					
Deposit Amount†	110,098	3.86	3.32	-5.26	4.16	15.03
Nu. of Account	110,098	1.54	1.55	0.00	1.00	30.00
Loan Size†	110,098	8.52	1.00	5.67	8.56	14.25
Maturity	110,098	25.52	14.85	1.00	24.00	120.00
Low Credit Score	110,098	0.19	0.39	0.00	0.00	1.00
Mid Credit Score	110,098	0.68	0.47	0.00	1.00	1.00
High Credit Score	110,098	0.13	0.34	0.00	0.00	1.00
Interest Rate	110,098	1.49	0.60	0.00	1.46	3.29
Income†	110,098	7.44	1.76	-4.96	7.67	18.51
Private Sector	110,098	0.75	0.43	0.00	1.00	1.00
Public Sector	110,098	0.14	0.35	0.00	0.00	1.00
Self Employed	110,098	0.05	0.21	0.00	0.00	1.00
Retired	110,098	0.05	0.21	0.00	0.00	1.00
Unemployed	110,098	0.00	0.05	0.00	0.00	1.00
Primary School	110,098	0.08	0.27	0.00	0.00	1.00
High School	110,098	0.31	0.46	0.00	0.00	1.00
Undergraduate	110,098	0.53	0.50	0.00	1.00	1.00
Graduate	110,098	0.08	0.27	0.00	0.00	1.00
Male	110,098	0.77	0.42	0.00	1.00	1.00
Age	110,098	33.35	8.16	18.00	32.00	72.00
Young	110,098	0.90	0.29	0.00	1.00	1.00
Default	110,098	0.01	0.11	0.00	0.00	1.00

Table 3.21: Descriptive Statistics of Only Bank and Mutual Borrowers

To examine and compare the loan performance of the mutual borrowers in comparison with only bank borrowers, I run the following specification and model:

$$Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma FintechLoanCust_{i,c,t} + \varepsilon_{i,c,t} \qquad (6)$$

The dependent variable is the default binary variable that was explained in previous chapters; it takes the value one if the borrower i, in city c who obtain a loan in year t, defaults on his/her debt. This time since only conventional loans are analyzed, I cannot use the binary variable *Fintech* as the treatment variable, instead I used *FintechLoanCust*. *FintechLoanCust* is a dummy variable that takes 1 if the corresponding conventional loan used by an individual i, in city c, at time t and who is also a fintech borrower, 0 otherwise.

Tables 3.22 and 3.23 provide the estimates of the model presented in (6) with credit and demographic attributes as independent variables, respectively. The tables report the linear probability regression results of the model (6) with credit attributes as independent variables in 3.23 and demographic variables as independent variables in 3.22. Both the univariate and multivariate regression results are presented. The regressions control for city and year effects on fintech via corresponding fixed effects. The values in parentheses are corresponding t-statistics of the coefficients. * indicates statistical significance at 1% level.

The univariate and multivariate regression results are in line with the baseline findings that is described in part 3.3 for mutual independent variables. For bank loans, borrowers with higher education are less likely to default. As the borrower gets younger, he/she become more likely to default. Individuals that work in private sector are more likely to default and public sector employees are less likely to default. If we analyze the credit attributes, we confirm the previous findings that implied borrowers with lower credit scores, lower level of deposit amounts and with higher loan size, higher maturity and higher interest rates are more likely to default; which are all expected.

When we analyze the *FintechLoanCust* variable we can see that, among bank loans and in bank loan setting, without the interference of Fintech loan setting, being a Fintech borrower decreases the probability of default even after controlling all the credit and demographic attributes. The coefficient that measures to be a fintech loan customer varies between -200 and -300 bps. The borrowers who use consumer loan from only the bank are more likely to default.

These results give further evidence that being a Fintech borrower lowers the probability of default even after controlling all variables. On top of previous results, these are especially important since these mutual borrowers have used consumer loans from both Fintech and the bank, one can assume that since these mutual borrowers have higher debt levels, they are more likely to default. Instead, this finding shows that being a fintech borrower verifies the credibility of that individual.

Demographic Attributes														
Dep. Var	Default Indicator													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income†	0.000126*													0.000835*
	(2.67)													(17.18)
Primary School		0.0111*												-
		(49.74)												-
High School			0.00664*											-0.0059*
			(33.90)											(-24.84)
Undergraduate				-0.0180*										-0.0237*
				(-78.60)										(-82.46)
Graduate					-0.0177*									-0.0271*
					(-26.55)									(-39.27)
Private Sector						0.0129*								-0.0327*
						(62.82)								(-44.08)
Public Sector							-0.0199*							-0.0482*
							(-62.34)							(-60.72)
Self Employed								0.0191*						-0.019*
								(45.84)						(-22.71)
Retired									-0.0189*					-0.0439*
									(-73.91)					(-55.14)
Unemployed										0.00726*				-
										(4.70)				-
Male											0.00620*			0.00326*
											(27.35)			(14.13)
Age												-0.00063*		-0.00056*
												(-74.87)		(-47.74)
Young													0.0120*	-
													(57.76)	-
Fintech Loan Cust.	-0.0264*	-0.0244*	-0.0255*	-0.0212*	-0.0253*	-0.0276*	-0.0255*	-0.0262*	-0.0288*	-0.0263*	-0.0265*	-0.0306*	-0.0291*	-0.0235*
	(-44.24)	(-40.84)	(-42.72)	(-35.42)	(-42.41)	(-46.22)	(-42.78)	(-44.00)	(-48.20)	(-44.17)	(-44.45)	(-51.14)	(-48.69)	(-38.97)
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986
R^2	1.7%	1.8%	1.7%	1.9%	1.7%	1.8%	1.8%	1.8%	1.8%	1.7%	1.7%	1.8%	1.8%	2.3%
Constant Term	-0.0391	-0.0398	-0.0407	-0.0299	-0.0369	-0.0438	-0.036	-0.0386	-0.0306	-0.0381	-0.0421	-0.00875	-0.0436	0.0311

Table 3.22: Default characteristics of Mutual Borrowers - Demographic Attributes

Credit Attributes									
Dep. Var	Default Indicator								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit Amount†	-0.00364*								-0.0021*
	(-109.85)								(-62.92)
No. of positive account		-0.0103*							-
		(-102.77)							-
Loan Size†			0.00543*						0.00101*
			(53.44)						(8.62)
Inst. Cnt				0.00126*					0.00116*
				(173.83)					(142.13)
Low Credit Score					0.0731*				0.0689*
					(304.29)				(279.47)
Mid Credit Score						-0.0365*			-
						(-173.59)			-
High Credit Score							-0.0376*		-0.0123*
							(-125.60)		(-39.73)
Interest Rate								0.0163*	0.0156*
								(84.43)	(79.31)
Fintech Loan Cust.	-0.0209*	-0.0191*	-0.0257*	-0.0248*	-0.0256*	-0.0262*	-0.0261*	-0.0263*	-0.0208*
	(-34.99)	(-31.92)	(-43.12)	(-41.66)	(-43.44)	(-44.17)	(-43.84)	(-44.15)	(-35.29)
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986	4,059,986
R^2	2.0%	2.0%	1.8%	2.4%	3.9%	2.4%	2.1%	1.9%	4.9%
Constant Term	-0.0239	-0.0234	-0.088	-0.0779	-0.0405	-0.0106	-0.03	-0.06	-0.0966

Table 3.23: Default characteristics of Mutual Borrowers - Credit Attributes

3.8 Concluding Remarks

In this chapter, I examine whether there are significant differences in the performance of consumer loans in fintech and traditional lending in Turkey. My results indicate that fintech borrowers are less likely to default even after controlling for borrower characteristics such as income, savings, gender, age, education, occupation, and credit score or loan characteristics such as interest, maturity, and loan size. These results are in contrary to the findings of the studies that conducted in developed countries.

Fintech companies already have reduced costs compared to conventional banks but these results also show that in emerging countries fintech loans can outperform conventional loans. In addition to cost advantage, these firms can give high-quality borrowers with even more low priced credits and dominate conventional banks in the loan market.

Taken together with the baseline findings in part 3.3 and 3.4, the findings from the propensity score matching analysis, the extended regression analysis using interaction terms further supports the conclusion that fintech loans have significantly lower levels of default compared to conventional bank borrowers. Moreover, the mechanism for the superior performance of fintech firm seems to be driven from identifying individuals that are in a neglected subsample of the market. Specifically, the results indicate that through sophisticated machine learning and data analysis tools, fintech firm can successfully identify creditworthy individuals among the group of borrowers who are less educated and who have low-credit scores. This reduces the quality of the pool of borrowers in those subsegments of the market for the bank, decreasing the overall performance of the bank loans as the ratio of borrowers who are unemployed, less educated or who have low credit score in the portfolio of the bank is much larger compared to the portfolio of the Fintech firm. At last, it has been shown that among bank loans, individuals that also used a consumer loan from the Fintech are less likely to default.

4. CONCLUSION

The credit business, lending loans has been the core business of any banking system since the establishment of the first bank in the history. It is not an overstatement to say that without its intermediary role in the monetary system between the depositors and borrowers, banks' role in any economic system would not be vital for socioeconomic well-being of the society. Therefore, regarding credit business and lending, the academic literature is extensive, but when it comes to lending through online channels and platforms it is rather a new topic. However, this topic should be -and I believe it will be- researched in a more extensive manner. As technology develops in this rapid pace that we have seen in last 2 decades, society's adoption to this technology and evolution within this adoption will be drastic. We are surrounded by all these new online features, channels, platforms that change our lives from its core and create a new way of living through digital personas that we have not seen before. Banking sector is not an exception to this change, especially with this new generation of customers or loan customers in this thesis' case. Through these new start-up's, social media companies and in this new digital world where the big data is shared and analyzed; customer or borrower characteristics, behaviors destined to evolve with the society. As I stated before in this thesis; in the past, individuals who use banking services were only consumers in the eyes of the banks, nowadays they are customers and tomorrow they will be clients, in other words users of the digital banks. Banks have to adapt to their changing user base, otherwise they will be replaced with any firm, and these firms will not be necessarily banks; only the banking system is necessary.

In Turkey, lending through online banking channels has been regulated since 2014. In other countries worldwide, there are regulations and examples before 2014 regarding online lending by not only through banking channels but also through online lending platforms that are not subject to banking regulations. So there are some studies that are investigating the characteristics of online lending in the literature. These studies' research topics often relate to peer-to-peer lending which is not legal in Turkey, some analyze online lending through financial technology (fintech) firms. To the best of my knowledge, the empirical studies regarding fintech lending have been done only in developed countries.

In this thesis, my first aim is to analyze fintech loan customer base and try to understand the characteristics of online lending, compare it to the conventional borrower characteristics. My goal is to test prior studies' results on this matter, but this time in a developing country setup which was not investigated before. To that aim, I gathered the data from one of Turkey's 5 biggest commercial banks and its fintech subsidiary's consumer loan data disbursed between 2014 and 2020. Since financial technology firms that is not subject to banking regulations are not allowed to lend loans in Turkey (as of 2020 at least), the fintech subsidiary of the bank which is established as a separate entity within the conventional bank, with a different and separated customer base, is the closest entity to a fintech, described in fintech literature.

Prior empirical evidence in the developed countries implies that fintech industry target specific segments that can be called as underserved individuals by the banking system (Tang 2019, 1900-1938) (Erel and Liebersohn 2020, 3) (Di Maggio and Yao 2020, 2) (Jagtiani and Lemieux 2018, 43-54). On the contrary, my results indicate that fintech borrowers are on average younger, better educated, have higher income and savings, pay less interest, and have better credit scores than the borrowers of the conventional bank. This is actually new evidence for market equilibrium whereby fintech companies grow their market share by identifying high-quality borrowers in an emerging market. Actually, my results also imply that conventional banks in emerging markets can either establish its own fintech subsidiary or make collaboration with an existing fintech lending platform to target high-quality borrowers for even better credit pricing for the high-quality borrowers. With the reduced operational cost of the fintech ecosystem, the conventional banks that conduct these operations through fintech platforms can gain a competitive advantage.

After analyzing and understanding fintech borrower characteristics and loan customer base, my second aim is to examine their loan repayment performance and default behavior. Although this new generation customers are proven to be well-educated and have a higher borrower profile in my setting, their credit performance can be worse compared to a conventional bank. Conventional bank uses human banking agents to be intermediaries, on the other hand fintech lending has no banking agents involved in the lending process and can be called as a "self-service banking". So from a conventional point of view, fintech lending is open for uncontrollable fraud and opportunistic behaviors that can result in bad credit performance. To that end, I analyzed whether there are significant differences in the performance of consumer loans in fintech and traditional lending in Turkey. My results indicate that fintech borrowers are less likely to default even after controlling for borrower characteristics such as income, savings, gender, age, education, occupation, and credit score or loan characteristics such as interest, maturity, and loan size. These results are in contrary to the findings of the studies that conducted in developed countries. Prior studies in the developed countries show that fintech borrowers tend to perform worse when compared to conventional banks.

My baseline findings regarding fintech borrowers' credit performance, even after controlling for demographic and credit variables were open to unobserved selection bias in the data. Thus, I try to test my robustness of my results through subsampling using propensity score matching (PSM) and analyzed the subsamples. My results through PSM analysis further support the conclusion that fintech loans have significantly lower levels of defaults when compared to conventional bank consumer loans and imply that my baseline findings are in fact robust.

In addition to these results, I conducted interaction analysis via using interaction terms in my regression models. The results showed the mechanism for the superior performance of fintech firm seems to be driven from identifying individuals that are in a neglected subsample of the market. The results indicate that fintech firm can successfully identify creditworthy individuals among the group of borrowers who are less educated and who have low-credit scores. Fintech firm not only targets the "creme de la creme" segment in the loan business; through sophisticated machine learning algorithms, it can find a borrower mass in the lower segments that can perform better than expected. At last, I showed in the conventional bank setting, among bank loans, mutual borrowers who also used a conventional loan from the Fintech firm are less likely to default when compared to only bank borrowers, even after controlling all the credit and demographic variables.

Fintech literature are open for further studies not only concerning the lending part of banking business but also regarding behaviors in the deposit market and investing. For instance, interest rate elasticity of the digital customers that have the online tools to compare and evaluate different deposit prices in the market is an interesting topic to study. The different behaviors of these digital deposit customers compared to conventional bank customers whom used to get deposit prices through a banking agent in a physical branch, the cultural elements surrounding this phenomenon again can be studied with a behavioral finance perspective. The digital currency, bitcoin, again is a rather new topic and should be studied thoroughly in comparison with different investing products.

Regarding this thesis' subject, online lending, future studies should analyze the evolution of the conventional bank borrowers' characteristics and behaviors. I believe and some of my results imply that as time passes, conventional bank customers' characteristics have been beginning to look like to fintech borrowers'. This can be as a result of technology adoption and the evolution of the society and banking sector or it can be a marketing move of the bank I studied; future studies can decide on that. However, I believe that in not-too-distant future, as technology becomes the core element in our daily lives, the retail banking as we know it, will become the digital banking with the absence of physical branches and without human interaction. In that case, the studies with the comparison between the conventional bank and digital banks will be pointless.

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