RISK ASSESSMENT OF FINTECH LENDING PLATFORM BUSINESS MODELS

Part I: Risk & FinTech – Challenging Regulators to Balance Innovation and Financial Stability

Part II: Testing the Cyclicality of FinTech Lending Platforms

Constanze Alves[1]

M.Sc. Thesis

Department of Finance

Stockholm School of Economics

October 2018

Abstract

This thesis analyzes risks related to FinTech lending platforms and consists of two parts. Part I examines the risks arising from innovations in the FinTech lending platform sphere and their impact on the regulatory framework. A qualitative analysis maps the innovation's effect on risk factors and finds altogether increased risk levels for the financial system, financial institutions and users. Furthermore, loan volume is identified as a profitability driver of FinTech lending platforms and a quantitative study is conducted on macroeconomic and firm-specific factors that impact the loan volume. The analysis finds that FinTech lending platforms suspend the problem of procyclical credit provision inherent to conventional lending models and that firm-specific scandals have a negative impact on loan volume. The discussion of current regulatory frameworks finds that there is an international divergence and that current policies are inadequate in addressing the identified risk factors. Therefore, this thesis proposes the introduction of stress testing to FinTech lending platforms in order to better assess risks, adapt regulation and prepare companies to sustain crises. Part II reruns the quantitative analysis for a second company and the results reinforce the countercyclical pattern found in analysis I. Moreover, the loss of investor confidence from a scandal is identified as a firm-specific risk and does not affect other companies in the system.

Key Words: FinTech. P2P lending, financial regulation, risk mapping, credit cyclicality

Supervisor: Part I: Anna Omarini[2], Bocconi University
Part II: Michael Halling[3], Stockholm School of Economics

[1] 40987@student.hhs.se
[2] anna.omarini@unibocconi.it
[3] michael.halling@hhs.se

Disclaimer

This thesis was written in accordance with the regulations of the double degree program in Finance between Stockholm School of Economics and Bocconi University. The first part of this thesis has been submitted as an independent Master of Science thesis at Bocconi University on September 10th, 2018, with the title "Risk & FinTech – Challenging Regulators to Balance Innovation and Financial Stability ".

The second part is added as an extension to fulfill the requirements of a second Master of Science degree at Stockholm School of Economics.

Therefore, the first part of this thesis is the previously submitted work, while the second part contains new research.

Acknowledgements

I would like to thank my thesis supervisor Anna Omarini at Bocconi University for her insights on the topic and ideas for the discussion and Michael Halling at Stockholm School of Economics for his valuable advice on methodological questions.

Table of Contents

Abbreviations

BIS – Bank for International Settlements

B2B – business-to-business

B2P – business-to-person

ECB – European Central Bank

EU – European Union

FED – Federal Reserve System

FinTech – Financial Technology

FSB – Financial Stability Board

FTSE – Financial Times Stock Exchange

GDP – Gross Domestic Product

IOSCO – International Organisation of Securities Commissions

IPO – Initial Public Offering

IT – Information Technology

LC – LendingClub

LSE – London Stock Exchange

M&A – Mergers and Acquisitions

NYSE – New York Stock Exchange

OECD – Organisation for Economic Co-operation and Development

P2B – person-to-business

P2P – person-to-person

PE – Private Equity

RegTech – Regulatory Technology

UK – United Kingdom

US – United States of America

VC – Venture Capital

VIX – Chicago Board Options Exchange Volatility Index

PART I

I. Risk & FinTech – Challenging Regulators to Balance Innovation and Financial Stability

I.1. **Introduction**

After the financial crisis of 2008, Financial Technology (FinTech) companies evolved and disrupted the financial industry with innovative business models. These are characterized by the unbundling of services, cheaper and better product and service offers, improved customer experience and financial inclusion. Despite these benefits of FinTech innovation, products became increasingly complex, the market structure changed, and risks arose. These risks are neither well defined nor researched but FinTech is gaining importance a decade after its first appearance.

Financial markets are special in that they are heavily regulated because they provide critical services and are prone to failure. The financial crisis of 2008 demonstrated the fragility of the system and stressed the necessity of elaborate regulation. The changes imposed by FinTechs challenge regulators to overthink their current frameworks and policies. According to Draghi (2009), "Regulation must not prevent innovation […]. But we need to ensure that innovation does not compromise other clearly stated goals, including systemic stability and consumer protection." Therefore, the right balance between pursuing objectives of financial regulation and fostering innovation has to be found.

This study focuses on FinTech lending platforms that facilitate credit provision to private borrowers by matching private or institutional investors that are willing to provide funds. FinTech lending platforms currently represent a small portion of the entire credit provision but exhibited a strong increase in the past years. Therefore, it is essential to investigate their impact on the risk faced by the financial market, financial institutions as well as consumer and investors.

However, there is a lack of data to assess the significance of risk implications of FinTech lending platforms. Especially worrisome is that the innovations have not been tested through a full economic cycle and that the markets have been thriving since its emergence. In the past two years, several reports on the risk of FinTech lending platforms or FinTech in general have been published by regulators, but they lack empirical studies.

Therefore, this thesis aims at firstly identifying risks associated with FinTech lending platforms in a systematic manner and secondly performing a quantitative analysis on selected risk factors, using data from the FinTech lending platform LendingClub (LC).

Moreover, regulatory responses are analyzed and further actions are proposed. To our knowledge, this is the first study that relates a quantitative analysis on FinTech lending platforms to system-wide risk and regulatory implications.

The risk mapping finds increased risk factors from the introduction of FinTech lending platforms for financial markets, financial institutions and users. The findings from the data analysis are two-sided. On the one hand, a positive effect of reduced credit provision procyclicality in FinTech lending platforms is detected. This reduces a major systemic risk factor inherent to conventional lending models. On the other hand, the risk arising from firm-specific scandals is quantified by finding a significant negative impact on loan volumes. Moreover, current regulations diverge across borders and are evaluated to be insufficient and not well adjusted to existing risk factors, because regulators lack a comprehensive understanding of business models and risk factors. Therefore, it is suggested to use the methodology of stress testing on FinTech lending platforms to improve the understanding of regulators and hence the appropriateness of regulation, facilitate international convergence of policies and support companies in their planning processes.

This thesis is structured as follows: The first part includes an introduction on FinTech (I.2), a motivation for financial regulation (I.3) and a detailed risk mapping for FinTech lending platforms (I.4). The second part comprises the quantitative analysis and includes the definition of the research question and related hypothesis (I.5), a presentation of the selected data (I.6), a review on the methodology (I.7) and a discussion of the results (I.8). The third part extends this thesis to the assessment of current regulation (I.9) and proposals for extensions and a conclusion of this thesis (I.10).

I.2. **FinTech**

I.2.1. Terminology

There is no single agreed upon definition of the term FinTech in scientific literature since the sector is very diverse and changing (Nicoletti, 2017). In order to ensure a common understanding, the term FinTech has to be discussed and defined prior to any analysis.

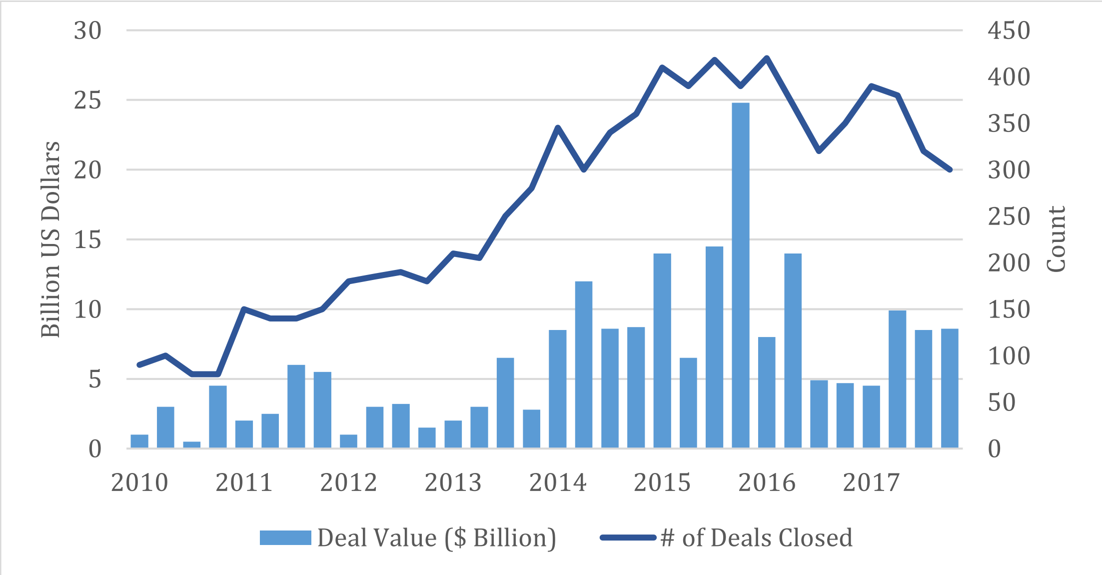
Financial innovation is a term used to summarize new products, technologies and institutions in the financial sector (Beck, 2017). FinTech is a subordinate area to financial innovation. Sironi (2016) defines FinTechs as “a global phenomenon, born at the intersection between financial firms and technology providers, attempting to leverage on digital technology and advanced analytics to unbundle financial services and harness economies of scale by targeting long-tail consumers”. According to a report by the International Organisation of Securities Commissions (IOSCO), FinTech is used to describe various innovative business models and technologies that can potentially disrupt the financial service industry by unbundling financial services and offering them in an automated way using the internet (International Organisation of Securities Commissions, 2017). The Financial Stability Board (FSB) uses a more concise definition and defines FinTech as “technology-enabled innovation in financial services” (Financial Stability Board, 2017). In this study, FinTechs are defined as companies that introduce financial innovation through leveraging technological advances with the goal to improve financial services, by reducing cost, increasing efficiency or increasing customer experience.

This study focuses on companies in the FinTech sector, since they face unparalleled challenges. According to Houman Shadab, professor at New York Law School, “Fintech is different from many other startup sectors because the financial world is heavily regulated and mostly consists of a relatively few number of large, well-established companies”. Despite these challenges, FinTech companies have disrupted the financial service industry by unbundling services, offering better and more innovative services at lower prices, improving customer experience and targeting undersupplied markets by implementing innovative business models (Nicoletti, 2017). In developing countries, the rise of FinTechs is not solely focused on improving existing services but rather on the creation of novel infrastructure and financial inclusion (Chishti & Barberis, 2016).

I.2.2. Development

Global investment activities in the FinTech sector have increased steadily in the past years. Figure 1 shows the investments from Venture Capital (VC) funds, Private Equity (PE) funds and Mergers and Acquisitions (M&A) activities as well as the number of closed deals per quarter for the years 2010 to 2017. The investment development indicates an increased maturity of the sector from experimental deals to recurring, large investments (KPMG, 2018).

Figure 1: Global Investment Activity in FinTech Companies per Quarter from 2010 to 2017.
Adapted from: KPMG. (2018). The Pulse of Fintech Q4 2017. p.10



Most FinTechs began conducting their business between 2008 and 2010 (Sironi), shortly after the global financial crisis of 2008. The main reasons that made the business climate preferable for this development at the time were an increased distrust in the financial industry and an increased digitalization of the society with the rise of technology.

After the credit crunch of 2008, banks were experiencing a trust crisis which offered FinTech companies the opportunity to introduce technology-based financial services that promised transparency and low cost as an alternative to those provided by traditional banks (Menat, 2016).

Moreover, the rise of technology decreased entry barriers into the financial industry greatly. One reason explaining this decrease is the reduction in cost of technology resulting from advances in technology and the mass-production of computer parts in low cost countries. Therefore, not much capital has to be raised to employ complex financial models for new applications in risk analysis or portfolio management and the importance of economies of scale for the profitability of large computing powers is reduced (Aldridge & Krawciw, 2017). This means that more ventures are able to fulfill the capital requirements to enter the market.

Secondly, advances in technology changed the way that businesses can interact with the consumer. An important factor in being a successful financial service provider is developing a lasting customer relationship, since this increases the value of the service for the customer and decreases the cost of acquiring new customers and offers potential for cross-selling (Omarini, 2015). Traditionally, a large network of branches allowed to strengthen customer relationships. However, with the rise of technology and digital communication channels, costly channels become less important and, in some cases, even obsolete which decreases the cost of establishing and running a financial service. With the introduction of big data analysis and the increase in available data, financial service providers have the opportunity to analyze customer behavior even without owning a customer relationship and can unbundle financial services and adapt their service to offer highly specialized products (Sironi, 2016).

I.2.3. Market Participants

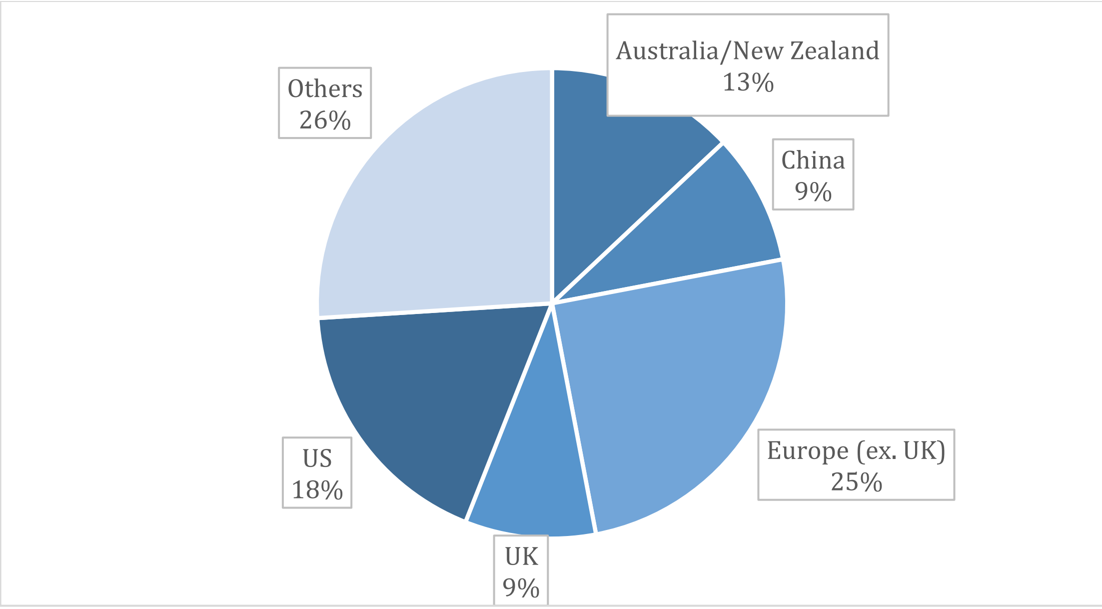
Facilitators of these innovations are diverse. They range from startups that enter the industry, incumbents defending their market share to government initiatives and supraorganizations trying to understand and moderate the change in the industry (Schueffel, 2016).

KPMG together with H2 Ventures annually publishes a list of the 50 leading and 50 emerging FinTechs. This list is cited in several academic publications ((Nicoletti, 2017), (Yeoh, 2016)) and the 2017 report will be used to provide an overview of the industry. An analysis of the companies included in the list shows that FinTech activity is a truly global phenomenon present on all continents apart from Antarctica. The leading 50 FinTechs originate from 19 countries across the globe and the complete list of 100 companies counts 28 origin countries. For 2017, 5 out of the top 10 companies originated from China, 3 from the United States of America (US) and the remaining two from the United Kingdom (UK) and Germany (Appendix 1). (KPMG & H2 Ventures, 2017)

Figure 2 shows that the majority of companies on the FinTech100 list originate in Australia and New Zealand, China, Europe (excluding the UK), UK and the US.

Figure 2: Origin of FinTech100 Companies by Percentage of all Companies

Created from: KPMG & H2 Ventures. (2017). 2017 Fintech100 - Leading Global Fintech Innovators. p.5



I.2.4. FinTech Sectors

The FinTech sector is extremely diverse, which requires a clear clustering of service offerings to define subsectors that allow for precise and meaningful analyses.

An interesting point to consider when defining categories for offered services is, who the parties involved in the transaction are. Services can either be person-to-person (P2P), business-to-person (B2P), person-to-business (P2B), or business-to-business (B2B). Depending on the service model, companies have different underlying business models and multiple risks can be identified.

Reports on FinTech provide various forms of grouping the FinTech sector, IOSCO (2017) for instance defines 8 subsectors: payments, insurance, planning, lending and crowdfunding, blockchain, trading and investments, data and analytics, and security. Likewise, KPMG & H2 Ventures (2017) categorize 8 sectors: payments, insurance, wealth, lending, blockchain and digital currencies, transaction and capital markets, data and analytics, Regulatory Technology (RegTech) and cyber security.

Consolidating the subsectors from these reports and extending their definition, 8 subsectors and related fields are defined for this thesis, as depicted in Figure 3.

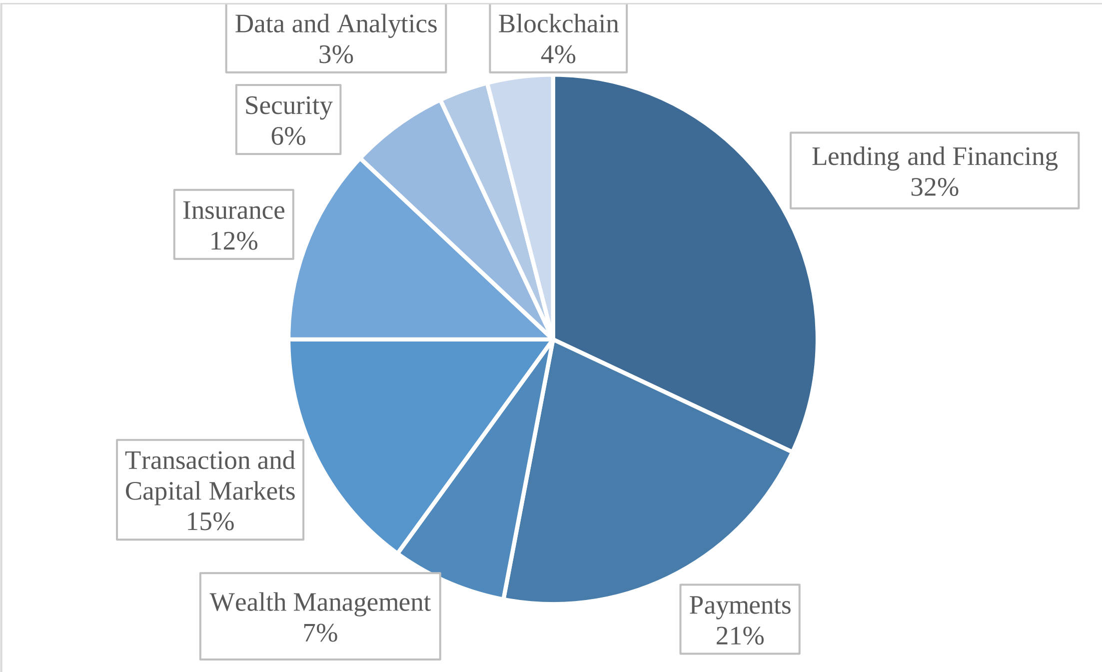
Figure 3: FinTech Subsectors and Related Fields

Lending and Financing - Lending Platforms - Equity Financing - Crowdfunding	**Payments** - Payment Processing - Digital Payments - International Transfers
Wealth Management - Robo Advisory - Personal Finance	**Transactions & Capital Markets** - Trading - Exchanges
Insurance - Brokerage and Underwriting - Risk Tools	**Security** - Cyber Security - RegTech - Fraud Management
Data and Analytics - Big Data Provision - Predictive Analytics	**Blockchain** - Digital Currencies - Smart Contracts

Applying the clustering to the Fintech100 list by KMPG & H2 Ventures (2017), the development of the different subsectors can be analyzed. Figure 4 shows, that most of the companies in the FinTech100 list operate in the Lending and Financing, Payments and Transactions and Capital Markets subsector.

Figure 4: Sectorial Breakup of FinTech100 Companies by Number

Created from: KPMG & H2 Ventures. (2017). 2017 Fintech100 - Leading Global Fintech Innovators. p.7



This study focuses on FinTech lending platforms that are classified within the Lending and Financing subsector and further described in the following section.

I.2.5. FinTech Lending Platforms

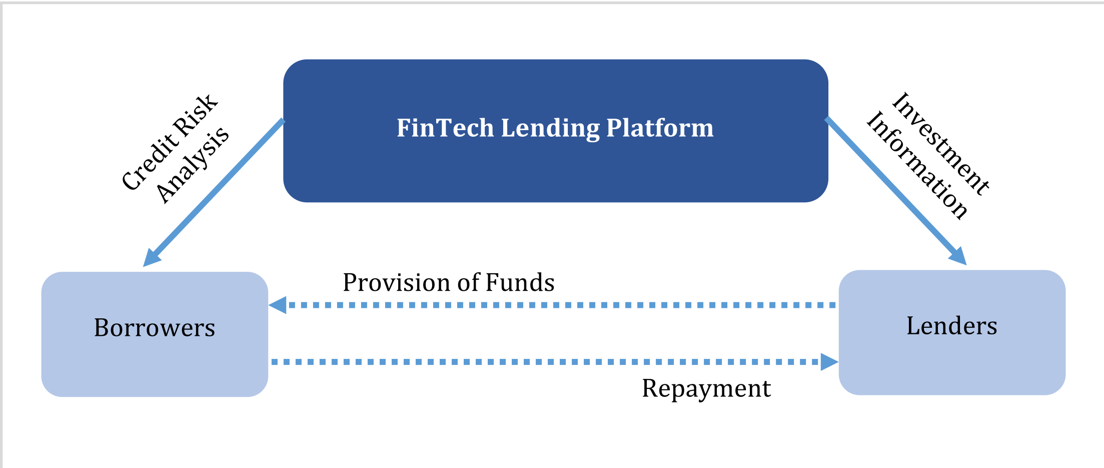
Granting credit is a defining function of credit institutions and traditionally a B2P or B2B service, where the bank lends capital to a borrower and sets the interest rate as a function of the credit worthiness (Aldridge & Krawciw, 2017). FinTech has changed this service by tackling the two parameters of lending: credit risk estimation and source of funding.

Firstly, a range of FinTechs developed new credit risk assessment methodologies that take into account a wider range of data than conventional financial institutions do, so called big data which is real-time. Therefore, they claim to improve the accuracy of risk assessment. Moreover, the automation of data collection and loan approval processes allow for an online loan application as well as much faster approvals at generally lower interest rates. Secondly, FinTech companies reintroduced lending as a P2P or P2B service where individual investors provide the funds and the FinTech provides a platform for matchmaking. This thesis uses the term FinTech lending platforms to consolidate P2P platforms that also allow for P2B, B2P and B2B matching.

The business models of FinTech lending platforms are diverse but can be classified into a traditional model and three adaptations as outlined in a report on FinTech credit by the Bank for International Settlements (BIS) and the FSB (2017). In the traditional FinTech lending model, the platform matches borrowers and lenders and originates the corresponding loans. A stylized business model is presented in Figure 5. The platform provides credit risk analysis of borrowers, distributes results to investors and sets interest rates based on risk characteristics and adapts these for supply and demand factors. Investors can be both retail investors as well as institutional investors that purchase large loan portfolios. The platform is not concerned with regular repayment cashflows, however performs recovery services if loans default. There is no guarantee for full or partial repayment of loans. The platform obtains revenues from fees related to account setup, loan origination and ongoing loan repayment.

Figure 5: Traditional FinTech Lending Platform Business Model

Adapted from: Bank for International Settlements & Financial Stability Board. (2017). FinTech Credit - Market Structure, Business Models and Financial Stability Implications. p. 11

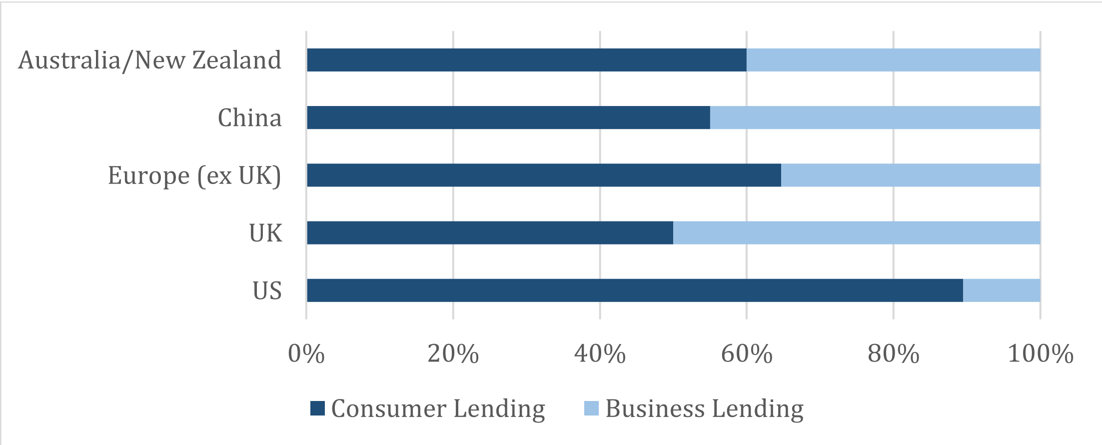


In certain jurisdictions, non-authorized institutions are prohibited to originate loans which requires the inclusion of a partner bank that originates the loans and sells them to previously determined creditors. This model is called a notary model and FinTechs receive revenues by charging fees to the partner bank for origination as well as to investors on ongoing loan repayments. Under another alteration of the traditional model, the FinTech keeps the loans on its own balance sheet after origination, while investors can solely purchase claims on the repayments. This model is wide-spread, mostly in Canada, Australia and the US. A third adjustment is defined as the guaranteed return model in which the FinTech guarantees the payment of interest rates as well as the repayment of the principal in full or to a predefined amount. This model is not very common as past ventures applying it went bankrupt quickly and is excluded from the business models analyzed in this study.

The parties involved in the fund matching are diverse. Borrowers applying for funds from FinTech lending platforms can be either individual consumers or businesses. Figure 6 shows that the split between borrower types diverges across countries. A common trend is that in all countries 50% or more of loan volume is originated to consumers.

Figure 6: Loan Volume by Borrower Type across Regions (Data from 2015)

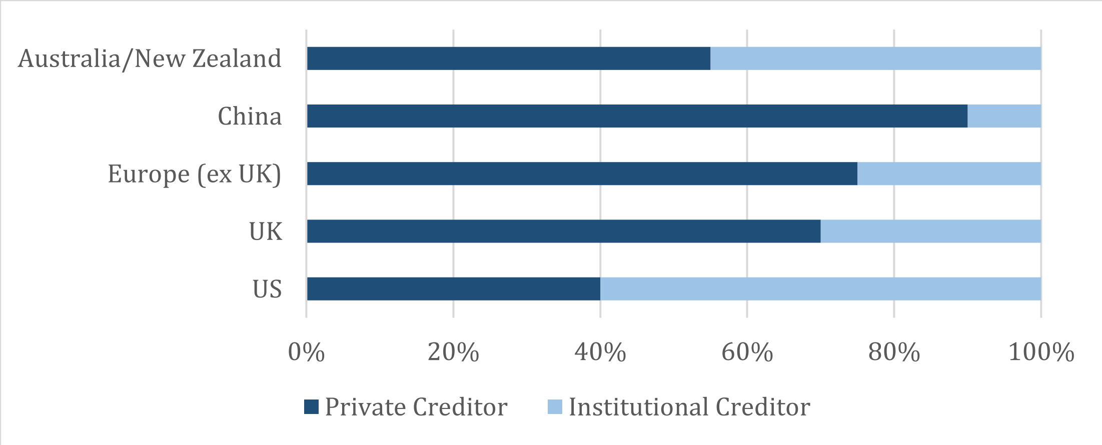
Adapted from: Bank for International Settlements & Financial Stability Board. (2017). FinTech Credit - Market Structure, Business Models and Financial Stability Implications. p. 8



Investors that fund these loans are split into two groups as well: private creditors and institutional creditors. The breakdown across markets is shown in Figure 7 and it is important to note, that a large fraction of funds comes from institutional investors and not private ones. In the US, the amount of loans funded by institutional investors even excels that funded privately. Institutional creditors are money managers, pension funds or life insurance companies that in general have a large amount of funds under management and look for diversification benefits (Lin, Sias, & Wei, 2017).

Figure 7: Loan Volume by Investor Type across Regions (Data from 2015)

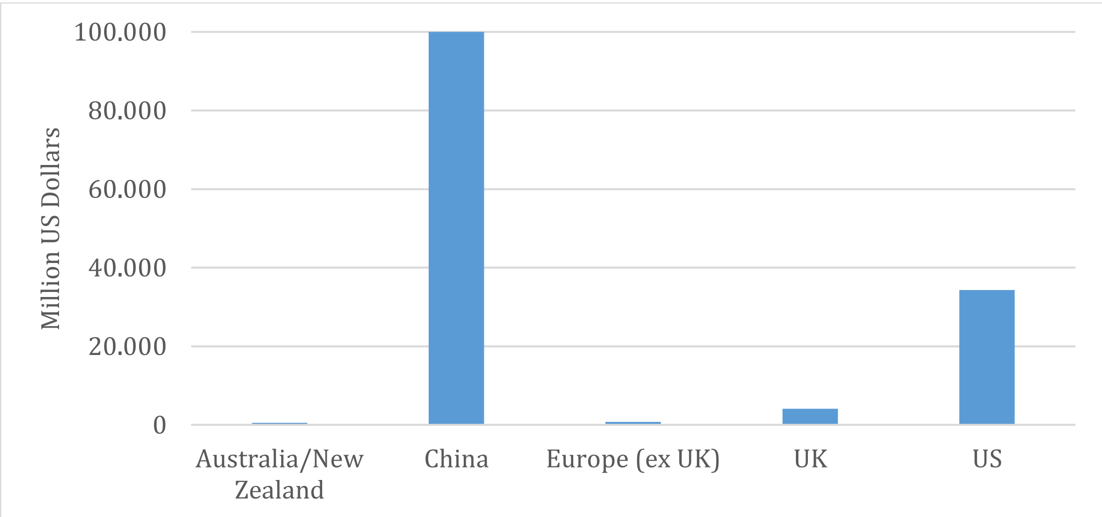
Adapted from: Bank for International Settlements & Financial Stability Board. (2017). FinTech Credit - Market Structure, Business Models and Financial Stability Implications. p. 18



FinTech lending platforms emerged globally, with its main markets by far being China, followed by the UK and the US as shown Figure 8.

Figure 8: Size of FinTech Lending Markets Across Regions (Credit Volume in 2015)

Adapted from: Bank for International Settlements & Financial Stability Board. (2017). FinTech Credit - Market Structure, Business Models and Financial Stability Implications. p. 7



The current share of FinTech lending activity in total loan origination is negligible but high growth rates indicate increasing importance. According to the Federal Reserve Bank of Cleveland (2014), US FinTech loan origination volumes have increased an average of 84% per quarter from 2007 to 2014. PwC (2015) projects that by 2025, P2P lending is reaching a share of 10% to 15% of consumer debt. Therefore, an analysis of this sector is inevitable to ensure continued financial stability.

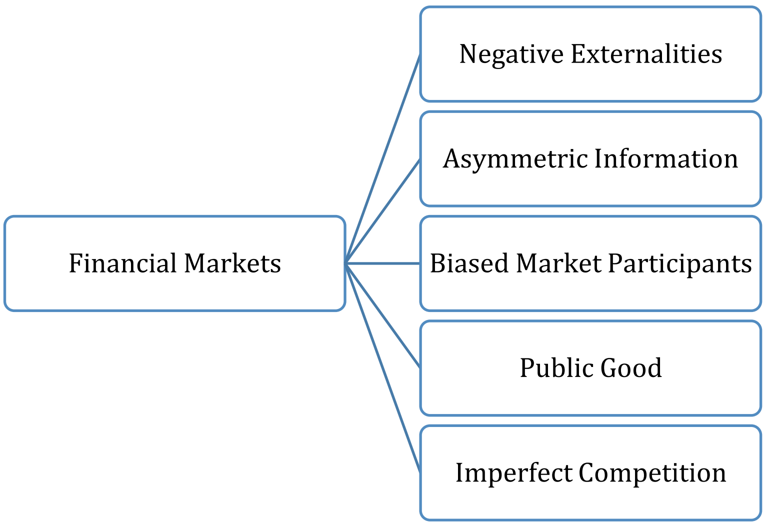
I.3. **Theoretical Framework for Financial Regulation**

The analysis of how innovations in the FinTech lending sphere change regulatory requirements calls for a complete understanding of the theoretical framework for financial regulation. Regulation influences the behavior and actions of market participants in order to achieve predetermined outcomes in the financial system. The desired outcomes are economically efficient financial markets, that is to say the avoidance of a market failure (Armour, et al., 2016).
Therefore, this section firstly analyzes the reasons for potential market failures in order to then discuss the objectives of financial regulation.

I.3.1. Rationale for Financial Regulation

In order to achieve the regulatory objective of economically efficient markets, the peculiarities of financial markets need to be analyzed and potential activators for market failures identified. Armour et al. (2016) identify 5 characteristics of financial markets, illustrated in Figure 9, that provide the framework to analyze the need for government intervention.

Figure 9: Characteristics of Financial Markets



Negative Externalities

Negative externalities describe the adverse effect actions of one entity have on other entities. In financial markets, these negative externalities can lead to market failures due to the interconnectedness of financial institutions, which lead to contagion and propagation of financial losses (Agur & Sharma, 2015).

There is high correlation of risk among financial institutions and the real economy, which implies that the failure of a financial institution could lead to a disruption in the payments system or to a halt in credit provision to non-financial firms due to bank runs, cash-hoarding or weakened balance sheets of financial institutions (Armour, et al., 2016). This means that financial shocks can result in crises affecting the economy at large.

Moreover, the broad distribution of losses arising from a failure of financial institutions can lead to moral hazard problems. Since shareholders of financial institutions bear only a fraction of the cost in case of a failure but claim the totality of profits from high-risk and high-return strategies, they have an incentive to take on excessive risk. This increases the risk of a failure of the financial institution and hence the risk of an economic crisis (Armour, et al., 2016).

Asymmetric Information

Financial products are highly complex and classify as credence goods, where the quality of the product cannot be identified before the purchase or through consumption, but only after some time by comparing it to a benchmark (Armour, et al., 2016). Therefore, at the time of the purchase, consumers have to trust the seller's judgment on quality and there is especially pronounced information asymmetry.

Moreover, consumers are usually financially illiterate, which means that they lack proper understanding of financial markets and its products to assess the benefits and risks arising from participation in the market. They have to rely on the information provided by sellers.

These conditions create a classical lemons problem as described by George Akerlof in his research paper in 1970. If there is information asymmetry and the quality of a product can only be evaluated after some time, sellers have the incentive to provide bad products and exploit customers. This leads to economically inefficient outcomes and a failure of the market.

Biased Market Participants

The goal of regulation is to ensure efficient markets, where according to a main assumption of the efficient capital markets hypothesis, market participants act rational and use all available information to take decisions that maximize their own utility (Berk & DeMarzo, 2014). In reality however, financial market participants are biased in their decision-making, for example by following herd-behavior or simplified rules of thumb (Armour, et al., 2016).

As a result, reserves are misallocated and prices might deviate from the theoretical equilibrium, which is constituted as a failure of efficient markets.

Public Good

A good or service providing benefits to everyone, irrespective of whether a contribution to its provision has been made, is called a public good. In other words, the provision of these goods creates positive externalities and it cannot be controlled who can enjoy these benefits. Financial markets offer public goods, for example by providing liquidity and a payment system (Armour, et al., 2016).

Public goods entail a free-riding problem, which means that users do not need to pay to use it and hence revenue generation is limited. Therefore, the delivery of public goods has a limited profitability which leads to an under-provision of the good. Since financial markets provide public goods that are necessary for efficient markets, an under-provision would entail a market failure.

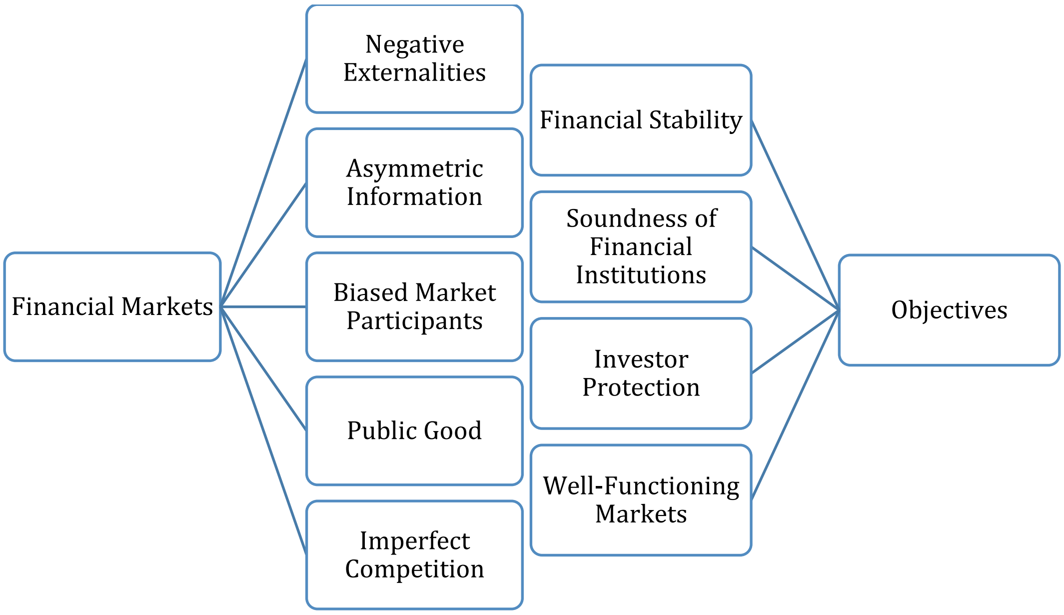
Imperfect Competition

Financial markets foster imperfect competition due to network effects and economies of scale and scope inherent to financial institutions. Banks with large customer bases achieve market dominance, and high entry barriers due to high set-up costs deter new entrants. Consequently, suppliers can set excessively high prices or provide poor quality products and services (Armour, et al., 2016), a clearly inefficient market outcome.

I.3.2. Objectives of Financial Regulation

According to the framework for financial regulation published by the Organisation for Economic Co-operation and Development (OECD) (2010), "policy objectives for the financial system should be clearly defined and should correspond to the beneficial outcomes anticipated from government intervention.". Since the overall goal of financial regulation is to avert market failures and enhance the working of the financial system (Armour, et al., 2016), the discussion in the previous section is helpful in defining several objectives. Moreover, managerial and regulatory literature state a wide range of objectives of financial regulation which are aggregated in Appendix 2. Combining the activators of market failure and objectives stated in relevant literature, 4 main objectives of financial regulation can be defined: financial stability, soundness of financial institutions, investor protection and well-functioning markets.

Figure 10: Characteristics of Financial Markets and Objectives of Financial Regulation



Financial Stability

The OECD (2010) defines the goal of financial stability as the system being resilient against external adverse events and not vulnerable to contagion among financially sound institutions resulting in a systemic failure. Closely connected to this, is the goal to uphold confidence in the financial system in order to ensure the effective operation of key functions of the financial system (Organisation for Economic Co-Operation and

Development, 2010). These functions include working payment mechanisms and access to bank accounts at all times, the sustained flow of funds between savers and investors as well as refinancing of banks, the possibility to trade, the provision of an insurance function and risk management. Financial stability is a crucial premise for economic growth. It comprises all previously described activators of market failure and specifically addresses negative externalities and the public good characteristic. (European Central Bank, 2018) (Bank of England, 2017) (Reserve Bank Australia, 2017) (Bank of Canada, 2017)

Armour, et. al. (2016) place emphasis on the fact that the global financial crisis showed how detrimental financial instability can be for the world economy, leading to an estimated loss of over 15 trillion US Dollars. Moreover, it raised awareness that protecting individual banks from failure is not adequate to protect the entire financial system from a breakdown, and that it is necessary to formulate separate objectives for the collective behavior of banks and for the individual behavior (Zinkin, 2014).

Soundness of Financial Institutions

This objective aims to ensure a prudential management of financial institutions, in order to avoid failure of individual entities (Organisation for Economic Co-Operation and Development, 2010). In contrast to the objective of financial stability, the objective of sound financial institutions is focused on the individual institutions and not on the entire system. Moreover, this objective responds to all mentioned market failures from a company perspective.

Investor Protection

In order to avoid market failures from the asymmetric information and biased market participants characteristics, the objective of investor protection is defined.

Protecting investors and users of financial markets entails a fair, transparent and professional interaction between providers of financial products and services and their customers, in order to decrease information asymmetries and prevent mistreatment of customers due to conflicts of interest. Moreover, investors should be protected from the exploitation of their biases, their interests should be secured and their needs considered.

The level of protection has to be adjusted to the financial literacy of the individual investor. (Armour, et al., 2016) (Organisation for Economic Co-Operation and Development, 2010)

Well-Functioning Markets

The objective of orderly and well-functioning markets (Kremers & Schoenmaker, 2015) regards the subjects of market efficiency, competition and integrity. Efficient markets channel capital to the most productive uses, that is to say where they are valued the most. Another aspect of efficiency is informational efficiency, which exists if prices reflect all available information in a timely and accurate manner and returns appropriately include all risk. Informationally efficient markets are desirable because they stimulate liquidity (Armour, et al., 2016).

A further important factor for the well-functioning markets objective is competition. In order to prevent the market failure arising from imperfect competition, entry barriers to new comers and to international competition should be reduced (Armour, et al., 2016).

Market integrity is achieved when a system operates fairly, without fraud, market abuse or further financial crime (Organisation for Economic Co-Operation and Development, 2010).

Interaction and Hierarchy of Objectives

The previously defined objectives impact each other and tensions or conflicts may arise. Therefore, it is critical to discuss the interrelation of the objectives and define a hierarchy among them.

Firstly, the compatibility of the objectives of soundness of financial institutions and financial stability has to be revisited. Kremers & Schoenmaker (2015) stress that one reason for the obsolescence of the Basel I regulations was the belief that the safeguarding of individual institutions automatically safeguards the entire system. The financial crisis showed, that microprudential policies might be destructive at a macro level since they ignore correlations and common exposures across institutions (Borio, 2003).

Secondly, the objective of investor protection might undermine the efforts to ensure financial stability as well as well-functioning markets. Since the objective of investor protection limits the set of possible investment opportunities offered to consumers, the diversity of the financial system is reduced, correlation between investment strategies is increased and hence the resilience of the system to shocks decreases. Therefore, financial stability is threatened if investor protection is followed rigorously. Moreover, the high possibility of herd behavior arising from the reduction in investment opportunities will reduce informational efficiency and prices might stay at artificial levels. (Armour, et al., 2016)

Thirdly, efforts to ensure well-functioning markets will also impact the objectives of financial stability and investor protection. The objective of well-functioning markets promotes perfect competition, which entails low profitability. Institutions look for ways to improve profitability by taking on more risk to increase return or to cut costs. The increased risk taking creates vulnerabilities for financial stability and the cost saving operations could result in inferior products which negatively impacts the investor protection objective. (Armour, et al., 2016)

Fourthly, it has to be mentioned that regulating financial markets to achieve any of the four objectives reduces the freedom of markets and hence limits competition and creates incentives for regulatory abuses. (Armour, et al., 2016)

For the described tensions between regulatory objectives, it is necessary to define a hierarchy. Kremers & Schoenmaker (2010, 2015) argue that the objectives aimed at the system, such as financial stability, are more important than those aimed at the individual level, since in case the system fails, the individual components will fail as well but not vice versa. Likewise, the OECD (2010) stresses that maintaining confidence in the financial system and upholding financial stability should be the priorities of financial regulation. Moreover, the global financial crisis showed that the fragmentation of the value chain lead to a vast and nontransparent distribution of risk and to the neglect of system integrity (Zinkin, 2014). Since the responsibility for system integrity is not assumed by anyone, regulation should take on this role. Armour et. al. (2016) present a quantitative argument for placing the objective of financial stability on top of the hierarchy. Comparing the costs and benefits of an investor protection measure to one safeguarding financial stability, they find that the Sarbanes-Oxley Act of 2002 has costs of around 290 billion US Dollars and benefits of 320 billion US Dollars, whereas Basel III measures costs in trillions and benefits in tens of trillions of US Dollars. Based on the amounts at stake for the objective, financial stability should therefore be given priority over the other objectives.

I.4. **Risk Mapping for FinTech Lending Platforms**

The traditional innovation growth view predicts that innovation to financial markets through FinTech business models is reducing market deficiencies in several ways. In contrast to this, the innovation-fragility view identifies financial innovation as one of the key contributors to systemic risk and as the cause for recent crises. (Beck, 2017)

This section examines the development of FinTech lending platforms from both views and analyzes its impact on the financial system, financial institutions and platform users. A detailed risk mapping is developed in order to understand the need for regulatory changes arising from changes in exposure to certain risks. The effect on the financial system is closely connected to the regulatory objectives of financial stability and well-functioning markets, whereas the impact on financial institutions is related to the objective of soundness of financial institutions and the effect on platform users to investor protection.

There is little managerial literature or academic research published on the risk arising from FinTechs, likely due to the business models' novelty and continuously changing nature. Moreover, FinTech lending platforms have not yet reached a critical size to pose significant risk to the financial system. The most comprehensive reports come from regulators that are concerned with potential future financial stability impacts and therefore assess business models more critically. These reports form the basis for the following analysis.

I.4.1. Financial System

A report on Financial Stability Implications from FinTech published by the FSB (2017) places macro financial risk among three priority areas for international cooperation. The report stresses the limited availability of data and the need for authorities to develop procedures to aggregate relevant information (Financial Stability Board, 2017).

As discussed previously, the need for regulation of financial markets arises from the potential market failures through negative externalities, asymmetric information, biased market participants, the characteristics of public goods and imperfect competition. It is important to understand how FinTech innovations affect market structure as well as to address these issues and to subsequently revisit the need for and extend of regulation.

Negative Externalities

According to the FSB (2017), the unbundling of financial services and the entry of non-financial entities as market participants led to a decentralization of the financial system. By introducing different sources for credit from outside the conventional financial system, opportunities for diversification are found (Bank for International Settlements & Financial Stability Board, 2017). This may result in lower interconnectedness and correlation of the financial system, reducing negative externalities and the potential of spillovers across institutions. Hence the system becomes more resilient and the objective of financial stability is supported.

However, FinTech lending services rely on a functioning financial system or are directly connected to conventional financial institutions. Together with the securitization of FinTech loans, FinTech lending is expanding the interconnection of the financial system also to other sectors (International Organisation of Securities Commissions, 2017). Moreover, individual investors bear the losses from loan defaults and, in contrast to conventional lenders, do not fall under any prudential capital requirements and are not backed by any public safety net (Financial Stability Board, 2017). This could lead to further defaults and increases the possibility of a market failure arising from negative externalities. A precise estimation of its extend is intricate, since FinTech lending platforms have not been tested through a full cycle and default rates may be biased by good market conditions (International Organisation of Securities Commissions, 2017).

Lastly, the mentioned positive decentralization effect can be reduced by the importance of network effects and economies of scale and scope for ensuring competitiveness in financial markets (Financial Stability Board, 2017). In the future, this could lead to a concentration in the FinTech lending sector and hence higher interconnectedness which undermines the regulatory goal of financial stability.

Therefore, the introduction of FinTech lending will likely increase contagion risk.

A second development in the area of negative externalities arises from systemically important institutions, which “are perceived as not being allowed to fail due to their size, interconnectedness, complexity, lack of substitutability or global scope” (Bank for International Settlements, 2013). Decisions taken by these institutions influence the whole system and, through negative externalities, could harm the financial system.

Additionally, the guarantee of government support may trigger a moral hazard problem and promote risk-taking, lower market discipline and a distortion in competition (Bank for International Settlements, 2013). Therefore, systemic importance is a threat to the stability of financial markets as it decreases the efficiency of the market and the soundness of financial institutions.

Systemically important FinTech lending companies are less inclined to perform accurate due diligence and tend to increase risk-taking, for instance by extending credit to high risk clients, since potential losses will then be covered by the relevant authorities. This agency problem is particularly critical in a FinTech, since governance of these novel companies is on average not as sophisticated as in incumbents and therefore moral hazards problems cannot be controlled easily. Moreover, since some of the FinTech lending activities fall outside prudential regulation, disruptive behavior such as excess risk taking cannot be averted sufficiently. This constitutes a further factor undermining the objective of financial stability.

For these reasons, the risk arising from a potentially systemic importance of a FinTech lending company is higher than that of an incumbent financial institution.

Asymmetric Information

In FinTech lending business models, asymmetric information problems arise from three sides. Firstly, lenders typically do not know the drivers of interest rate offers and cannot assess whether they are at a fair level. Secondly, a creditors' true ability and willingness to pay back a loan is unknown to the lending platform at initiation. Thirdly, the thoroughness of the credit risk assessment performed by the lending platform is unknown to the investor at initiation.

Considering the first information asymmetry problem, FinTech companies promise greater transparency and easily understandable products (Financial Stability Board, 2017). Through better information provision to and education of the customer before, during and after the purchase, as well as quoting rate offers quickly and comparing interest rates online, information asymmetries on the lender's side are reduced. In this way, the introduction of FinTech lending platforms supports the regulators goals of investor protection and well-functioning markets.

Lending platforms intervene at the second side of asymmetric information, through using big data models and alternative data sources for better borrower screening and credit risk assessment. In this way, FinTechs reduce information asymmetries and circumvent the market failure arising from a lemon's problem. However, the promise of FinTech lenders to provide loans based on different risk criteria than banks might lead to adverse selection problems. Individuals that cannot obtain a loan at a conventional financial institution due to high risk might shift to a lending platform, whereas creditworthy individuals stay at the conventional financial institution.

The third problem concerns investors of the lending platform. They have to trust the company's risk assessment and resulting loan parameters when investing in the loans and hence, investor confidence is extremely important. Lending platforms aim to create trust by publishing past performance data and promising full transparency. However, since FinTech business models are new to the market, investor confidence in the sector is not firmly established and fragile (International Organisation of Securities Commissions, 2017). Should investor confidence be lost due to a scandal or increased default rates from platform lending, agency cost from information asymmetry may lead to market failures, which undermines financial stability.

FinTech innovations reduce information asymmetries in lending activities and hence contribute to the regulatory goals of investor protection and well-functioning markets when trust is high. Therefore, the potential loss from losing investor confidence is high and the related risk is increased in FinTech lending.

Biased Market Participants

Market participants may be biased in their beliefs and may take irrational decisions. In lending activities, loan parameters may be impacted by an agent's biases and not set at equilibrium level.

Aldridge and Krawciw (2017) emphasize, that FinTech business models rely on machine learning, which discards biases, and can therefore restore market equilibria which is conducive to the regulatory objective of well-functioning markets.

A further aspect that is related to biased market participants is procyclicality, which describes fluctuations in financial variables resulting from financial institutions' and other market participants' alternating behavior across the economic cycle. Regarding lending activities, one can observe high credit provision and low credit spreads in an up-state economy as opposed to restricted credit provision and high credit spreads in down-states where investors risk appetite is low (Financial Stability Board, 2017). This implies a procyclicality problem of conventional credit supply.

On the one hand, this phenomenon is reduced through using a wide range of data points, especially if data that is not correlated with economic cycles is taken into consideration and if the objectivity of credit pricing is ensured through automated models (Aldridge & Krawciw, 2017).

On the other hand, FinTech business models bear the risk to increase the impact and degree of such fluctuations through aligning market participants' behavior (Aldridge & Krawciw, 2017). Moreover, FinTech lending business models rely on continuous investments to facilitate loans and to ultimately generate fee-based revenues (Bank for International Settlements & Financial Stability Board, 2017). Since the risk appetite and investment volume is very dependent on the economic cycle, the procyclicality will increase and the risk of resulting credit crunches increases. Furthermore, FinTech is very dependent on the trust placed in its business models, a variable which is closely related to the economic condition. This will amplify procyclicality even further.

Therefore, risks arising from procyclicality, such as the occurrence of a credit crunch, are likely to be higher for FinTech lending and pose a threat to financial stability.

Public Good

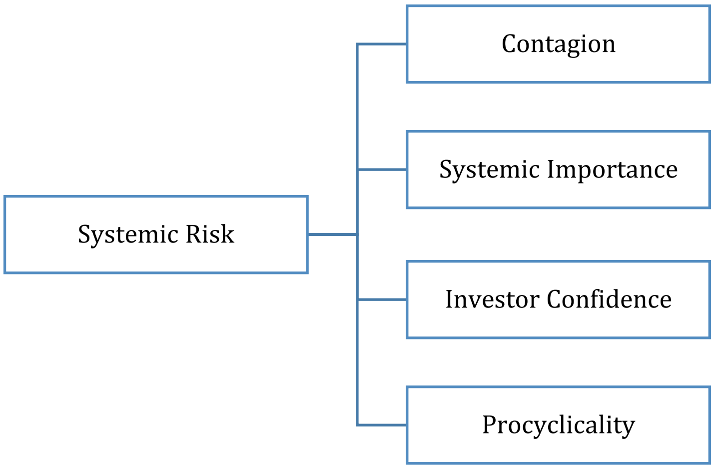
In a speech given at the International FinTech Conference in 2017, the Governor of the Bank of England Mark Carney points out that FinTech companies increase the offer of financial services available to consumers and provide positive externalities through for example liquidity provision. Since FinTech companies have a lower cost structure from automation or are based on different business models that aim at data collection, the free-rider problem is not as severe for FinTech companies as it is for conventional financial institutions. This overcomes the problem of under-provision of public goods. Moreover, the use of alternative data sources provides more affordable financing opportunities than previously available for people with poor credit history and promotes financial inclusion (Bank for International Settlements & Financial Stability Board, 2017). Especially in emerging economies, where the financial system is not as developed, people will profit from better connectivity, broader availability of information and the empowerment of individuals (Carney, 2017). This development supports the well-functioning of markets.

Imperfect Competition

A further effect from the lowered entry barriers and the resulting increased diversity and redundancy may be the decreased market dominance of single market participants. In other words, there exist sufficient substitutes so that excessively high prices or poor quality will deter demand for that institution's products and market outcomes will be more efficient. The use of big data analysis improves borrower screening and allows for a more accurate risk pricing and the automation of screening processes increases speed and reduces cost of a credit risk assessment process, which is reflected in lower rates (Bank for International Settlements & Financial Stability Board, 2017). Incumbents will improve their services in order to stay competitive and consumers will benefit from lower prices and better services (Carney, 2017). Therefore, FinTech seems to have the ability to overcome the problem of imperfect competition in financial markets and to contribute towards the goal of well-functioning markets.

According to a report by the FSB (2017), FinTech companies achieve financial inclusion and foster sustainable growth in the financial industry, as long as risks are appropriately managed and trust in the system is maintained. The risks arising from FinTech lending activities identified in this section are presented in Figure 11.

Figure 11: Systemic Risk Factors Impacted by FinTech Lending Platforms



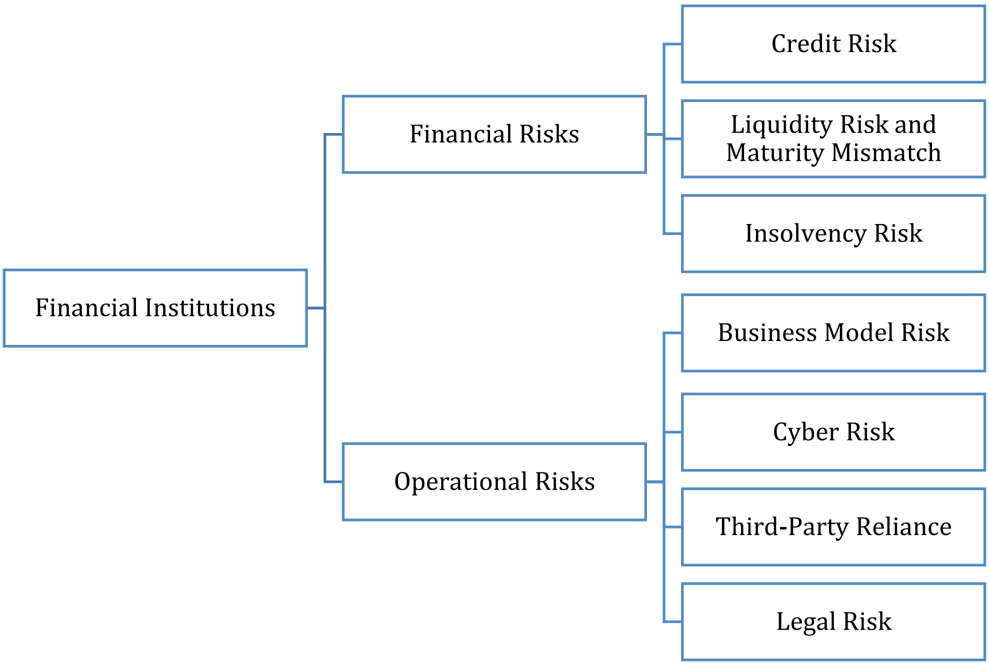
I.4.2. Financial Institutions

Financial institutions face numerous risks that directly affect business models, and if they provide critical services or if there is high interconnectedness, the losses of one company may destabilize the financial system (Financial Stability Board, 2017). The introduction of FinTech innovations impacts these risks significantly, whether in FinTech companies themselves or in incumbents. These changes are important in order to assess the appropriateness of current regulation to achieve the objective of sound financial institutions.

Several academic publications, articles and regulatory reports identify risks regarding FinTech activities. Appendix 3 illustrates the detailed sources and risks mentioned. The aggregated risk framework for firm-specific risk developed for this analysis is presented in Figure 12. Idiosyncratic risks of financial institutions arise from both financial and operational sources. Financial sources are credit risk, liquidity risk and maturity mismatch, as well as insolvency risk, whereas operational sources are business model risk, cyber risk, third-party reliance and legal risk.

The following sections will discuss each risk in detail.

Figure 12: Firm-Specific Risk Factors Impacted by FinTech Lending Platforms



I.4.2.1. Credit Risk

Credit risk describes the possibility that "promised cash flows from loans and securities held by financial institutions may not be paid in full" (Saunders & Millon Cornett, 2017). In order to minimize losses arising from this risk, financial institutions spend a lot of resources on credit risk assessment to fund creditworthy loans and on risk pricing, which entails setting the interest rate to a level that reflects the potential future losses the institution will incur.

FinTech

FinTech lending platforms facilitate a matching of borrowers and lenders and have no claim on future cashflows of fully funded loans. Therefore, the exposure to credit risk is obviated and passed on to investors. Only if the company decides to fund parts of matched loans themselves, for investment or market making purposes, it is exposed to credit risk.

Therefore, FinTech business models innovate the financial industry by partially releasing financial institutions from credit risk.

Incumbents

Conventional financial institutions keep loans on their balance sheet and sell no claims. They are hence highly exposed to credit risk. Collaborations with FinTechs allow the introduction of innovative credit risk assessment models to the conventional process and could improve the borrower screening. However, the increased competition in the lending sphere puts immense pressure on incumbents and may incite them to underprice risk in order to retain market share (Financial Stability Board, 2017).

Credit risk for incumbents is not affected by the introduction of FinTech lending platforms.

I.4.2.2. Liquidity Risk and Maturity Mismatch

Liquidity risk arises when balance sheet items have different liquidity characteristics. The sudden withdrawal of liabilities forces financial institutions to sell less-liquid assets quickly at prices below market value. These so-called fire sales decrease asset value and could threaten the profitability and solvency of the institution (Saunders & Millon Cornett, 2017).

Maturity mismatch or interest rate risk originates when a company's assets have a longer maturity than its liabilities. The risk arises from rolling over financing and incurring higher cost and reduced margins as a result and is therefore also called interest rate risk.

FinTech

Since investments and loans are duration matched and investors can only liquidate their position by finding a new investor to take over the position, liquidity risk and maturity mismatch are suspended in the FinTech lending sphere. The FinTech is only exposed to liquidity risk arising from the low liquidity of their invested share in the loan, which is an asset on its balance sheet. Liquidity of FinTech platform loans is limited, since these investments are highly specific products and there are problems of information asymmetry (International Organisation of Securities Commissions, 2017). Similarly, maturity mismatch only occurs for these loan assets on the FinTech's balance sheet.

Therefore, liquidity risk and maturity mismatch are alleviated for FinTech lending platforms.

Incumbents

Incumbents follow the conventional lending model, where liquidity risk is high because loans are funded by highly liquid liabilities such as deposits. Maturity mismatch occurs as well, since loans are extended for a longer period than financing is contracted (Financial Stability Board, 2017).

Incumbents might experience even higher liquidity risk and maturity mismatch through the introduction of FinTech lending platforms. Firstly, with new competition, the demand for loans from incumbents decreases and conventional lenders have to look for alternative assets that might be less liquid and have a longer maturity. These characteristics will reinforce the risk described previously. Secondly, since borrowers can refinance their loans from incumbents at lower rates through FinTech lending platforms, loans will be paid back prematurely and maturity mismatches form.

Incumbents will incur higher liquidity risk and maturity mismatch.

I.4.2.3. Insolvency Risk

Insolvency occurs if the capital of a financial institution is eliminated or closely eliminated through financial losses (Saunders & Millon Cornett, 2017). The higher the leverage of an entity, the lower the equity available to absorb losses. Therefore, insolvency risk increases with the leverage of a financial institution.

FinTech

FinTech lending platforms have only developed recently and are hence in the beginning stages of their business. Aggressive pricing strategies to obtain market share and untested business models increase the risk of financial losses (European Central Bank, 2017). Moreover, through automation, the variable costs of processing additional loans are small compared to the fix cost and companies need to keep their loan volume at high levels in order to benefit from economies of scale and keep costs low. Additionally, the new companies have low own funds to begin with and therefore insolvency risk is high. However, this risk does not arise from high leverage as in conventional financial institutions; FinTech lending platforms show low leverage but high risk of financial losses. (Bank for International Settlements & Financial Stability Board, 2017)

Therefore, insolvency risk is high for FinTech lending platforms.

Incumbents

Incumbent financial institutions are under pressure since the emergence of FinTech lending platforms and have incentives for greater risk-taking (Financial Stability Board, 2017). Moreover, income sources erode with the increased competition (Bank of England, 2017).

Therefore, the risk of financial losses is increased through FinTech innovation which in turn increases insolvency risk for incumbents.

I.4.2.4. Business Model Risk

A weak governance structure or poor process control can lead to disruptions in the financial company directly. Misaligned incentives, for instance regarding assumed risk and expected return, and conflicts of interest can lead to disastrous outcomes for the company or the entire financial system (International Organisation of Securities Commissions, 2017). Without proper risk management expertise, the company lacks awareness of its risks and cannot appropriately respond to the exposure.

FinTech

Lending platforms are in a higher need to ensure strong governance compared to conventional lending for the following reasons. Firstly, a report by the BIS and FSB in 2017 specifies that “maintaining investor interest and trust is crucial to a platform’s business viability”, which is why strong governance is essential for FinTech lending platforms’ probability of survival. Trust can be lost by poor information provision on financial indicators of the securities or the identity of the borrower. Moreover, the possibility of a failure, fraudulent activities or malpractice by the FinTech due to insufficient governance can lead to a bad reputation and loss in investor confidence (Bank for International Settlements & Financial Stability Board, 2017). Secondly, business success in the highly volatile FinTech industry is difficult to forecast and the risk of financial losses is higher in the start-up phase. Therefore, a well-developed governance structure is essential to avoid early failure and FinTechs are encouraged to set aside sufficient funds and prepare an exit plan (European Central Bank, 2017). Thirdly, FinTech lenders follow a so called "originate-to-distribute" model since they generate profit from approving loans but do not bear the credit risks on these (Bank for International Settlements & Financial Stability Board, 2017). Therefore, they are inclined to approve even high-risk loans in order to improve their revenues, which constitutes an agency problem; hence a strong governance system is needed to align incentives.

Since a FinTech's governance structure and process controls are on average not exposed to the same extent of review as regulated financial institutions are (Financial Stability Board, 2017), it is critical that the FinTech develops an adequate governance structure internally. However, FinTechs are relatively new and have limited resources and experience, which is why governance is expected to be less sophisticated than for incumbent lenders.

The need for strong governance is higher compared to incumbents, while the current state is lower. Therefore, business model risk is higher for FinTech lending platforms.

Incumbents

In the 2017 stress test of the UK banking system, the evolvement of FinTech is displayed as a threat to bank's business models. Increased competition fosters price pressure and revenues will decrease. Moreover, it will be more difficult to attract and retain customers and banks cannot rely strongly on cross-selling anymore (Bank of England, 2017). The resulting erosion of profitability puts pressure on incumbents and induces excess risk taking (Financial Stability Board, 2017). Therefore, a strong governance system that monitors and controls the incumbent's activities is needed more than ever. In order to release this pressure in the long term, banks have to reorganize their business plans and "become more productive, with lower transaction costs, greater capital efficiency and stronger operational resilience" according to Mark Carney, Governor of the Bank of England (2017).

Hence, business model risk is increased.

I.4.2.5. Cyber Risk

Cyber risk summarizes "any risk of financial loss, disruption or damage to the reputation of an organization from some sort of failure of its information technology systems" (Institute of Risk Management, 2018). The extent of cybercrime is tremendous and it even exceeds illegal drugs trafficking in value (Saunders & Millon Cornett, 2017).

FinTech

FinTech lending platform operators rely strongly on IT systems and store sensitive client data which makes it a target for cyber risk. Due to the on average less sophisticated cybersecurity programs of FinTechs and the fact that more data is stored (Financial Stability Board, 2017), this risk is higher compared to incumbents.

Therefore, FinTechs in the lending sector are highly exposed to cyber risk and need to develop strong programs to mitigate this risk.

Incumbents

As incumbents try to match the offer by FinTech lending platforms by offering more digital services and automating processes, an exposure to cyber risk arises. This is a critical development, since capital requirements for operational risk are not as advanced as those for financial risk. Therefore, capital buffers might not be enough to absorb losses arising from a cyber-attack. (Financial Stability Board, 2017)

Hence, cyber risk is increased.

I.4.2.6. Third-Party Reliance

The unbundling of financial services and disintermediation of the financial service value chain entails outsourcing of services and hence a stronger dependence on third-party providers. These could for be for instance data providers, cloud service providers, other FinTech companies or traditional financial institutions.

A disruption in these providers will directly impact the operations of a company and therefore pose an idiosyncratic risk that is difficult to control, or even evolve into systemic risk if the third-party providers are concentrated (Financial Stability Board, 2017).

FinTech

FinTech lending platforms depend on various data source providers, cloud computing providers, as well as partner banks for the origination of loans in some business models.

The reliance on third parties creates vulnerability to disruptions in these services. (Bank for International Settlements & Financial Stability Board, 2017)

Incumbents

Incumbents are even less likely to develop these digital innovations inhouse in their pursuit to improve their service offering.

Hence, they are also increasingly exposed to risk arising from third-party reliance.

I.4.2.7. Legal Risk

Legal or regulatory risk describes the possibility of financial or reputational loss resulting from a misunderstanding, unawareness or indifference towards law and regulations affecting a business (EY, 2016).

FinTech

Since FinTech innovations are novel and constantly changing, regulatory frameworks are not fully adapted to the new services, products and processes and there is no international standardization. Therefore, there is a high legal uncertainty for FinTechs and especially companies that operate across borders are highly exposed to legal risk (Financial Stability Board, 2017). Another point raising legal risk is the fact that investors and lenders are quite anonymous and are never met in person. Platforms could facilitate fraudulent activities if they do not engage in accurate due diligence. (Bank for International Settlements & Financial Stability Board, 2017)

For these reasons, FinTech lending platforms have increased legal risk.

Incumbents

The pressure to increase the speed of loan approval originating from the introduction of FinTech lending platforms might dilute the due diligence traditionally performed by incumbents.

Therefore, new legal risk related to identity fraud and terrorist financing might arise also for incumbents.

I.4.3. Platform Users

The third stakeholder group that is impacted by the introduction of FinTech lending platforms are the users of the platform, borrowers and investors. One objective of regulation is investor protection, which entails both the protection of investors as well as the protection of consumers in retail finance (Armour, et al., 2016). To enable well directed regulations, any changes arising from the evolvement of FinTech lending platforms on users have to be discussed.

I.4.3.1. Borrowers

Borrowers benefit from the introduction of FinTech lending platforms. Easier applications, faster loan approvals and lower rates improve the customer experience for borrowers (Bank for International Settlements & Financial Stability Board, 2017). Information asymmetries are reduced and the borrower is less exposed to lenders' biases. Moreover, FinTech lending services are available to a broader group of borrowers and previously excluded individuals can apply for loans. Broadly speaking, FinTech lending platforms promise a fairer service to borrowers.

I.4.3.2. Investors

Investors also benefit from the reduced information asymmetry. Better knowledge of the borrower and platform performance history enhances risk-return considerations and FinTech lending platforms offer a new investment opportunity.

In the FinTech lending platform business model however, a lot of risk that traditionally occurs for the financial institution providing the loan is shifted to the investor.

Credit risk is transferred to the investor and is even increased, since individual investors can never diversify as well as a financial institution in giving out credit. Furthermore, part of the P2P Lending platform business proposition aims at improving credit risk assessment models by using alternative data sources, which in theory should lead to a higher predictability of such risk and could decrease credit risk by allowing investors to select more creditworthy loans. If these models are precise, also under varying economic conditions, this would present a reduction of credit risk. However, there is no evidence supporting any improvement, since models are untested through most of the credit cycle (Bank for International Settlements & Financial Stability Board, 2017) (Financial Stability Board, 2017). Credit risk for FinTech investors could therefore be much higher than for incumbents that use established models. What is more, FinTechs might focus too much on new data sources and their model fit while failing to consider economically relevant factors on credit worthiness such as income and total debt outstanding (Bank for International Settlements & Financial Stability Board, 2017). Another point to consider is that the FinTech credit risk assessment procedure is fully automated and considers only hard data while neglecting soft data that is case specific (Bank for International

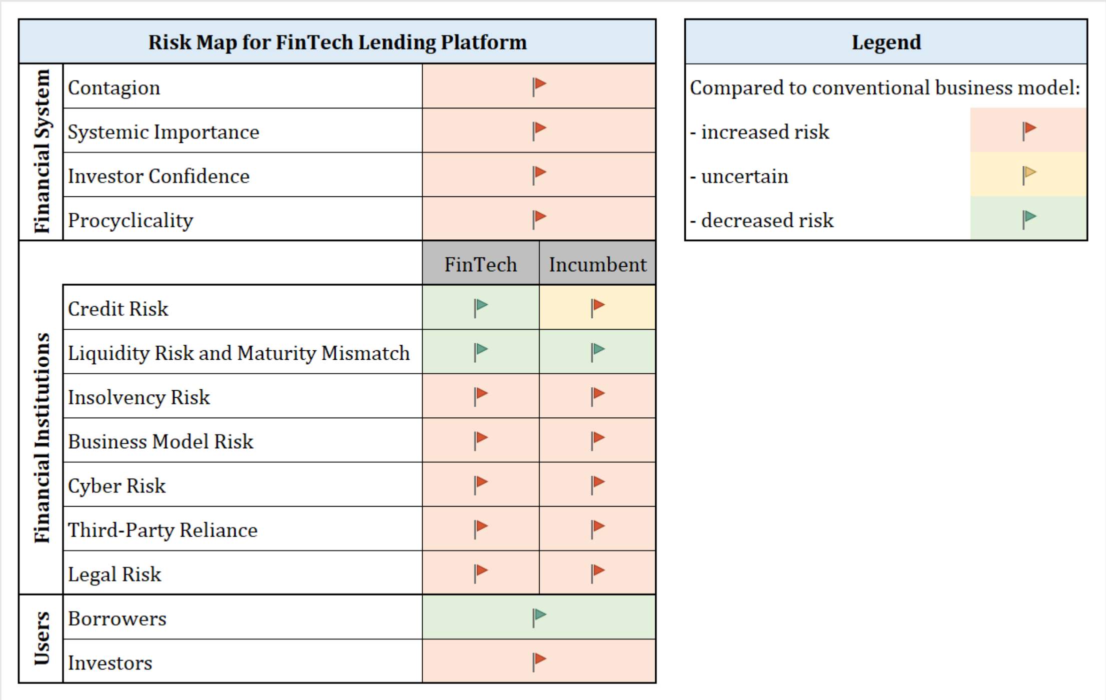
Settlements & Financial Stability Board, 2017). Conventional credit risk assessment methods include a face-to-face interview where such issues can be discussed and are factored into the risk assessment.

Moreover, the lack of secondary market liquidity for the investments due to high product specificity and information asymmetry raises liquidity risk and maturity risk for the investor (International Organisation of Securities Commissions, 2017).

I.4.4. Risk Map

The findings from this analysis are aggregated in Figure 13. In conclusion, the introduction of FinTech lending platforms has a strong impact on the financial system, financial institutions and its users. Both positive and negative effects were discussed and the risk map shows the diverse influence.

Figure 13: Risk Map for FinTech Lending Platforms



Risks in the financial system have increased, though the effect on contagion and procyclicality is ambiguous. However, it can be concluded from the previous discussion that the regulatory objective for financial stability is undermined by the introduction of FinTech lending platforms.

Considering the objective of sound financial institutions, the risk map indicates both contributing and interfering factors. Despite the ease regarding credit and liquidity risk and maturity mismatch, new risks arise and therefore challenge the regulatory objective.

Investor protection shows two effects as well. While borrowers benefit greatly from FinTech lending platforms, investors are worse of and are left out the progress made towards achieving investor protection.

Solely the objective of well-functioning markets is clearly supported by the introduction of FinTech lending platforms.

I.5. **Research Question & Hypotheses**

The aim of this study is to contribute to the research field by providing more insight on the issue of how regulators can ensure financial stability without limiting financial innovation. Since data availability is low, there are few papers providing a quantitative perspective to the discussion of risk in FinTech activities. This study should be seen as a starting point to fill this gap.

The hypotheses to be tested are as follows:

H1: FinTech lending volumes are procyclical.

The previous analysis finds that financial stability is the superior objective in financial regulation and is inflicted by the introduction of FinTech lending platforms. Contagion risk, systemic importance, loss of investor confidence and procyclicality are identified as risk factors to the financial system. The available literature is definite in the increased risk levels concerning systemic importance and loss of investor confidence, but there are different opinions about the effect of FinTech lending platforms on contagion risk and procyclicality. Levels of contagion risk are difficult to measure and available data is scarce. Therefore, this study focuses on procyclicality and starts from the null hypothesis of increased risk level originating from the procyclicality of loan volumes. This hypothesis implies that the loan volumes of FinTech lending platforms are driven by supply factors.

H2: The purpose of the loan is critical for the extent of procyclicality.

FinTech lending platforms match or originate loans for various purposes, for example debt consolidation consumer credits. The demand for and the risk of these loans are diverse and they are expected to be driven by different variables to different extends.

H3: Investor confidence is essential for a FinTech lending platform's viability.

The preceding discussion finds that business model risk is high for FinTech lending companies and the impact of a scandal would be detrimental. A loss of investor confidence following a scandal would negatively impact loan volumes and hence decrease the FinTech's profitability.

I.6. **Data**

I.6.1. FinTech Lending Platform

The company chosen for this study is LendingClub (LC), a FinTech lending platform operating in the US. It started operations in 2007 and has grown into the largest lending platform in the US; until 2017 it was even considered the biggest world-wide. In 2014, the company raised 1 billion US Dollar in an initial public offering (IPO) which was classified as the biggest technology IPO of 2014 in the US. (LendingClub, 2018)

LC was selected due to the extensive availability of loan statistics on their website dating back to June 2007. Moreover, the company is listed on the New York Stock Exchange (NYSE) since 2014 and therefore a lot of information about the business model and financial statements is publicly available.

LC operates under a notary model where it cooperates with a partner bank that originates the loans. As illustrated in Figure 14, LC performs a risk assessment of borrowers and approves loan applications. In a next step, it lists the loan with related parameters set by LC on its platform to obtain investor commitment. The listed loans have a fixed period of 3 or 5 years. Once a sufficient level is reached, the bank is instructed to originate the loan and LC purchases the loan directly after origination with the investors' funds. Any gap between investor commitment and loan amount can be covered by LC's own capital. Moreover, LC processes any payments from the borrower to the investor. (LendingClub, 2018)

Figure 14: LendingClub Business Model

From: LendingClub. (2018). Annual Report 2017. p. 10

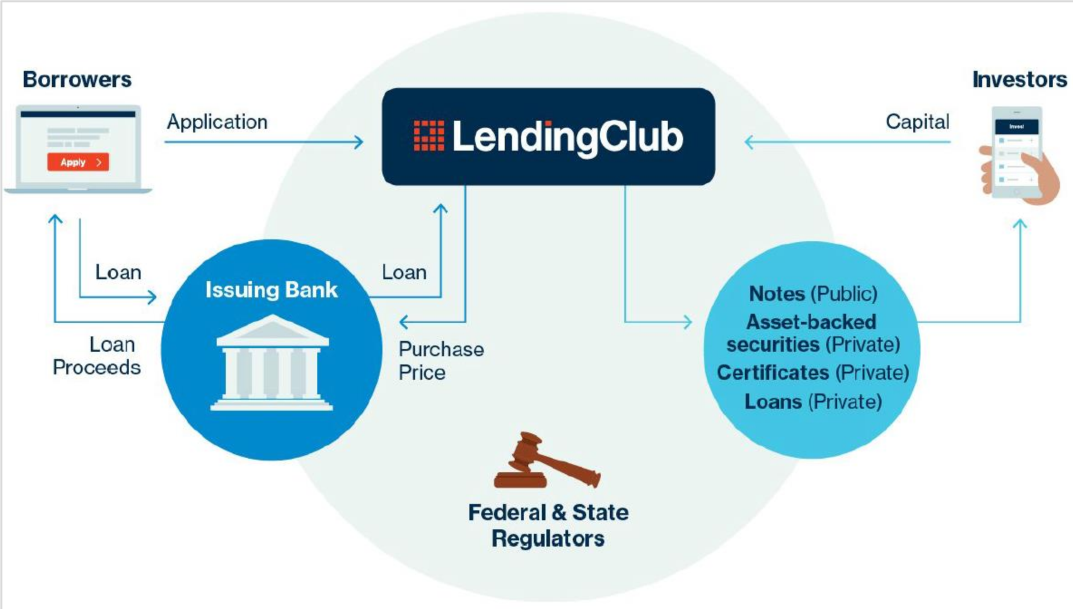


Table 1 shows the different revenue sources of LC in the financial years 2017, 2016 and 2015 by share of total net revenues. The main fraction of revenues is generated from two sources. The first one is investor fees charged to the partner bank for loan origination as a percentage of the loan principal. The second is investor fees charged to investors for brokerage or handling of interest payments. The remaining sources are gains or losses on sales of loans and fair value adjustments. (LendingClub, 2015-2018)

Table 1: Revenue Sources

Created from: LendingClub. (2015-2018). Quarterly Earnings Release

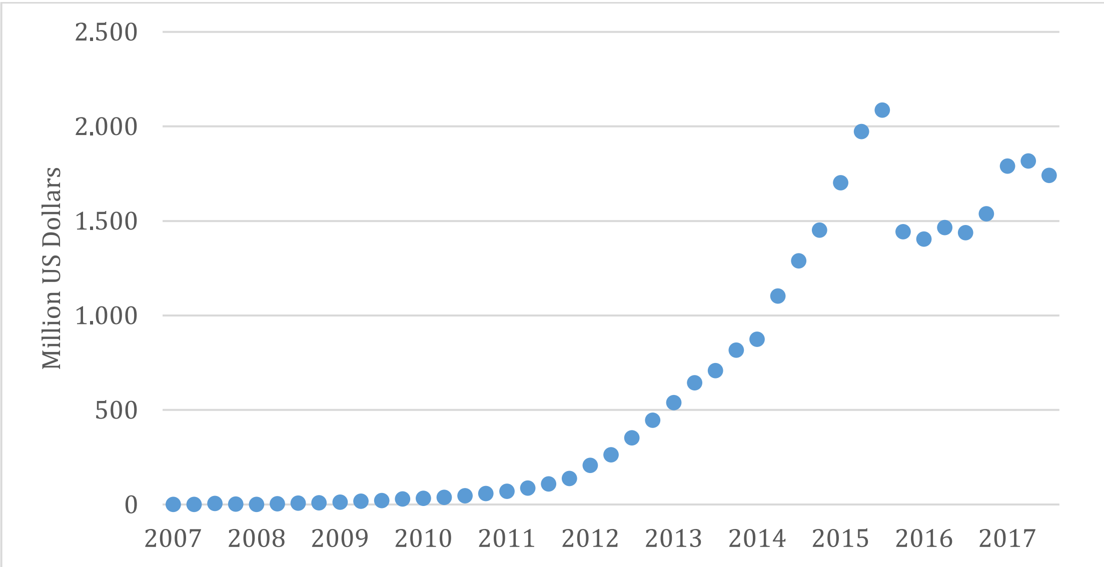
Year Ended December 31,	**2017**	**2016**	**2015**
% of net revenue:			
Transaction fees (from issuing bank)	78%	85%	87%
Investor fees (from investors)	15%	16%	10%
Gain (Loss) on sales of loans	4%	-3%	1%
Other revenue	1%	2%	1%
Net interest income and fair value adjustments	2%	1%	1%

The Annual Report for 2017 lists various factors that can affect LC's revenues, such as volume and quality of loan applications, investment appetite, investor confidence in LC's data or the performance of loans (LendingClub, 2018). Since transaction fees were identified as the main revenue source and are generated on originated loan principals, the loan volume per period is identified as a strong and easy to measure revenue driver for this study.

Figure 15 shows the loan volume of LC since initiation, aggregated by quarter. Detailed loan statistics were retrieved from LC's website and data on a total of 1,870,541 loans was processed for this study. The loan volume increases exponentially until the second quarter 2016, where a scandal concerning manipulated loan data occurred. The company was accused to have changed loan application data in an effort to match investors' criteria. LC stated that the "company's internal control over financial reporting was ineffective", which underlines the importance of a robust governance system. Moreover, it was uncovered that LC executives failed to disclose their personal investment in a vehicle that purchased large amounts of LC loans. (Williams-Grut, 2016)

Figure 15: LC Loan Volume by Quarter

Created from: LendingClub. (2007-2018). Loan Statistics



In order to understand the loan volume development, the demand and supply factors for funds have to be analyzed.

In this case, demand constitutes the amount of loan approvals. LC categorizes loans along 14 purposes. As Table 2 summarizes, there are three main categories that include 90% of all originated loan volume since LC's start of business in 2007. These are Debt Consolidation, Credit Card and Home Improvement. Debt Consolidation constitutes the refinancing of various debts with one single loan at more favorable terms. This action releases pressure from borrowers, as lower interest rates and longer maturities reduce the periodic payment amount. Credit Card comprises the repayment of credit card debt and Home Improvement groups loans for renovation or similar home refurbishing activities. Moreover, it should be noted that merely 1.2% of the total loan volume are small business loans. This purpose constitutes the P2B or B2B matching and is far below the US average of 10% business lending of total loans (Bank for International Settlements & Financial Stability Board, 2017). For the purpose of this study it is assumed that demand is purely from private borrowers.

Table 2: Loan Purpose Categories Defined by LC

Created from: LendingClub. (2007-2018). Loan Statistics

Purpose	% of Total
Debt Consolidation	60.7%
Credit Card	22.7%
Home Improvement	6.5%
Other	4.2%
Major Purchase	1.9%
Small Business	1.2%
Medical	0.8%
Car	0.7%
House	0.6%
Moving	0.4%
Vacation	0.3%
Wedding	0.1%
Renewable Energy	0.0%
Educational	0.0%

The amount of approved loans also depends on the willingness of partner banks to originate loans. Since the loans are directly purchased by LC after origination, the partner banks can obtain a steady and low risk income from this partnership. Therefore, it is assumed that every funded loan will be originated by the partner banks.

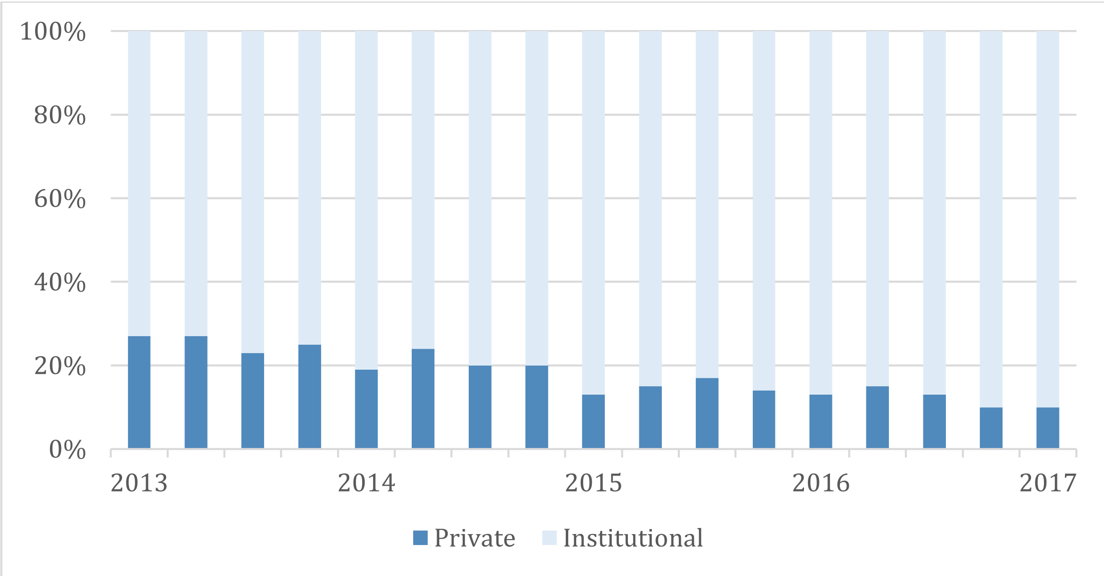
The supply factor is the amount of investor commitment. There are different types of investors and different investment vehicles.

As discussed previously, investors in FinTech lending platforms can be divided into private and institutional creditors. Different to what is observed in the industry, LC has a very low share of private investors, ranging from 27% in 2013 to 10% in 2017. In 2015, the overall share of private investors in the US market was roughly 40% (Bank for

International Settlements & Financial Stability Board, 2017). Moreover, LC also disclosed its own share in investments for the last two quarters of 2017, at 9% and 11% respectively. From the financial statements, it can be concluded that 2015 was the first year were the company invested in its own loans.

Figure 16: LC Loan Volume by Investor Type per Quarter

Created from: LendingClub. (2015-2018). Quarterly Earnings Release



LC offers four different investment vehicles to investors. Notes, certificates, secured borrowings that are asset-backed and the sale of whole loans. The first instrument is publicly traded whereas the last three are private. The majority of investments are executed through the sale of whole loans, followed by notes and certificates. Secured borrowings are only available since 2017.

Demand as well as supply and hence the resulting loan volume are influenced by various factors that will be described in the following sections.

I.6.2. Macroeconomic Factors

General Economy

The US Gross Domestic Product (GDP) is a general indicator of the economic performance of the country and will therefore influence both demand for and supply of funds. When

GDP is high, on the one hand, borrowers are better off financially and have a lower demand for credit. On the other hand, investors will have more money to invest and supply will increase. Therefore, the effect on loan volume is ambiguous. Data is available only on a quarterly basis and this study uses nominal values from the Federal Reserve Bank of St. Louis' FRED database.

The US unemployment rate (UNEMP) quantifies the employment level of the economy. If there is higher unemployment, there will be a higher demand for credit since household income decreases. Due to the fact that investors are mainly institutional, unemployment will only have a weak effect on loan supply. Therefore, unemployment is expected to have a positive relation with the loan volume. The unemployment data for this study is summarized quarterly and taken from the United States Department of Labor Statistics.

The US consumer price index (CPI) measures the price level over time. With a higher index, the real household income decreases and the demand for loans will increase. Quarterly data from the Federal Reserve Bank of St. Louis' FRED database is used.

US treasury yields (TY36 and TY60) with a fixed maturity of 3 and 5 years respectively represent the return on a risk-free investment with same maturity as LC's loans. If risk-free rates are high, the demand for loans decreases because of increased borrowing cost. The supply is expected to decrease as well, since more risk averse investors might switch to the low risk alternative that provides a sufficient yield now. Combined, the effects suggest a negative relation between loan volume and treasury yields. Monthly yields are obtained from the Federal Reserve Bank of St. Louis' FRED database and are transformed to quarterly intervals.

Industry

The amount invested in deals targeting FinTech companies in the US (FinTech) is a proxy for rising popularity of FinTech. With rising popularity, investor trust is gained and loan volume will increase. The data is taken from the CBInsight website and aggregated quarterly.

The total credit provided by US banks to the private non-financial sector in the US (Credit) is a proxy for the demand for loans. It includes all loans given to non-financial corporations and households and therefore overstates the target market of FinTech lending platforms. The quarterly data comes from the Federal Reserve Bank of St. Louis' FRED database.

The volume of outstanding consumer loans at all commercial banks in the US (ConsumerLoans) is another proxy for loan demand. It covers most credit extended to individuals, excluding loans secured by real estate. This means that mortgage loans are excluded and therefore this variable understates the target market of FinTech lending platforms. The quarterly data comes from the Federal Reserve Bank of St. Louis' FRED database.

US household debt volume (Debt) is a third proxy for loan demand. Two of its components, mortgage debt and credit card debt are added as separate variables in the analysis. Data is taken from the Quarterly Report on Household Debt and Credit in May 2018 from the Federal Reserve Bank of New York.

Household Financial Situation

Household financial obligations as a percentage of disposable income (FODSP) quantifies the ability of servicing financial commitments. The lower the ratio, the better the financial situation of the household. Debt consolidation and credit card debt refinancing make up most of the loans matched through LC. This demand will increase with financial burden since households will look for cheaper financing options. The approval rate for loan applications might decrease, since households will be less likely to be able to meet commitments to LC. Therefore, the true effect on loan demand is ambiguous. In order to find the most accurate measure, household debt service payments as a percentage of disposable income (DDSP), consumer debt service payments as a percent of disposable personal income (CDSP) and mortgage debt service payments as a percent of disposable personal income (MDSP) are included in the analysis as well. The data sets are quarterly and from the Federal Reserve Bank of St. Louis' FRED database.

The real disposable income in the US (RealDSP) shows how much income households have. Loan demand will increase with falling income whereas loan supply from institutional investors should remain relatively unaffected. Therefore, a negative relation with loan demand is expected. The data is obtained from the Federal Reserve Bank of St. Louis' FRED database and is quarterly aggregated.

Risk Indicators

The St. Louis Fed Financial Stress Index (StressIndex) measures the degree of financial stress in the US market. It is derived from a portfolio of interest rates, yield spreads and other indicators. Values below zero indicate subpar financial market stress, zero indicates normal market conditions and values above zero indicate above average financial market stress levels. A higher financial stress is assumed to increase loan demand but simultaneously reduce investment appetite for risky investments such as FinTech loans and its effect is therefore ambiguous. The index is quarterly and obtained from the Federal Reserve Bank of St. Louis' FRED database.

The Chicago Board Options Exchange Volatility Index (VIX) quantifies expectations on future volatility in financial markets. This means, a high VIX index indicates that investors expect large movements in the market, either positive or negative. A low VIX index indicates that investors expect small or no movements in either direction. This risk indicator captures the risk experienced by investors and is therefore expected to negatively influence loan volume, since a high index relates to high expected volatility and lower risk appetite. Quarterly data points are obtained from Yahoo Finance.

Equity Markets

The Standard & Poor's 500 index (SP500) is a US stock market index representing the market capitalization of the 500 largest companies listed on the NYSE. It is an indicator for the state of the US economy and displays business cycles. Since loan demand is expected to move countercyclically and loan supply procyclically, the effect on loan volume is uncertain. Quarterly data points are obtained from Yahoo Finance.

The Fama & French Three-Factor Asset Pricing Model (1993) describes equity returns that investors can earn in the US with different factors (Fama & French, 1993). The market return over the risk-free rate (Mkt-RF) shows the excess return from market risk. The Small-Minus-Big factor (SMB) is the size factor that measures the excess return of small over big companies. The High-Minus-Low factor (HML) is the value factor that measures the excess return of companies with a high book-to-market ratio over those with a low ratio. These factors are included to show how alternative investments are performing. High performance of these factors is expected to decrease loan supply since investors have attractive alternatives. Quarterly data is obtained from the Kenneth R. French website.

I.6.3. Firm-Specific Factors

The average interest rate on LC loans (LCRate) is a volume-weighted average annual rate calculated from the loan database. A high interest rate has a negative effect on loan demand since it increases borrowing costs but has a positive effect on fund supply since the return is increased. The overall effect on loan volume is therefore ambiguous.

The excess interest rate over the risk-free rate (LCSpread) is the interest rate charged by LC minus the treasury yield with respective maturity. It represents the risk premium of the borrower or the excess return on an investment in a LC loan. The expected effects mirror the ones suggested for the average interest rate but might be more concise since movements in the risk-free rate are factored out. A volume-weighted average is calculated from the loan database in a quarterly interval.

The spread between the interest rate on high and low risk loans (AFSpread) is calculated as the difference between excess interest rates on F grade loans and A grade loans with the same maturity. This spread indicates the risk premium charged on high risk loans. With increasing value, the riskiness of low grade loans is assumed to increase. This factor is included to gauge the effect of increased portfolio risk on loan volume. The spread is calculated from the loan database by taking volume-weighted quarterly averages.

The default rate on LC loans (Default) shows how many defaults occurred in a period in relation to the total outstanding loan volume. A high default rate is expected to deter investors and therefore decrease loan supply and loan volume. The rate is calculated from the loan database by defining default to include the loan status of “Default”, “Charged Off” and the two “Late” status of 16-30 and 31-120 days. The default period is set to be the date of the last received payment.

I.7. **Research Methodology**

I.7.1. Literature Review

There is no previous research testing the effect of macroeconomic variables on FinTech lending loan volumes. However, some papers studied factors that affect default rates and funding success of FinTech lending platforms. More closely related to this study, there is some academic literature on the effect of macroeconomic variables on FinTech lending credit spreads.

For instance, Foo, Lim & Wong (2017) test whether a set of macroeconomic variables is significant in explaining systematic variation in P2P credit spreads. They also use loan data from LC for their analysis but use the change in LC's credit spread as a dependent variable. Multiple regressions and canonical correlation analysis factor regressions are performed on the data. Only the results to the first analysis are discussed here since the second one is beyond the scope of this study. Foo, Lim & Wong (2017) find that changes in the risk-free rate (-), the unemployment rate (-), the size (-) and value factor (+), change in the VIX index (+) and the CPI (-) are significant in explaining changes in P2P spreads. (Foo, Lim, & Wong, 2017)

Dietrich & Wernli (2016) test determining factors of P2P interest rates using a dataset from a Swiss FinTech lending platform. As explanatory input, loan-specific variables, borrower-specific variables and macroeconomic variables were used. The study uses ordinary least squares regression with robust standard errors and performs as a first step univariate tests using t-tests to detect significant variables and subsequently applies multiple regression analysis. They find that most variation in interest rates could be explained by macroeconomic variables which are unemployment (+), the 3-year Swiss government bond yield (+) and the Swiss market index (-). (Dietrich & Wernli, 2016)

Comparing the findings from these two studies, it seems that the resulting associations are not consistent across datasets.

I.7.2. Data Set Construction

The interval for the time series data analysis was chosen to be quarterly for two reasons: Firstly, data about the US economy such as GDP is only available on a quarterly basis and secondly, the longer time frame ensures that effects have time to show in the loan volume.

From LC's website, 41 quarters of loan statistics are available, starting from the first quarter of 2008.

Before running analyses on the data sample, robustness checks were performed. Following Foo, Lim & Wong (2017)'s findings, the time series were checked for unit roots in order to avoid spurious regressions. The application of an augmented Dickey–Fuller (ADF) test found that the majority of selected variables has unit roots in their levels. Appendix 4 shows the complete results. Therefore, first difference of all variables was used in the following analysis, except for the Fama-French factors that were provided as returns from the source. Tests were also run for simple differences and log differences, but the results were most robust for the first differences. This modification reduced the sample size to 40 quarters or 10 years of observations.

In an effort to also capture effects exceeding one quarter, independent variables were duplicated and lagged for one period. Since the default rate can only affect borrower and investor decisions after the period, this was lagged once as the base variable and twice as the lagged variable. As a result, the sample size was reduced to 39 quarters.

To analyze the event effect of the scandal that happened in the second quarter of 2016, a scandal dummy was introduced. It is assumed that the effect of the scandal impacts loan volume for 1 year and therefore a dummy variable including 4 quarters after the scandal was added to the dataset.

Moreover, a range of t-tests were performed to test whether there was a significant difference in the loan volume growth across different subgroups.

Firstly, the data was grouped by quarters in order to detect seasonal effects. The results from the two-samples t-test show that only the fourth quarter shows a significantly different mean to the remaining observations and is therefore included as a dummy variable.

Secondly, it was measured whether the different purposes showed significantly different loan volume growth compared to each other and the entire sample. No subgroup was found to have a statistically different mean from the other and the related p-values were extremely high. Therefore, the loan purpose was not included as a dummy variable in the dataset. The detailed outcomes of the t-test are shown in Appendix 4.

Descriptive statistics on the entire database are in Appendix 5.

I.7.3. Univariate Analysis

This study aims at understanding the relationship between LC's loan volume growth and a selection of variables. To detect whether there is an association between two quantitative variables, it is useful to fit a linear model. A wide range of variables were suggested in the previous parts to have a relation with loan volume growth. In total, 54 independent variables were tested, by running 54 separate linear regressions with loan volume growth as a dependent variable as shown in equation 1.

$$\Delta LoanVolume = Intercept + \beta * Independent\ Variable \tag{1}$$

The relevant results are aggregated in Table 3.

The regression outcomes are ordered by their R^2 score, which indicates the suitability of a variable as an explanatory input for the dependent variable. It shows the fraction of loan volume growth's variation accounted for by the model and a value of 30-50% is evidence of a useful regression (Sharpe, De Veaux, & Velleman, 2012). Since these regressions only used one explanatory variable, all variables that resulted in a R^2 above 5% and the two dummy variables were included in the further discussion.

The output further compares the expected sign of association to what is found in the analysis. For firm-specific variables, one deviation is found for the default rate, which shows an extremely high R^2, with a counter-intuitive coefficient sign. The results suggest that a higher default rate two quarters ago increases loan volume growth. A more realistic interpretation is however, that there is a lurking variable. This means that the default rate has similar associations with the variables affecting loan volume growth and therefore the interpretation of coefficients is flawed. In order to avoid spurious regression problems, the default rate variable will be excluded from the further analysis. There are also macroeconomic variables that show associations different to what is expected. However, since the effect of macroeconomic variables can be multi-layered, the variables are included and further interpretations of the sign of association are provided in the results discussion.

The final important output in the results table is the coefficient of the independent variable and its significance. Only variables with a significant coefficient are useful in understanding the drivers for loan volume growth. All coefficients apart from the scandal dummy are significant at a 5% significance level and will therefore be used in the further analysis. The scandal dummy will be included nevertheless, since it is needed for hypothesis testing.

Table 3: Univariate Regression Results

Variable	R^2	Shapiro-Wilk (p)	Exp. Sign	Coeff-icient	P-Value		Inter-cept	P-Value	
Default (% -2)	0.876	0.004	-	0.622	0.000	***	0.147	0.000	***
CPI (%)	0.556	0.001	+	- 50.225	0.000	***	0.426	0.000	***
GDP (%)	0.358	0.000	~	- 45.022	0.000	***	0.573	0.000	***
LCSpread (%)	0.293	0.000	~	4.603	0.000	***	0.194	0.012	*
SP500 (%)	0.277	0.000	~	- 3.971	0.000	***	0.305	0.000	***
RealDSP (% -1)	0.172	0.000	-	19.598	0.009	**	0.345	0.000	***
Credit (%)	0.171	0.000	+	- 27.128	0.008	**	0.336	0.001	***
HML (% -1)	0.155	0.000	-	3.480	0.013	*	0.251	0.003	**
Mkt.RF (%)	0.148	0.000	-	- 2.550	0.014	*	0.291	0.001	**
TY36 (%)	0.146	0.000	-	- 0.916	0.015	*	0.248	0.004	**
UNEMP (% -1)	0.145	0.000	+	3.366	0.017	*	0.257	0.003	**
VIX (%)	0.141	0.000	-	0.656	0.017	*	0.206	0.015	*
StressIndex(%)	0.132	0.000	~	0.292	0.021	*	0.184	0.032	*
UNEMP (%)	0.106	0.000	+	2.982	0.040	*	0.233	0.007	**
Scandal4	0.043	0.000	-	- 0.360	0.204		0.282	0.003	**
Q4	0.089	0.000	+	0.359	0.065	°	0.153	0.118	

**** p<0.001; **p<0.01; *p<0.05; °p<0.1*

I.7.4. Multivariate Analysis

The final step of this data analysis is concerned with developing multiple regression equations that can model loan volume growth. For this purpose, more than one predictor variable was included in the regression to find a reasonable model that shows to have a good fit.

In order to avoid multicollinearity and a resulting poor coefficient estimation, the correlation of dependent variables has to be considered. Appendix 6 includes a correlation matrix of the explanatory variables that showed strong associations with the change in loan volume. There are 4 pairs of independent variables that have a critically high absolute correlation value of above 0.7. GDP growth with unemployment change, change in SP500 with the excess market return, excess market return with change in VIX index and change in unemployment with its lagged variable. When constructing the models, these pairs have to be regarded critically.

The first multiple regression includes the variables that were tested to have the strongest association with loan volume growth ($R^2 > 25\%$) plus the two dummy variables for seasonal effects and the scandal. The regression model is stated in equation 2.

$$\Delta LoanVolume = Intercept + \beta_1 * \Delta CPI + \beta_2 * \Delta GDP + \beta_3 * \Delta LCSpread + \beta_4 * \Delta SP500 + \beta_5 * Scandal4 + \beta_6 * Q4 \tag{2}$$

Table 4 summarizes the results of this model and a trimmed version including only significant variables. The adjusted R^2, which includes a penalty for the number of variables included, is 67% and higher than what could be achieved with a single variable. The only statistically significant independent variables in this model are inflation, GDP growth and the change in interest rate spread of LC's loans.

Table 4: Model 1 Regression Results

	Model 1			Model 1 (reduced)		
R Squared	0.673			0.653		
Observations	39			39		
	Coefficient	**P-Value**		**Coefficient**	**P-Value**	
Intercept	0.496	0.000	***	0.495	0.000	***
CPI (%)	- 34.754	0.006	**	- 35.860	0.000	***
GDP (%)	- 19.233	0.048	*	- 18.014	0.047	*
LCSpread (%)	2.556	0.028	*	2.077	0.030	*
SP500 (%)	0.626	0.592				
Scandal4 (Dummy)	- 0.228	0.209				
Q4 (Dummy)	0.043	0.790				

**** p<0.001; **p<0.01; *p<0.05; °p<0.1*

In a second model, all explanatory variables with an R^2 above 15% plus the two dummy variables were included, which means 3 variables were added to model 1.

$$\Delta LoanVolume = Intercept + \beta_1 * \Delta CPI + \beta_2 * \Delta GDP + \beta_3 * \Delta LCSpread + \beta_4 * \Delta SP500$$
$$+\beta_5 * \Delta RealDSP(-1) + \beta_6 * \Delta Credit + \beta_7 * HML(-1) + \beta_8 * Scandal4 + \beta_9 * Q4 \quad (3)$$

The results are shown in Table 5. The model's adjusted R^2 is increased to almost 80%. There are 2 more explanatory variables compared to model 1: the lagged return on the value factor and the scandal dummy, which is enforced in the reduced model.

Table 5: Model 2 Regression Results

	Model 2			Model 2 (reduced)		
R Squared	0.792			0.768		
Observations	39			39		
	Coefficient	**P-Value**		**Coefficient**	**P-Value**	
Intercept	0.555	0.000	***	0.545	0.000	***
CPI (%)	- 30.838	0.004	**	- 28.674	0.000	***
GDP (%)	- 15.757	0.086	°	- 21.314	0.007	**
LCSpread (%)	1.815	0.070	°	1.720	0.035	*
SP500 (%)	0.266	0.790				
RealDSP (% -1)	- 3.337	0.476				
Credit (%)	- 9.461	0.138				
HML (% -1)	2.688	0.004	**	3.067	0.001	***
Scandal4 (Dummy)	- 0.329	0.056	°	- 0.403	0.014	*
Q4 (Dummy)	- 0.017	0.901				

**** p<0.001; **p<0.01; *p<0.05; °p<0.1*

The third model expands the explanatory variables to those with an R^2 above 10%, which are 6 additional variables to model 2. The model is presented in equation 4.

$$\Delta LoanVolume = Intercept + \beta_1 * \Delta CPI + \beta_2 * \Delta GDP + \beta_3 * \Delta LCSpread + \beta_4 * \Delta SP500$$
$$+\beta_5 * \Delta RealDSP(-1) + \beta_6 * \Delta Credit + \beta_7 * HML(-1) + \beta_8 * Mkt - RF + \beta_9 * \Delta TY36$$
$$+\beta_{10} * \Delta UNEMP(-1) + \beta_{11} * \Delta VIX + \beta_{12} * \Delta StressIndex + \beta_{13} * \Delta UNEMP$$
$$+\beta_{14} * Scandal4 + \beta_{15} * Q4 \quad (4)$$

Table 6 summarizes the results. The adjusted R^2 is at 85%. This model includes correlated explanatory variables and therefore the reduced model, which eliminates the problem of multicollinearity, should be considered in the further discussion. GDP growth is not a significant explanatory variable anymore due to its correlation with unemployment rate change, but the number of explanatory variables is increased from 5 to 6. Inflation, the change in LC's interest rate spread, the lagged return on the value factor, the lagged change in unemployment, the change in the stress index as well as the scandal dummy are significant.

Table 6: Model 3 Regression Results

	Model 3			Model 3 (reduced)		
R Squared	0.853			0.826		
Observations	39			39		
	Coefficient	**P-Value**		**Coefficient**	**P-Value**	
Intercept	0.415	0.002	**	0.378	0.000	***
CPI (%)	- 34.668	0.004	**	- 30.761	0.000	***
GDP (%)	- 7.217	0.557				
LCSpread (%)	2.832	0.037	*	1.819	0.011	*
SP500 (%)	2.712	0.245				
RealDSP (% -1)	0.878	0.863				
Credit (%)	- 4.604	0.547				
HML (% -1)	2.602	0.010	**	3.372	0.000	***
Mkt.RF (%)	- 1.678	0.338				
TY36 (%)	0.118	0.685				
UNEMP (% -1)	2.573	0.095	°	2.545	0.001	***
VIX (%)	0.104	0.728				
Stress Index (%)	0.194	0.018	*	0.167	0.008	**
UNEMP (%)	- 1.115	0.492				
Scandal4 (Dummy)	- 0.390	0.026	*	- 0.449	0.002	**
Q4 (Dummy)	0.025	0.855				

**** p<0.001; **p<0.01; *p<0.05; °p<0.1*

I.7.5. Robustness Tests

Before analyzing the implications of these regression results, it has to be confirmed that the regression models are robust. Therefore, the residuals of the models are tested for normality and autocorrelation.

Normality of residuals is an underlying assumption of regression analysis. The Shapiro-Wilk test for normality assesses whether the residuals of the regression are normally distributed and a high p-value (>10%) indicates normality. Table 7 shows that all models have normal residuals at a 5% significance level.

Secondly, it has to be tested whether the residuals of the regression are autocorrelated. For this purpose, the significance of the slope coefficient of a model which regresses residuals on lagged residuals is examined. The related p-values are presented in Table 7. Only model 3 and the reduced model 1 have no autocorrelation in their residuals. Therefore, the interpretation of the GDP coefficient should be considered carefully.

Table 7: Results from Robustness Checks of Models 1 to 3

	Model 1 (reduced)	**Model 2 (reduced)**	**Model 3 (reduced)**
Shapiro-Wilk	0.094 ° (0.373)	0.518 (0.643)	0.162 (0.244)
Autocorrelation	0.009 ** (0.061) °	0.007 ** (0.007) **	0.141 0.118

*** $p<0.001$; **$p<0.01$; *$p<0.05$; °$p<0.1$

I.8. **Results**

I.8.1. Discussion

The results from the multiple regressions indicate, that there is indeed a strong association between macroeconomic factors and LC's loan supply. Since the loan volume of LC is too small to affect any of the independent variables, it is assumed that the direction of the relationship has loan volume as the dependent.

7 variables showed to be significant in modelling the change in loan volume. The signs of their association were consistent in all models from the univariate over to the multivariate regressions and are summarized in Table 8.

Table 8: Significant Variables from the Multiple Regressions and their Coefficient's Sign

Variable	Sign of Association
CPI (%)	-
GDP (%)	-
LCSpread (%)	+
HML (% -1)	+
UNEMP (% -1)	+
Stress Index (%)	+
Scandal4 (Dummy)	-

The analysis results suggest that inflation has a negative relation with loan volume growth, meaning that a high inflation coincides with decreasing loan volumes. The economic intuition discussed earlier would suggest a positive relation considering the effect inflation has on demand. However, this negative sign can be explained by the Fisher effect, which states that a high inflation leads to higher nominal interest rates (Blanchard, Amighini, & Giavazzi, 2010). Higher interest rates imply raised cost of borrowing and therefore explain the decrease in loan volume. High inflation usually occurs when the economic state is positive, and therefore this finding suggests a countercyclical movement of loan volume.

GDP growth has a negative sign of association to loan volume growth which matches the economic intuition. Higher GDP suggests a higher household wealth and therefore a lower need for credit from private borrowers. This result shows that the negative effect of the demand factor exceeds the positive effect of the supply factor, which could indicate that demand has been driving loan volumes of LC since initiation. Moreover, this relation suggests a countercyclical movement of loan volume.

An increase in LC's interest rate spread leads to an increase in LC's loan volume. This finding suggests that the spread's positive effect on supply is stronger than its negative effect on demand. In other words, setting high interest rates to attract investors is more important than keeping rates low to create demand. However, this interpretation should be handled with care, since Foo, Lim, & Wong (2017) find a significant negative association between LC's spread and the economic conditions. They have discovered that a good economic condition, indicated by high GDP and low unemployment, decreases the default probability of P2P loans and hence the charged interest rate spread. Therefore, the association found in this analysis may be impacted by a lurking variable of economic condition. A good economic condition was associated with both low loan volume and low interest rate spread. The positive association found in this analysis is most likely originated from this fallacy.

The lagged return on the value factor, HML, shows a positive association with loan volume change in this analysis. This finding is contrary to what was expected, since the value factor was included to model alternative investment returns. A low or even negative return on an alternative investment would theoretically increase investor demand for FinTech loans and therefore increase the loan volume. The positive association detected in this analysis could again be generated by lurking variables.

The analysis finds a positive association between the lagged unemployment growth and loan volume growth. In other words, a decrease in the unemployment rate coincides with a lower loan volume in the next period. This finding agrees with the expectations since less credit is needed when households have more income sources. Moreover, this variable presents another influence on demand which drives a countercyclical development of loan volumes.

According to the model, an increase in the Stress Index increases loan volumes. Higher economic tension leads to a higher demand for credit and the negative effects on credit supply are overshadowed by this demand effect. Similar to the previous variables, this finding supports the existence of a countercyclical property of loan volumes.

The occurrence of a scandal in the past 4 quarters coincides with a lower loan volume growth. This effect is expected and can either originate from lower demand or lower supply due to loss of trust. This effect quantifies the risk of the previously discussed business model risk and the results support research hypothesis 3. A scandal significantly reduces investor trust and the loan volume and could, if FinTech lending were to become systemically important, lead to a credit crunch.

These preliminary findings indicate, that loan volume behaves countercyclically and not procyclically as suggested in the literature. Therefore, research hypothesis 1 has to be rejected. Inflation, GDP growth, unemployment growth and changes in the stress index indicate that the demand effects influence changes in loan volume more than the effect on supply. This is an interesting finding, since it suggests that the conventional lending problem of procyclicality could be overcome through FinTech lending platforms.

Moreover, it should be discussed which variables showed no significant association with loan volume growth and were excluded from the models. None of the treasury yields had a significant coefficient in the multiple regression models, which could indicate that the demand and supply effect discussed earlier cancel each other out. None of the industry variables showed a significant association with loan volume in the multivariate models. A possible interpretation of this finding could be that the demand for FinTech credit behaves differently than the one for conventional credit. Moreover, no variable describing the financial situation of households was significant in the multiple regressions. From the stress indicators, the VIX index, closely connected to financial markets, was not significant. The S&P 500 and the excess market return as well as the size factor from the Fama-French factor model showed no significance in the multivariate analysis. Firm-specific factors such as the average interest rate charged by LC, the spread between high risk and low risk loan interest rates and the default rate were insignificant in the multiple regression. This can be explained by the significance of the LC interest rate spread, which captures variations in the average interest rate and risk spreads. The default rate was excluded from the analysis because it showed a high association with loan volume, but with an economically counterintuitive sign. This finding can be explained by the high dependency of the default rate on macroeconomic conditions and the resulting spurious regression.

Interestingly, the analysis detected that the purpose of the loan does not affect its association with the explanatory variables. The two main purposes for loans brokered through LC, debt consolidation and credit card repayment might be too alike in their demand characteristics to show any difference in their cyclicality. Therefore, the second research hypothesis cannot be confirmed by this study and has to be rejected.

In conclusion, the findings suggest that FinTech lending platforms reduce systemic risk arising from procyclicality. However, it is critical that FinTech platforms are able to sustain their business under adverse conditions where loan demand is highest and avoid scandals that reduce loan volume significantly. Moreover, rising default rates in economically adverse settings should be taken into consideration since they imply losses for investors and will reduce the supply of funds or require increased returns. This resulting procyclical pattern of loan supply may impact loan volume negatively in periods of economic recession and reduce the countercyclical pattern found in the analysis. Therefore, focus should be placed on reducing firm-specific risk, such as scandals and high default rates, in order to foster the benefits arising from this FinTech innovation.

I.8.2. Research Limitations

The findings of this data analysis should be handled with care, since only one company was analyzed. In further analyses, the same models should be run on data from other FinTech lending platforms in order to back test the results.

Another point to take into consideration is the fact that the analyzed time frame is from 2008 to 2018, which is dominated by a growing economy with few declines. Therefore, the findings concerning cyclicality may not prove to be robust in times of crises. Additionally, the quarterly intervals may aggregate information too much and conceal effects. In further studies, monthly data series should be examined, and GDP interpolated.

Moreover, this analysis has to cope with lurking variables, since the chosen explanatory variables affect a broad range of factors and not only loan volume. Therefore, the associations found in the models may not capture the complete relationships between the variables.

Another limitation constitutes the fact that the variables chosen as inputs for this study should impact either the demand or supply for loans and therefore show an association to the loan volume. However, a lot of information is available on borrowers and therefore loan demand, while there is almost no information on investors. Therefore, the variables that proxy loan demand may be picked more precisely than those chosen to reflect loan supply, due to missing information on the drivers of loan supply.

I.9. **Regulatory Architecture for FinTech Lending Platforms**

The findings from data analysis suggests a countercyclical movement of loan volume for FinTech lending platforms. This means loan volume and the FinTech lending platform's profit will be highest in a recession, where GDP falls, unemployment increases and stock markets plummet. In order to seize this opportunity for increased profits, the companies have to be robust enough to sustain these adverse conditions. Therefore, the findings suggest that regulation should aim to ensure the resilience of FinTechs in times of economic recessions.

I.9.1. Theoretical Dynamics between FinTech and Regulation

Differences in regulation lead to migration of financial activities towards the weakest regulator. This movement could be across sectors or regions and is referred to as regulatory arbitrage (Saunders & Millon Cornett, 2017).

In order to attract businesses, governments have incentives to keep regulation lax to benefit from regulatory arbitrage and foster business development in their country. Hence, it is important that regulators communicate across borders to create consistency in approaches and requirements (Board of Governors of the Federal Reserve System, 2016). Moreover, internationally operating companies demand a level playing field to reduce the burden placed on these companies (Organisation for Economic Co-Operation and Development, 2010).

A second dynamic is that financial institutions adapt to avoid regulatory restrictions, which implies that financial innovation can be caused by regulation. These movements of activities and related risks outside the regulatory perimeter challenges regulators to adapt their framework. The whole process can be compared to a cat-and-mouse game. (Beck, 2017)

Therefore, the response of regulators to FinTech innovations is a very critical topic. The previously discussed increased systemic risk points towards the importance of setting macroprudential policies that consider the entire financial system (Beck, 2017).

In general, the same rules placed on conventional financial institutions regarding fairness and transparency should be applied to FinTech companies. However, this approach might create issues since existing laws and regulations are based on conventional products and delivery channels. (Board of Governors of the Federal Reserve System, 2016)

Moreover, if financial innovation is outside the regulatory perimeter, it should not be stopped by unnecessarily complex regulations. These might reestablish entry barriers that protect incumbents (Nicoletti, 2017) or drive innovation towards the periphery with increased risk and low transparency (Board of Governors of the Federal Reserve System, 2016). It would be better to formulate regulation in a way that favors newcomers in order to support financial innovation and limit risks.

Additionally, also FinTechs have to be open to cooperate with regulators. In contrast to the technology industry, financial services depend on trust and confidence and newcomers have to be careful to create a strong compliance culture (Board of Governors of the Federal Reserve System, 2016).

I.9.2. Current Regulation

In practice, no internationally consistent standards or frameworks concerning FinTech lending platforms have been established. Relevant authorities have reacted separately, following three main strategies: treating FinTech lending platforms within the existing framework, adding new policies or entire frameworks, and creating environments that promote FinTech innovation.

Countries such as the US, Germany, Hong Kong and Singapore apply the same rules to FinTechs as to conventional financial institutions. Especially rules constituting investor protection, risk management practices and capital requirements are enforced to the same extent and depending on their business model, FinTech lending platforms have to apply for banking licenses.

Alternatively, some countries such as the UK, Switzerland, France and Spain introduced a new license specific to FinTech activities that is less expensive to obtain and has requirements adapted to the altered risk. Focus is placed on governance systems, capital requirements, IT systems and consumer protection. Moreover, a separate regulatory regime for FinTechs is introduced or discussed in Canada, Korea and China. Since regulation of conventional lending activities in these countries places too high barriers on FinTechs, the need for such action arises.

Next to these core regulatory setups, regulation can also promote FinTech activities in other ways. For instance, through tax incentives, as established in China, France and the UK or through the introduction of innovation facilitators. These facilitators can take three forms: regulatory sandboxes, where new technology is tested in a controlled environment; innovation hubs, where FinTechs obtain support in navigating through regulation; and accelerators, where funding support is provided to FinTech companies. (Bank for International Settlements & Financial Stability Board, 2017)

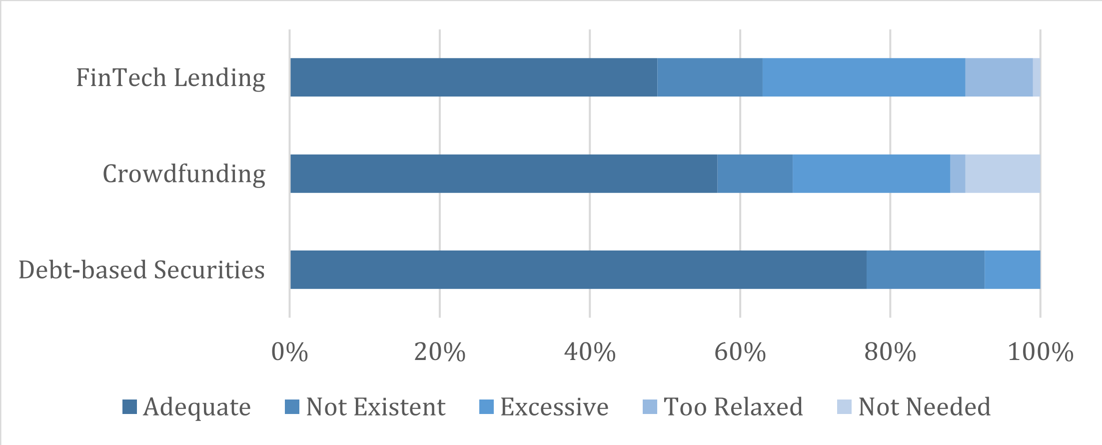
I.9.3. Evaluation

Despite the regulators' efforts, current regulation has to be analyzed and its appropriateness has to be assessed.

The Alternative Finance Industry Benchmarking survey, which is annually distributed by the Cambridge Centre for Alternative Finance (2018), gathered data on 267 European active alternative finance platforms. One question of the survey inquired the platform's perception of current regulation in their home market. Figure 17 presents the answers by type of platform, showing the focus type of this thesis, FinTech lending platforms, as well as two comparison types, crowdfunding and debt-based securities, which are regulated separately. The survey found that in Europe, the FinTech lending platforms' perception towards existing regulation is on average more discerning compared to the other alternative finance platform types. Less than 50% of respondents are satisfied with the regulation in place for FinTech lending platforms, whereas crowdfunding and debt-based securities platforms show satisfaction levels of over 55% and 75% respectively. Moreover, almost 30% of the interviewed FinTech lending platforms perceive current regulation as too strict, while this number is at 20% and less than 10% for crowdfunding and debt-based securities platforms. (Cambridge Centre for Alternative Finance, 2018)

Figure 17: FinTech's Perception Towards Existing Regulation by Platform Type (for Europe ex UK)

Adapted from: Cambridge Centre for Alternative Finance. (2018). Expanding Horizons: The 3rd European Alternative Finance Industry Report. p. 51



In order to approach this discontent regarding regulation, the policy initiatives can be mapped towards the risk they are addressing. For this purpose, the factors identified in the risk map in Figure 13 are used.

Systemic risk is only addressed regarding the loss of investor confidence, through the application of investor protection rules and the introduction of regulation to FinTech in general. This will strengthen the trust in the FinTech lending platforms and hence make the occurrence of a general loss of trust in the business model less likely. Contagion risk and risk arising from systemic importance are not addressed in any of the policy frameworks.

Increases in firm-specific risk were found in insolvency risk, business model risk, cyber risk, third-party reliance and legal risk. Insolvency risk is addressed through specific capital requirements for FinTechs and business model risk through an increased focus on governance requirements for FinTech lending platforms. Specific IT governance policies address cyber risk and through facilitators such as innovation hubs, legal risk is approached. Third-party risk is not explicitly addressed, however separate regulations of these businesses may take care of these issues.

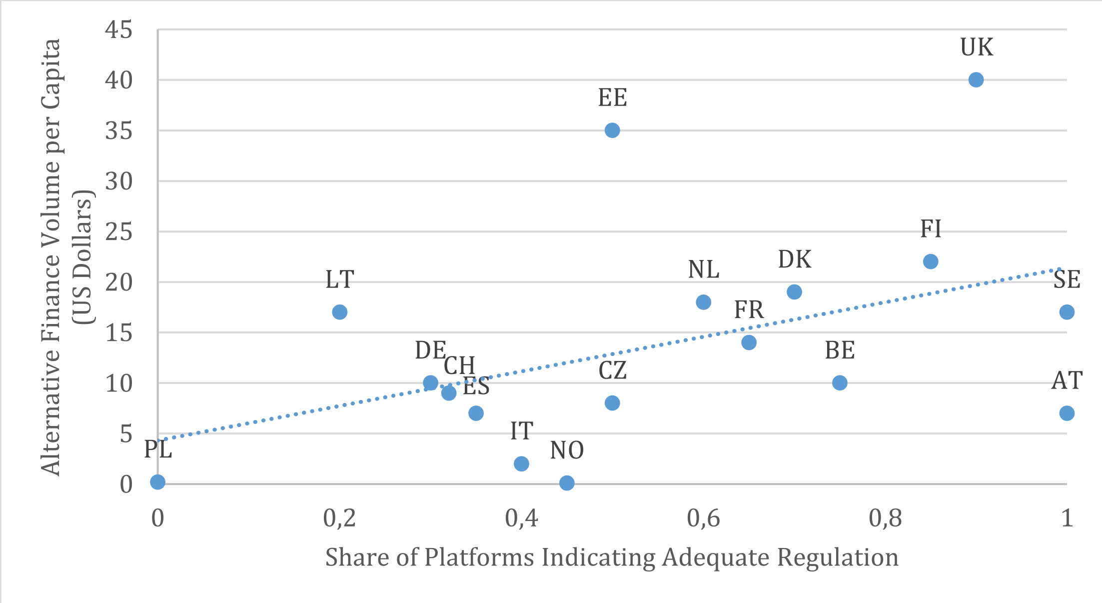
Users of FinTech lending platforms are also included in current regulation. Through applying consumer and investor protection rules in a similar intensity on FinTechs as on banks, these risks are considered.

All current policies combined seem to address most of the identified risks, however a lot of the systemic risk factors appear to be disregarded. If FinTech lending platforms perceive regulation to be excessively strict, this might indicate that policies are not proportional to the risk perceived by companies. Moreover, there is no international consent in regulatory frameworks which creates barriers for internationally operating FinTechs and hinders proper risk management. Especially systemic risk needs to be controlled across borders since FinTech lending markets grow together. Additionally, the sufficiency of current regulation concerning firm-specific risk is unsure. Business models have not been tested through an entire cycle and hence a lot of uncertainty remains. Regulators have to understand the ever-evolving business models in order to formulate appropriate regulation.

Naturally, it has to be considered that the extent of FinTech activities compared to the entire financial market is still small and therefore not the center of regulatory focus. However, regulation should be proactive and prepare for an amplification in FinTech activity. For countries across Europe, Figure 18 plots the perceived adequacy of national regulation against the volume of alternative finance in the country. A positive pattern can be seen in the scatterplot. According to the interpretation of the Cambridge Centre for Alternative Finance, this suggests that regulation should be improved to facilitate alternative finance volume growth. Therefore, an adaptation of the regulation of FinTech lending platforms is necessary to foster further growth.

Figure 18: Alternative Finance Volume per Capita vs Perceived Adequacy of Regulation (Data from 2016)

From: Cambridge Centre for Alternative Finance. (2018). Expanding Horizons: The 3rd European Alternative Finance Industry Report. p. 53



PL – Poland; LT – Lithuania; DE – Germany; CH – Switzerland; ES – Spain; IT – Italy; NO – Norway; EE – Estonia; NL – Netherlands; CZ – Czech Republic; FR – France; DK – Denmark; BE – Belgium; UK – United Kingdom; FI – Finland; SE – Sweden; AT – Austria

I.9.4. Recommendation

A better understanding of business models and risks can be achieved by applying stress testing methodology to FinTech companies.

Stress testing is applied commonly to banks since the financial crisis of 2008, in order to ensure sufficient capitalization of banks and avoid further crises. In the US, an annual stress test, the Dodd-Frank supervisory stress test, is applied together with a capital adequacy test, the Comprehensive Capital Analysis and Review, to systemically important financial institutions, namely "all Bank Holding Companies and US Intermediate Holding Companies with $50 billion or more in total consolidated assets" (Federal Reserve, 2017). In the European Union (EU), the European Banking Authority initiates EU-wide stress test exercises at regular intervals. The sample of banks in the test is chosen to cover about 70% of the banking sector of EU member states and Norway, including financial institutions having a minimum of 30 billion Euro in assets (European Banking Authority, 2017).

The key idea of stress testing is to identify and measure situations that lead to vast but extremely unlikely losses for financial institutions. Therefore, scenario analysis is conducted on adverse but plausible economic scenarios that are generated following different procedures. Purely quantitative approaches include using historic data or magnifying observations from historic events to create more extreme scenarios. If a group of variables is altered beyond their historic levels, it is necessary to include the interaction between variables. Moreover, scenario building can be enhanced by including qualitative judgement from expert panels such as senior management, that generate scenarios based on historical data while including current trends in the financial and economic environment. Importance is placed on the completeness of scenarios, in that they have to include systemic effects such as contagion as well as responses by the financial institution and other market participants. (Hull, 2012)

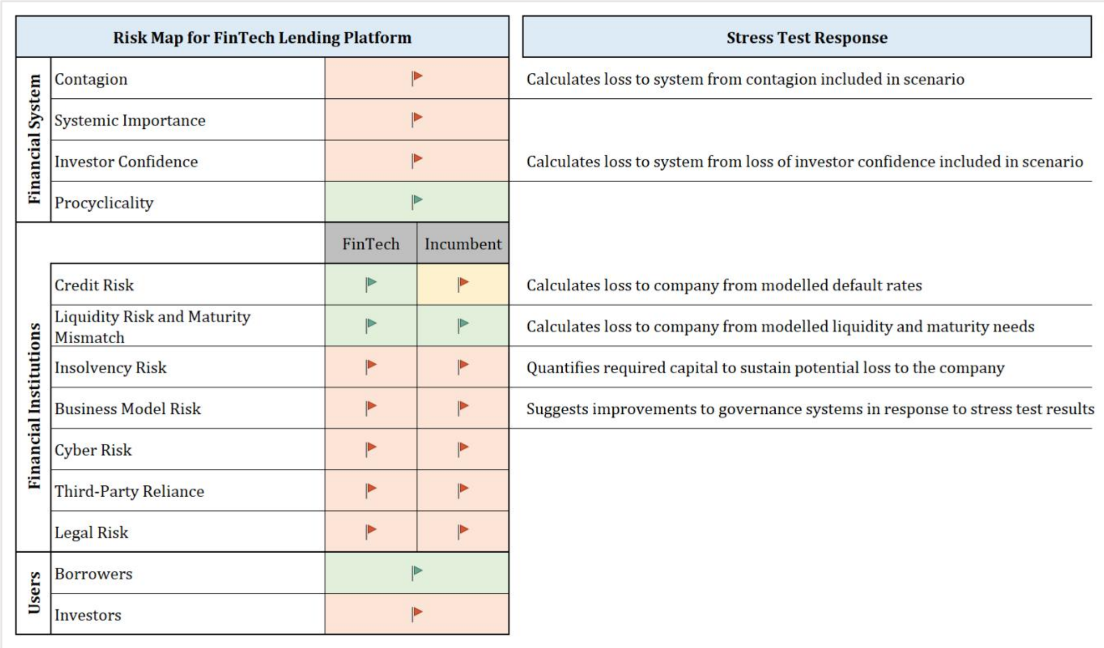
The advantages of this risk measurement technique are multifaceted. First, scenarios are not bound by historic data and therefore stress testing allows for forward looking results. Especially for analyzing the FinTech sphere where there is not much historic data for analysis and the industry is ever changing this will be beneficial. Second, there are no assumptions about the probability distribution of financial variables, which secures that computations are closer to reality. Third, stress testing assigns a value to the loss exhibited by the institution in an adverse scenario which enhances planning, especially for young companies that do not have a large capital buffer inherently. Additionally, the Basel Committee stresses the importance of stress testing after long periods of economically favorable conditions since these conditions tend to lead to complacency (Hull, 2012). FinTech companies have solely experienced favorable times so far, therefore a stress test in this moment could be a means to curtail over-confidence in business models. As a fourth advantage, stress testing includes systemic risk which was identified in the study as a major risk factor concerning FinTech lending platforms.

Further motivation for using a stress testing methodology can be found in financial regulation. Stress testing has become an important tool in calibrating microprudential and macroprudential regulations across major economies. The ability of financial institutions to withstand economically adverse scenarios is tested, in order to assess the adequacy of and ensure compliance to microprudential regulatory requirements such as capital requirements. Additionally, stress test results can be used to evaluate and measure vulnerabilities of the financial system to consequently adjust macroprudential regulations with the aim of preserving financial stability. (Berner, 2017)

In May 2009, the Basel Committee's stress testing principles were published as a response to the global financial crisis and an updated version of these principles was proposed in 2017. The principles include guidelines for banks and regulators but are not binding. A stress test for FinTech could be constructed following this example. Banks are directed to integrate stress testing into governance and risk management practices and allow for its results to impact decision making. According to the Basel principles, the results of these tests help in identifying risks and controlling them, in enhancing capital and liquidity management and in refining internal and external communication. Stress tests should be applied to all business areas of the bank to assess firm-wide risk. The scenarios chosen for the stress test should be forward looking and multifaceted and should include systemic as well as feedback effects. Supervisors are commended to assess banks' stress tests comprehensively on a regular basis and challenge the methodology if necessary. Additionally, they should require banks to act on the results of the stress test. The Basel Committee publishes no scenarios but advises regulators to perform stress tests based on common scenarios, which is the reason for regional differences in stress testing. (Basel Committee, 2017)

If these guidelines were implemented for a FinTech lending platform, stress testing could aid in approaching the previously identified risks. Figure 19 links the risk map to the proposed actions of and results from a stress test. The potential losses from the systemic risks of contagion and loss of investor confidence are modelled in the scenario. The extent of this risk can be assessed in the stress test and regulatory actions can be modified based on these results. The remaining systemic risk arising from systemic importance as well as procyclicality are not addressed through the stress test. Financial firm-specific risk is the main concern of a conventional stress test and therefore credit risk, liquidity risk and maturity mismatch are modelled in the test and insolvency risk is reduced by adjusting required capital amounts to the calculated potential losses. Concerning operational firm-specific risk, only business model risk is approached in the stress test by using the results to improve governance systems and risk management. Cyber risk, third-party reliance and legal risk are not addressed in the stress test.

Figure 19: The Interaction of Stress Testing with Risk Factors



FinTech stress test scenarios could be either created as reduced forms of the bank stress test scenarios that are published by major central banks such as the ECB and the FED, or stand-alone scenarios could be developed. This would be costly and considering the current size of FinTech impact, a cooperation across regulations in constructing the tests is advised. The cooperation could entail further positive effects, such as the international discussion of stress test outcomes and risk exposure of FinTech lending platforms. This in turn will spark the discussion on regulatory responses and could optimally lead to a much-needed convergence in regulation.

I.10. **Conclusion**

FinTech companies introduce financial innovation through leveraging technological advances with the goal to improve financial services by reducing cost, increasing efficiency or increasing customer experience. Their evolution began shortly after the financial crisis of 2008 when trust in conventional financial institutions was low and entry barriers reduced. However, the new entrants face unparalleled challenges in the new market. Financial markets are prone to failure due to problems arising from negative externalities, asymmetric information, biased market participants, the characteristics of a public good and imperfect competition. Therefore, they are heavily regulated to achieve the objectives of financial stability, soundness of financial institutions, investor protection and well-functioning markets.

This thesis focuses on FinTech lending platforms, which facilitate credit provision by matching private borrowers and private as well as institutional investors directly. FinTech lending platforms are currently small but have a large potential to become systemically important. Therefore, regulators have to understand business models, adapt regulation and react quickly to changing circumstances. However, there is limited data available to perform these tasks adequately and FinTech business models have not been tested through a full financial cycle.

The objective of this study is to detect risks associated with FinTech lending platforms and discuss regulatory implications. For this purpose, firstly a detailed risk mapping of FinTech lending platforms was conducted, regarding the impact on risk for the financial system, financial institutions and users. Secondly, a quantitative analysis on drivers of loan volume using data of the FinTech lending platform LendingClub was undertaken. Loan volume was identified as a revenue driver for the selected FinTech company and therefore the analysis aimed at identifying macroeconomic and firm-specific drivers of profitability.

The discussion finds increases in systematic risks with the introduction of FinTech lending platforms, such as contagion risk, risk arising from systemic importance, from loss of investor confidence and from the procyclicality of credit provision. Some firm-specific risks, for example credit and liquidity risk, are decreased compared to the conventional lending model, whereas others, such as insolvency risk, business model risk, cyber risk, risk arising from third-party reliance and legal risk, are increased both for incumbents as well as FinTechs. Borrowers experience decreased risk through FinTech lending platforms whereas investors are exposed to more risk.

The quantitative analysis finds that loan volume is driven by a number of macroeconomic variables, however their coefficients' signs suggest a countercyclical association. Therefore, the risk arising from procyclical credit provision that is inherent to the conventional lending model seems to be averted in FinTech lending platforms. However, the analysis finds that firm-specific risk, such as a scandal related to the platform, decreases loan volumes significantly and therefore poses high risk.

Regulators need to react to these changes in risk factors through FinTech lending platform business models. The analysis and further surveys suggest, that the current regulation is not appropriately addressing these risk factors. There is no international consistency whereas the FinTech lending market is integrating and a level playing field is needed for internationally operating companies. In order to improve the regulators' understanding of business models and related risk, it is suggested that stress tests are performed on FinTech lending platforms. It has not been observed how the business models behave under adverse economic conditions and therefore stress testing the companies on hypothetical adverse scenarios will support regulators in formulating appropriate regulations and companies in creating contingency plans.

There are various limitations to this study. Due to the high flexibility and agility of FinTech business models, risks change on an ongoing basis and have to be evaluated continuously (European Central Bank, 2017). This implies that the findings from this study might lose relevance with time. Moreover, the data used for this analysis is related to a single company and the effects detected could also be specific to this organization and therefore not generally applicable.

For further research, testing other FinTechs and conducting a cross-country comparison would be beneficial. Moreover, with the access to detailed firm-specific data, a stress test on a FinTech lending platform could be performed and the method's suitability for regulation setting could be assessed.

PART II

II. Testing the Cyclicality of FinTech Lending Platforms[1]

[1]Part II is required to exist independently of part I and therefore the following content contains summaries of several sections from part I, such as the data description of macroeconomic and firm-specific factors.

II.1. **Introduction**

The quantitative study presented in part I of this thesis, hereafter analysis I, examines the macroeconomic and firm-specific factors influencing a FinTech lending platform's revenue. These platforms match borrowers and investors directly and promise lower rates and higher returns than conventional financial institutions. The study finds that the systemic risk arising from procyclical credit provision appears in the conventional lending model but is suspended with the introduction of FinTech lending platforms. The study further finds that a scandal involving the platform reduces the revenues significantly and therefore identifies high firm-specific risk for FinTech lending platforms.

Analysis I analyzes only one company, the US based platform LC, and therefore also only one geographic market. It is problematic to generalize the findings, since the detected dependencies could also be firm- or country-specific. Moreover, a period without large financial disruptions is used for this analysis and therefore the findings might not hold under more adverse conditions.

The second part of this thesis expands the research to a second company, Zopa, and to a different region, because the company is based in the UK. Moreover, since the company already operates longer than LC, more data is available, and a longer time period can be analyzed. This allows to test the findings from analysis I out-of-sample and out-of-time.

In order to allow for a useful comparison, the back-testing exercise uses the same methodology as analysis I. It confirms the finding of countercyclicality in loan volumes of the analyzed platform. Moreover, it finds that the loss of investor confidence does not affect platforms in other markets and appears to be a firm-specific and not a systemic risk.

Part II is structured as follows: First, a description of the relevant data to conduct the analysis is given (II.2), then the applied methodology is summarized (II.3), followed by a discussion of the results (II.4) and a conclusion of this thesis (II.5).

II.2. **Data**

II.2.1. FinTech Lending Platform

Zopa is the FinTech lending platform which is chosen for the back testing. It operates in the UK and was launched in 2005, which makes it the first company world-wide to engage in a P2P lending business model (Zopa, 2018). The business was initiated before the financial crisis of 2008, which makes it an interesting target for this analysis.

The company operates the traditional FinTech lending platform business model, where it provides credit assessment of borrowers, matches borrowers and investors and sets the loan parameters as well as originates the corresponding loans (Bank for International Settlements & Financial Stability Board, 2017). The loans are originated for fixed periods of 1 to 5 years. In contrast to the notary model employed by LC, no partner bank is included in the loan origination process. However, since Zopa is not publicly listed, there is limited information available concerning the business model and it cannot be specified further.

Zopa generates revenues from customers through origination and loan servicing fees that are included in the charged interest rates and from fees charged to investors that want to liquidate their investments before maturity. There is no detailed information about the split between these sources, but for simplicity it is assumed that loan volume is the major revenue driver in Zopa's business model, similar to what was identified in analysis I.

Detailed loan statistics were retrieved from Zopa's website and a total of 498,442 loans were aggregated for this study. Comparing Zopa's loans to the loans processed for analysis I, this constitutes only ¼ in number and a little more than 10% in volume of loans. These numbers show that Zopa is much smaller than LC, even though it started 2 years before. The size difference of their respective home markets, the UK and the US, is an explanation for this difference. Table 9 compares relevant loan related statistics of the two companies, supporting a deeper understanding of the different time series underlying the analyses. Zopa originates loans with lower principals in comparison to LC, charges a lower spread over the risk-free rate and shows a lower default rate. From this comparison it can be inferred, that Zopa originates loans to more creditworthy borrowers and offers less risky investments to investors, compared to LC.

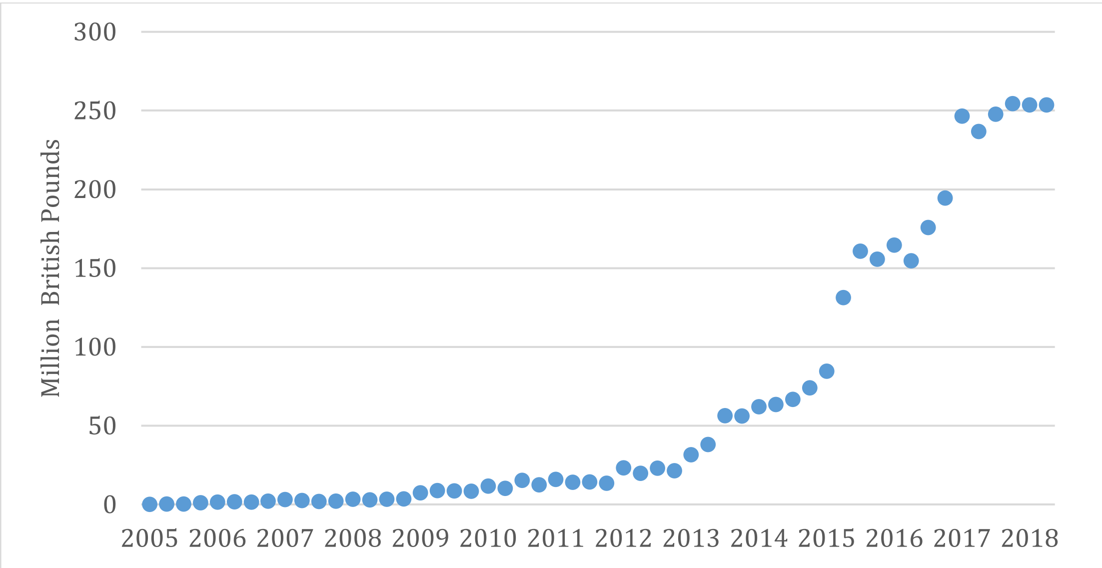
Table 9: Average Loan Statistics of Zopa and LendingClub

Company	Average Loan Amount	Average Interest Rate Spread	Average Default Rate
Zopa	£ 7031	5.6%	0.53%
LC	$14960	11.14%	1.12%

Similar to LC, the development of Zopa's loan volume is exponential but without apparent decreases in loan volumes. There have been no scandals involving Zopa or any other UK based FinTech lending platform.

Figure 20: Zopa Loan Volume by Quarter

Created from: Zopa. (2005-2018). Loan Statistics



The demand for loans relates to the loan applications received by Zopa. The loans are categorized by their purposes and from Zopa's website, it can be inferred that the most demanded ones are for cars, home improvement and debt consolidation. There are 20 further purposes, including credit card repayment and business loans, that borrowers can choose from. (Zopa, 2018)

The supply of loans entails the amount of funds invested through the platform. Investors were initially only private but since 2014, Zopa is collaborating with institutional investors as well. Zopa offers several investment products that differ in the riskiness of invested loans (Zopa, 2018).

The demand for and supply of loans are influenced by various factors, which are discussed in the following sections. These factors are important in understanding the drivers of loan volume and hence platform revenue.

II.2.2. Macroeconomic Factors

General Economy

The UK Gross Domestic Product (GDP) is a general indicator of the economic performance of the country and influences the demand for and supply of funds. A high GDP lowers the demand for credit because borrowers are better off financially, whereas the fund supply will increase because investors have more money to invest. Analysis I found a negative association between the changes in loan volume and GDP. Data is available only on a quarterly basis and nominal values from UK's national statistical institute, the Office for National Statistics, are used.

The unemployment rate in the UK (UNEMP) is expected to have an ambiguous effect on loan volume. Higher unemployment will increase the demand for credit, since a household's income may decrease abruptly. However, if investors are mainly private, higher unemployment rates may decrease the loan supply. Since there is no distinct information about the share of different investors, the direction of the association cannot be predicted. Analysis I finds a positive association between changes in loan volume and unemployment. For this analysis, quarterly data is taken from the Office for National Statistics.

The UK consumer price index (CPI) measures the price level in the UK over time. A higher price level decreases the real household income and leads to an increase in the demand for loans. The analysis for the US based company LC found a negative sign of association between the change in loans and inflation, which is contrary to economic intuition. In order to back-test these results, quarterly data from the Office for National Statistics is used.

UK government bond yields (TY12, TY24, TY36, TY48 and TY60) with a fixed maturity of 1, 2, 3, 4 and 5 years respectively represent the return on a risk-free investment with a same maturity as the loans originated by Zopa. High risk-free rates decrease the demand for loans because of increased borrowing cost. The supply is expected to decrease as well, since more risk averse investors might switch to the low risk alternative that provides a sufficient yield now. Combined, the effects suggest a negative relation between loan volume and treasury yields which is confirmed in analysis I. Monthly yields are obtained from Investing.com and are transformed to quarterly intervals.

Industry

The amount of funds invested in deals involving FinTech companies in the UK (FinTech) is included as a proxy for the rising popularity of FinTech. Investor trust is gained with rising popularity and hence loan volume will increase. The data is taken from the CBInsight website and is aggregated quarterly.

The total credit provided by UK banks to the private non-financial sector in the UK (Credit) is a proxy for the demand for loans. It includes all loans given to non-financial corporations and households and therefore overstates the target market of Zopa. The quarterly data is taken from the Federal Reserve Bank of St. Louis' FRED database.

The debt volume of households in the UK (Debt) is a further proxy for loan demand. Quarterly volumes are calculated using ratios obtained from the Federal Reserve Bank of St. Louis' FRED database.

Household Financial Situation

Household debt service payments as a percentage of disposable income (DDSP) quantifies the ability of households to service their financial commitments from debt. A higher debt service ratio indicates a worse financial situation of the household and loan demand for FinTech loans will increase, since households will look for cheaper financing options. However, the approval rate for loan applications might decrease, since households will be less likely to meet commitments to Zopa. Therefore, the true effect on loan demand is ambiguous. The data is quarterly and obtained from the BIS.

The aggregate disposable income in the UK (DSP) shows how much income households have at their disposal. Loan demand will increase with falling income whereas loan supply from private investors will decrease. Therefore, the relation to loan volume is ambiguous.

Annual data is obtained from the Office for National Statistics and is interpolated quarterly.

Risk Indicators

The Country-Level Index of Financial Stress for the UK which is published by the ECB (StressIndex) measures the degree of financial stress in the UK. It shows high levels for the periods of the financial crisis of 2008 and the Brexit referendum in 2016. A higher financial stress index is assumed to increase loan demand but simultaneously reduce investment appetite for risky investments such as FinTech loans and its effect is therefore ambiguous. The index is aggregated quarterly and obtained from the statistical data warehouse of the ECB.

The Financial Times Stock Exchange (FTSE) Implied Volatility Index (FTSE100VIX) measures the implied volatility of the FTSE100 which is a share index of the 100 biggest companies listed on the London Stock Exchange (LSE). It quantifies expectations on future volatility in the British financial market. A high index indicates that investors expect large movements in the market whereas a low index indicates expectations of small or no movements. This risk indicator captures the risk experienced by investors and is therefore expected to negatively influence loan volume, since a high index relates to high expected volatility and lower risk appetite. Quarterly data points are obtained from Investing.com.

Equity Markets

The FTSE250 Index (FSTE250) is an index comprising the 250 largest companies listed on the LSE. For the analysis, this broader index is used because it includes more British companies and therefore is a better indicator for the state of the British economy and its business cycles. Since loan demand is expected to move countercyclically and loan supply procyclically, the effect on loan volume is uncertain. Quarterly data is aggregated from Investing.com.

Furthermore, proxies for the performance of alternative investments are included. The Fama & French Three-Factor Asset Pricing Model (1993) describes equity returns that investors can earn with different factors (Fama & French, 1993). The market return over the risk-free rate (Mkt-RF) shows the excess return from market risk. The Small-Minus-Big factor (SMB) is the size factor that measures the excess return of small over big companies. The High-Minus-Low factor (HML) is the value factor that measures the excess return of companies with a high book-to-market ratio over those with a low ratio. High performance of these factors is expected to decrease loan supply since investors have attractive alternatives. Quarterly data is obtained from the Kenneth R. French website. There is no data available for the size factor, therefore it is not included in this analysis.

II.2.3. Firm-Specific Factors

The excess interest rate over the risk-free rate (ZopaSpread) is the interest rate charged by Zopa minus the UK government yield with the respective maturity. It represents the risk premium of the borrower or the excess return on an investment in a Zopa loan. A high premium has a negative effect on loan demand since borrowing costs are increased, but a positive effect on fund supply since the return is increased simultaneously. The overall effect on loan volume is therefore ambiguous. Analysis I found a positive association. A volume-weighted average is calculated from the loan database in a quarterly interval.

The default rate of Zopa's loans (Default) shows how many defaults occurred in a period in relation to the total outstanding loan volume. A high default rate is expected to deter investors and therefore decrease loan supply and loan volume. In analysis I, a negative relation is found which was attributed to lurking variables. The rate for this analysis is calculated from the loan database by defining default to include the loan status of "Default" and "Late".

Compared to analysis I, there are a few factors missing in this analysis due to issues of data availability. The factors that could not be included are the outstanding consumer loans, some indicators of the financial situation of households such as household financial obligations as a percentage of disposable income, the size factor from the Fama-French model and some firm-specific factors such as the spread between the interest charged on low and high-risk loans.

II.3. **Research Methodology**

In analysis I, a study on macroeconomic factors impacting loan volumes has been conducted to add quantitative arguments to the discussion of risk. However, since only one company was analyzed, it was uncertain whether the results were firm-specific or could be generalized. In order to expand the research, the same methodology used in analysis I is applied to Zopa, to test the models' findings out-of-sample. Moreover, by expanding also the time-frame of available data, the findings are tested out-of-time.

II.3.1. Data Set Construction

In order to ensure a meaningful back-testing, the data interval is quarterly, similar to analysis I. From the available data, two datasets were constructed: dataset 1 has the same timeframe as analysis I, which includes 39 observations starting from the third quarter of 2008. Dataset 2 starts with the initiation of Zopa, which is already in the third quarter of 2005 and has therefore 12 observations more. The three extra years are included in the analysis to back-test the models out of time. In the second dataset, the variables Debt, FinTech and Default are excluded since there is no data available earlier than 2008.

Following the methodology applied in analysis I, the time series are checked for unit roots by applying ADF testing. Appendix 7 shows that for both datasets all variables have unit roots in their levels. Taking the first difference removes the unit roots for all variables.

Moreover, the data set is extended by duplicating the independent variables and shifting them by one period forward, in order to account for lagged effects on loan volume. Since the default rate can only be observed after the period and hence affects the borrower's and lender's behavior later, this variable is shifted for one quarter as a base variable and for two as the lagged one.

In analysis I, a dummy variable for the scandal involving the company of interest was included in the models. Zopa never had any public scandal, but because the LC scandal impacted the entire FinTech Lending sphere it is included in this analysis as well. Since the effect is not specific to Zopa and therefore less precisely assessable, several dummies extending over different periods, from 1 to 4 quarters, are tested.

Furthermore, t-tests were performed to detect significant subgroups in the datasets. The tests find seasonal effects in dataset 1, for the first and the fourth quarter, but none in dataset 2. Therefore, two dummy variables for the respective quarter are included in the analysis of the first dataset. Since Zopa publishes no details on the purpose of the loans in their loan books, differences in purpose subgroups cannot be tested. The detailed results are shown in Appendix 7.

Further descriptive statistics on the two databases are presented in Appendix 8.

II.4. **Results**

II.4.1. Univariate Analysis

Linear models including only one explanatory variable are fitted in order to detect and understand the relationships between Zopa's loan volume growth and a range of independent variables, presented in the preceding section. For dataset 1, 48 independent variables were tested by running linear regressions applying equation 5. For dataset 2, 42 regressions were run.

$$\Delta LoanVolume = Intercept + \beta * Independent\ Variable \quad (5)$$

Table 10 and Table 11 show the relevant variables for dataset 1 and 2 respectively, which have a significant coefficient in the regression with the change in loan volume. Moreover, a dummy variable for the LC scandal spanning over 4 quarters is included for model building purposes, despite its insignificance. From these variables, multivariate models are constructed and therefore a careful analysis is required beforehand.

The regression outcomes are ordered by their respective R^2 score, which indicates the fit of a variable as an explanatory input for modelling the dependent variable. The variables that have significant coefficients all show R^2 scores of above 5% and therefore no variable is excluded based on this score.

Further, the tables show the expected sign of association from the data discussion and the ones found in analysis I. The results for dataset 1 are predominantly corresponding to the ones from analysis I, except for the lagged excess market return and the fourth quarter dummy variable. For dataset 2, Zopa's interest rate spread and the market index FSTE250 have different signs of association than the ones found in analysis I. Compared to the expected signs from economic intuition, the firm-specific variable of the default rate shows a different sign of association in both datasets. Similar to the discussion in analysis I, this deviation is assumed to originate from lurking variables that distort the interpretation of the coefficient. Therefore, the variable is excluded from further analysis in order to avoid spurious regression problems. There are further deviations affecting macroeconomic variables, however they are not as severe as the firm-specific ones, since associations are not as direct and might be multilayered.

Table 10: Univariate Regression Results – Dataset 1

Variable	R2	Exp. Sign	LC Sign	Coefficient	P-Value		Intercept	P-Value	
Δ Default-1	0.349	-	+	0.223	0.000	***	0.103	0.009	**
Δ Mkt.RF	0.321	-	-	- 2.079	0.000	***	0.161	0.000	***
Δ DDSP	0.260	~		- 9.413	0.001	**	0.078	0.068	°
Δ CPI	0.137	+	-	-18.881	0.021	*	0.251	0.000	***
Δ FTSE250 (-1)	0.127	~	-	- 1.092	0.026	*	0.171	0.000	***
Δ UNEMP	0.096	+	+	1.890	0.055	°	0.157	0.001	**
Δ GDP (-1)	0.090	~	-	- 9.021	0.064	°	0.207	0.000	***
Δ Mkt.RF (-1)	0.085	-	-	1.066	0.072	°	0.140	0.002	**
Δ TY12 (-1)	0.073	-	-	- 0.159	0.095	°	0.154	0.001	**
Q1 (Dummy)	0.224			0.285	0.002	**	0.074	0.104	
Q4 (Dummy)	0.118		+	- 0.207	0.032	*	0.200	0.000	***
LC4 (Dummy)	0.009	-	-	- 0.074	0.568		0.156	0.002	**

**** p<0.001; **p<0.01; *p<0.05; °p<0.1*

Table 11: Univariate Regression Results – Dataset 2

Variable	R2	Exp. Sign	LC Sign	Coefficient	P-Value		Intercept	P-Value	
Δ Mkt.RF	0.199	-	-	- 3.748	0.001	**	0.221	0.004	**
Δ ZopaSpread	0.183	~	+	- 0.973	0.002	**	0.264	0.001	**
Δ UNEMP	0.149	+	+	5.369	0.005	**	0.226	0.004	**
Δ FTSE250	0.056	~	-	1.663	0.094	°	0.179	0.036	*
LC4 (Dummy)	0.003	-	-	- 0.113	0.713		0.226	0.111	

**** p<0.001; **p<0.01; *p<0.05; °p<0.1*

II.4.2. Multivariate Analysis

The models for loan volume growth can be enhanced by including more than one independent variable.

Multiple regression models however, may estimate coefficients poorly due to multicollinearity problems. Therefore, the correlation between the independent variables has to be examined. Appendix 9 includes two correlation matrices for the two datasets. For dataset 1, the lagged change in GDP showed a critically high absolute correlation of above 0.7 with the change in unemployment. For dataset 2, no critically high correlation can be detected.

First, the results for dataset 1 are discussed. Equation 6 defines the first model, in which all independent variables with an R^2 score in the univariate regression of above 20% were included as well as three dummy variables.

$$\Delta LoanVolume = Intercept + \beta_1 * \Delta Mkt - RF + \beta_2 * \Delta DDSP + \beta_3 * Q1 + \beta_4 * Q4 + \beta_5 * LC4 \tag{6}$$

Table 12 shows the results of applying this model to dataset 1. The adjusted R^2 is approximately 55% and the statistically significant variables are the excess market return, the change in debt service as a percentage of disposable income and the first quarter dummy.

The second model expands model 1 to all variables with an R^2 of above 10%, which means that two variables are added.

$$\Delta LoanVolume = Intercept + \beta_1 * \Delta Mkt - RF + \beta_2 * \Delta DDSP + \beta_3 * \Delta CPI + \beta_4 * \Delta FTSE250(-1) + \beta_5 * Q1 + \beta_6 * Q4 + \beta_7 * LC4 \tag{7}$$

The results from the second model are presented in Table 12 as well. The adjusted R^2 of the model increases by 10% compared to model 1 to 65% and can thus explain more of the variation in the change of loan volume. The excess return on the market, the lagged market index and the first quarter dummy show a significant coefficient.

Model 3 is defined by equation 8 and includes all independent variables that had significant coefficients in the univariate analysis plus the three dummy variables.

$$\Delta LoanVolume = Intercept + \beta_1 * \Delta Mkt - RF + \beta_2 * \Delta DDSP + \beta_3 * \Delta CPI$$
$$+\beta_4 * \Delta FTSE250(-1) + \beta_5 * \Delta UNEMP + \beta_6 * \Delta GDP(-1) + \beta_7 * \Delta Mkt - RF(-1)$$
$$+ \beta_8 * \Delta TY12(-1) + \beta_9 * Q1 + \beta_{10} * Q4 + \beta_{11} * LC4 \qquad (8)$$

From Table 12 it can be seen that only the excess return on the market and the first quarter dummy have significant coefficients. There seems to be some interaction between the variables that erases their significance when analyzed together, even though the correlation matrix found only one strong correlation.

The fourth model focuses on macroeconomic variables. It includes 5 variables describing the general economic condition of the UK but excludes the market index. Moreover, only the first quarter dummy and the LC scandal dummy were added.

$$\Delta LoanVolume = Intercept + \beta_1 * \Delta Mkt - RF + \beta_2 * \Delta DDSP + \beta_3 * \Delta CPI$$
$$+ \beta_4 * \Delta UNEMP + \beta_5 * \Delta GDP(-1) + \beta_6 * Q1 + \beta_7 * Q4 + \beta_8 * LC4 \qquad (9)$$

Table 12 shows that the model achieves an R^2 score similar to the other models, even though a main explanatory variable, the market index, was excluded. In model 4, in contrast to the other models, inflation and unemployment have significant coefficients.

Table 12: Dataset 1 Multivariate Regression Results

	Model 1		Model 2		Model 3		Model 4	
R Squared	0.548		0.653		0.691		0.651	
Observations	39		39		39		39	
	Coefficient	**P-Value**	**Coefficient**	**P-Value**	**Coefficient**	**P-Value**	**Coefficient**	**P-Value**
Intercept	0.103	0.041 *	0.161	0.012 *	0.188	0.008 **	0.199	0.005 **
Δ Mkt-RF	- 1.394	0.006 **	- 1.596	0.001 ***	- 1.679	0.001 ***	- 1.534	0.002 **
Δ DDSP	- 5.246	0.044 *	- 3.083	0.205	- 0.946	0.737	- 1.539	0.573
Δ CPI			- 3.234	0.605	- 8.894	0.282	- 14.869	0.042 *
Δ FTSE250 (-1)			- 0.979	0.010 **	- 0.658	0.139		
Δ UNEMP					2.007	0.132	2.829	0.021 *
Δ GDP (-1)					3.857	0.496	5.714	0.302
Δ Mkt-RF (-1)					0.160	0.764		
Δ TY12 (-1)					0.001	0.991		
Q1 (Dummy)	0.162	0.046 *	0.162	0.042 *	0.162	0.053 °	0.142	0.076 °
Q4 (Dummy)	- 0.106	0.172	- 0.097	0.170	- 0.105	0.155	- 0.115	0.111
LC4 (Dummy)	0.012	0.913	- 0.026	0.785	- 0.028	0.782	- 0.002	0.984

****** p<0.001; **p<0.01; *p<0.05; °p<0.1***

Considering dataset 2, only four independent variables had significant coefficients in the univariate analysis and were available for model building. The measurable relationships between the changes in macroeconomic variables and the change in loan volume might be less strong for dataset 2, since it includes all periods of the financial crisis of 2008. The change in loan volume has a higher standard deviation in dataset 2, which means more variability has to be explained by the independent variables and the explanatory power of the models decreases.

Model 1 is defined by equation 10. It includes the variables with an R^2 of above 10% and a LC scandal dummy.

$$\Delta LoanVolume = Intercept + \beta_1 * \Delta Mkt - RF + \beta_2 * \Delta ZopaSpread + \beta_3 * \Delta UNEMP + \beta_4 * LC4 \quad (10)$$

Table 13 shows the result of applying model 1 to dataset 2. The R^2 is relatively low compared to the previous models, but all variables except for the scandal dummy have significant coefficients.

The second model for dataset 2 includes the change in the market index as an additional explanatory variable.

$$\Delta LoanVolume = Intercept + \beta_1 * \Delta Mkt - RF + \beta_2 * \Delta ZopaSpread + \beta_3 * \Delta UNEMP + \beta_4 * \Delta FTSE250 + \beta_5 * LC4 \tag{11}$$

The R^2 of the model increases slightly compared to model 1, however the added variable is not significant.

Table 13: Dataset 2 Multivariate Regression Results

	Model 1			**Model 2**		
R Squared	0.374			0.378		
Observations	51			51		
	Coefficient	**P-Value**		**Coefficient**	**P-Value**	
Intercept	0.257	0.001	***	0.245	0.002	**
Δ Mkt-RF	- 2.538	0.023	*	- 2.230	0.083	°
Δ ZopaSpread	- 0.604	0.045	*	- 0.597	0.049	*
Δ UNEMP	4.525	0.009	**	4.692	0.009	**
Δ FTSE250				0.486	0.628	
LC4 (Dummy)	0.001	0.998		0.001	0.997	

****** p<0.001; **p<0.01; *p<0.05; °p<0.1***

II.4.3. Robustness Tests

To assess the robustness of the models, the residuals are tested for normality and autocorrelation.

An underlying assumption of regression analysis is that the residuals of resulting models follow no pattern and are normally distributed. The Shapiro-Wilk test for normality was used to assess whether the residuals of the models from this analysis are normal and the results are presented in Tables 14 and 15. A high p-value (>10%) indicates normality, which is the case for all models from dataset 1 but not for dataset 2. Both models of dataset

2 have residuals that deviate from a normal distribution. However, since the results are not used for generating predictions, this deviation is not limiting to the interpretation of coefficients.

The second test concerns the autocorrelation of a model's residuals. The p-value indicates the significance of the slope coefficient of a model which regresses the residuals on lagged residuals. Hence, a high p-value indicates no autocorrelation, which is the case for all models of both datasets.

Table 14: Results from Robustness Checks of Models for Dataset 1

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Shapiro-Wilk	0.101	+	0.071	+	0.429	+	0.165	+
Autocorrelation	0.587	+	0.777	+	0.135	+	0.060	+

+ p>0.05; ! p<0.05

Table 15: Results from Robustness Checks of Models for Dataset 2

	Model 1		**Model 2**	
Shapiro-Wilk	0.000	!	0.000	!
Autocorrelation	0.256	+	0.288	+

+ p>0.05; ! p<0.05

II.4.4. Discussion

The multiple regressions confirm that there is a strong association between the change in Zopa's loan volume and macroeconomic variables. Table 16 summarizes the significant variables from dataset 1, 2 and from analysis I. Compared to the results from analysis I, different variables have significant coefficients. Only inflation, change in interest rate spread and change in unemployment are significant for both companies. Despite these differences, it can still be analyzed whether the change in loan volume is pro- or countercyclical.

Table 16: Significant Variables from the Multiple Regressions and their Coefficient's Sign

Variable	Sign of Association Dataset 1	Sign of Association Dataset 2	Sign of Association LC
Δ Mkt-RF	-	-	
Δ DDSP	-		
Δ CPI	-		-
Δ FTSE250 (-1)	-		
Δ UNEMP	+	+	+
Δ ZopaSpread		-	+
Q1	+		

The analysis shows a negative relation between the change in loan volume and the change in the excess market rate for both datasets. This indicates that an increase in the excess return on the market coincides with a decrease in loan volume. The variable was included as an alternative investment for investors in Zopa's loans and the detected negative relation matches the economic intuition of a substitute investment. A high return on the market usually coincides with a prosperous economic state and therefore this finding suggests a countercyclical movement of Zopa's loan volume.

The change in the debt service ratio has a significant negative relation with the change in loan volume in the first dataset. In other words, when the share of disposable income used for interest payments is high, loan volume growth is low. This can be explained by the lower creditworthiness of households and resulting rejections of loan applications.

For the two analyses with the shorter time frame (analysis I and dataset 1), inflation has a negative sign of association with the change in loan volume. As already discussed in analysis I, this sign does not follow the economic intuition which would suggest a positive relation. However, this finding can be explained by the Fisher effect, which states that a high inflation leads to higher interest rates (Blanchard, Amighini, & Giavazzi, 2010). Increases in the interest rate lead to higher borrowing costs and decrease the demand for loans. As high inflation usually occurs when the economy is thriving, this finding suggests a countercyclical movement of loan volume.

The lagged change in the market index shows a negative relation to the change in loan volume for dataset 1. Since this variable is often used as an indicator of business cycles, a negative relation supports the hypothesis of a countercyclical movement of loan volumes. This variable is significant in its lagged form, since investors make the decision to switch investments after they have observed the higher returns.

The change in unemployment shows a positive sign of association for all three datasets from the two analyses. Higher unemployment decreases household income and therefore increases the demand for credit. This variable drives a countercyclical development of loan volume.

The regressions using dataset 2 show a negative relation between the interest rate spread on Zopa's loans and the change in loan volume. A higher spread implies higher borrowing costs and hence decreases loan volume. In analysis I, a negative relation was detected and attributed to lurking variables. In dataset 2, the relation seems to be captured accurately.

The first quarter has a significant, positive association with the change in loan volume in the first dataset. This means that there are seasonal effects in the movement of loan volume and the first quarter shows significantly higher growth than the other quarters.

Interestingly, some of the variables that were significant in analysis I showed no significance in either dataset of Zopa. Specifically, the change in GDP, the return on the value factor, the change in the stress index and the LC scandal dummy had insignificant coefficients in explaining the change in loan volume.

In conclusion, these results confirm the finding from analysis I, that FinTech lending platforms reduce systemic risk arising from procyclicality. There are several macroeconomic variables that show a strong relationship with loan volume and the association is mostly countercyclical.

Moreover, the finding that default rates have a positive relation with loan volume and hence move countercyclically, indicates that default rates are high when there is economic stress and low when the economy is prosperous. This implies losses for investors in economically adverse times and lower loan supply or higher required rates, which would weaken the countercyclical pattern observed in the two analyses. Therefore, FinTech lending platforms should carefully screen borrowers to keep default rates low.

The scandal involving LC in the US did not impact the loan volume of Zopa in the UK, which leads to a new finding that the risk arising from loss of investor confidence is more firm-specific and less systemic. If one assumes that the US and UK FinTech lending markets are connected enough to have a shared investor confidence, there was no dispersion of uncertainty within the system.

II.4.5. Limitations

Some of the limitations of analysis I have been lifted. This analysis expands the sample to two companies in different countries and therefore the findings are not firm-specific anymore. Moreover, including a larger dataset also repeals the time-frame limitation and includes some more volatile economic times including the full financial crisis of 2008. However, there are still a few limitations in the analysis.

Firstly, the data is still on a quarterly interval, which may aggregate the information too much and may conceal effects. This could be improved by using monthly data and interpolating missing data points.

Secondly, the models have to cope with lurking variables, since broad macroeconomic factors affecting not only the dependent variable are chosen as independent inputs. Therefore, the interpretation of coefficients only involves the direction of association.

Thirdly, the variables chosen for the models should either influence demand for or supply of loans and thus impact loan volume. Since there is more public information about the customers than about the investors, the understanding of demand drivers is higher and these variables might have been picked more precisely. Further research should critically assess the fit of supply factors chosen in this analysis.

II.5. **Conclusion**

Part I of this thesis discusses the risk inherent to a FinTech lending platform's activities and the implications for regulation. Moreover, it includes a quantitative analysis that aims at finding statistical evidence of the identified risk for a single company in the US. Part II extends this analysis to a second company in a different country, the UK, to back-test the results. The chosen company is Zopa, the oldest P2P lending platform worldwide, and therefore a provider of a long history of loan statistics. The availability of longer time-series also allows for a back-testing out-of-time.

The analysis of part II supports the finding of part I, that FinTech lending platform loan volumes move countercyclically. This pattern is detected both in the out-of-sample and out-of-time analysis. The implications of this finding are favorable for financial systems, since the risk of procyclical credit provision inherent to the conventional lending model is repealed. Hence, the introduction of FinTech lending platforms reduces the systemic risk in the lending market.

Further, the analysis finds that a loss in investor confidence for one platform does not cause a similar loss for other platforms. Part I identified the risk arising from loss of investor confidence as a systemic risk, however, this finding proposes that it is rather firm-specific.

Therefore, the findings from the analysis of part II suggest that the introduction of FinTech lending business models reduces systemic risk by suspending it or transforming it into firm-specific risk. This increase in firm-specific risk is a further argument supporting the idea of stress testing proposed in part I, suggesting that FinTech lending platforms should be tested under adverse conditions in order to better assess firm-specific risk, improve regulatory frameworks and allow companies to develop contingency plans.

Part II of this thesis resolved some limitations mentioned in Part I, but the fast-paced development of FinTech markets and the related changing risks in business models are still limitations to the validity of the presented results over time.

For further research, it would be interesting to analyze a FinTech lending platform in an emerging market, such as China, in order to test whether the observed patterns extend to other market structures. Moreover, given the required data inputs, performing a stress test on a FinTech lending platform could add more insight to the discussion of risk exposure and to the assessment of the adequacy of regulatory policies.

References

Agur, I., & Sharma, S. (2015). Rules, discretion and macro-prudential policy. In R. H. Huang, & D. Schoenmaker, *Institutional Structure of Financial Regulation.* Routledge.

Akerlof, G. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics, 84*(3), 488-500.

Aldridge, I., & Krawciw, S. (2017). *Real-Time Risk: What Investors Should Know About FinTech, High-Frequency Trading, and Flash Crashes.* Wiley.

Armour, J., Awrey, D., Davies, P., Enriques, L., Gordon, J. N., Mayer, C., & Payne, J. (2016). *Principles of Financial Regulation.* Oxford University Press.

Bank for International Settlements & Financial Stability Board. (2017). *FinTech Credit - Market Structure, Business Models and Financial Stability Implications.* Retrieved from http://www.fsb.org/wp-content/uploads/CGFS-FSB-Report-on-FinTech-Credit.pdf

Bank for International Settlements. (2013). *Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement.* Retrieved from https://www.bis.org/publ/bcbs255.pdf

Bank for International Settlements. (2018). *Debt service ratios for the private non-financial sector*. Retrieved from https://www.bis.org/statistics/dsr.htm?m=6%7C380%7C671

Bank of Canada. (2017). *Financial System Review.* Retrieved from https://www.bankofcanada.ca/wp-content/uploads/2017/11/fsr-november2017.pdf

Bank of England. (2017). *Annual Report and Accounts - Financial Stability Strategy.* Retrieved from https://www.bankofengland.co.uk/-/media/boe/files/annual-report/2017/boe-2017.pdf?la=en&hash=E221A208FBD6BF5F95AEF2E468BC2FD135EF8525#page=38

Bank of England. (2017). *Financial Stability Report.* Retrieved from https://www.bankofengland.co.uk/-/media/boe/files/financial-stability-report/2017/november-2017.pdf?la=en&hash=F6D65F714A7DC28394BC4FCC9909CCD39E28AD10

Bank of England. (2017). *Stress testing the UK banking system: 2017 Results.* Retrieved from https://www.bankofengland.co.uk/-/media/boe/files/stress-testing/2017/stress-testing-the-uk-banking-system-2017-results

Basel Committee. (2017). *Stress Testing Principles Consultative Document.* Bank for International Settlements. Retrieved from https://www.bis.org/bcbs/publ/d428.pdf

Beck, T. (2017). Chapter 18: Financial Innovation and Regulation. In D. D. Evanoff, G. G. Kaufman, A. Leonello, & S. Manganelli, *Achieving Financial Stability: Challenges to Prudential Regulation* (pp. 249-257). World Scientific.

Berk, J., & DeMarzo, P. (2014). *Corporate Finance* (3 ed.). Pearson.

Berner, R. (2017). Chapter 24: The Macroprudential Toolkit. In D. D. Evanoff, G. G. Kaufman, A. Leonello, & S. Manganelli, *Achieving Financial Stability: Challenges to Prudential Regulation* (pp. 333-352). World Scientific.

Blanchard, O., Amighini, A., & Giavazzi, F. (2010). *Macroeconomics - A European Perspective.* Pearson.

Board of Governors of the Federal Reserve System. (2016). *The Opportunities and Challenges of Fintech.* Retrieved from Board of Governors of the Federal Reserve System: https://www.federalreserve.gov/newsevents/speech/brainard20161202a.htm

Borio, C. (2003). *Towards a macroprudential framework for financial supervision and regulation?* Bank for International Settlements. Retrieved from https://www.bis.org/publ/work128.pdf

Cambridge Centre for Alternative Finance. (2018). *Expanding Horizons: The 3rd European Alternative Finance Industry Report.* Retrieved from https://www.jbs.cam.ac.uk/fileadmin/user_upload/research/centres/alternative-finance/downloads/2018-02-ccaf-exp-horizons.pdf

Carney, M. (2017). *Bank of England.* Retrieved from Building the Infrastructure to Realise FinTech’s Promise: https://www.bankofengland.co.uk/-

/media/boe/files/speech/2017/building-the-infrastructure-to-realise-fintechs-promise.pdf?la=en&hash=50B79E4EA60F9C66898013DD0586061AE2E9392A

CBInsights. (2018). *Volume of FinTech deals in the UK, Q1 2005 to Q2 2008*. Retrieved from http://app.cbinsights.com/collections/

CBInsights. (2018). Volume of FinTech deals in the US, Q3 2007 to Q1 2018. Retrieved from http://app.cbinsights.com/collections/

Chishti, S., & Barberis, J. (2016). *The FinTech Book: The Financial Technology Handbook for Investors, Entrepreneurs and Visionaries.* Wiley.

Dietrich, A., & Wernli, R. (2016). *What Drives the Interest Rates in the P2P Consumer Lending Market? Empirical Evidence from Switzerland.* Retrieved from http://www.efmaefm.org/0EFMAMEETINGS/EFMA%20ANNUAL%20MEETINGS/2016-Switzerland/papers/EFMA2016_0240_fullpaper.pdf

Draghi, M. (2009). *Financial stability in the global environment? Learning the lessons from the market crisis.* Retrieved from Bank for International Settlements: https://www.bis.org/review/r090615a.pdf

European Banking Authority. (2017). *2018 EU-Wide Stress Test - Methodological Note.* Retrieved from http://www.eba.europa.eu/documents/10180/2106649/2018+EU-wide+stress+test+-+Methodological+Note.pdf

European Central Bank. (2016). *Spotlight on Financial Stability*. Retrieved from European Central Bank: https://www.ecb.europa.eu/explainers/tell-me-more/html/financial_stability.en.html

European Central Bank. (2017). *Guide to assessments of fintech credit institutions licence applications.* Retrieved from https://www.bankingsupervision.europa.eu/legalframework/publiccons/pdf/licensing_and_fintech/ssm.guide_on_assessment_for_licensing_of_fintech_credit_insts_draft.en.pdf

European Central Bank. (2018). *CLIFS - Country-Level Index of Financial Stress*. Retrieved from Statistical Data Warehouse: https://sdw.ecb.europa.eu/browse.do?node=9693347

European Central Bank. (2018). *Financial Stability Review.* Retrieved from https://www.ecb.europa.eu/pub/pdf/fsr/ecb.fsr201805.en.pdf?8b972cb39cc33e7e27761f47fdf817a5

Evanoff, D. D., Kaufman, G. G., Leonello, A., & Manganelli, S. (2017). *Achieving Financial Stability: Challenges to Prudential Regulation.* World Scientific.

EY. (2016). *Legal risk 2.0: Show you're in control.* Retrieved from http://www.ey.com/Publication/vwLUAssets/ey-legal-risk-2-show-you-are-in-control/$FILE/ey-legal-risk-2-show-you-are-in-control.pdf

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56.

Federal Reserve. (2017). *Dodd-Frank Act Stress Test 2017: Supervisory Stress Test Methodology and Results.* Washington: Board of Govenors of the Federal Reserve System. Retrieved from https://www.federalreserve.gov/publications/files/2017-dfast-methodology-results-20170622.pdf

Federal Reserve Bank of Cleveland. (2014). *Federal Reserve Bank of Cleveland*. Retrieved from Peer-to-Peer Lending Is Poised to Grow: https://www.clevelandfed.org/newsroom-and-events/publications/economic-trends/2014-economic-trends/et-20140814-peer-to-peer-lending-is-poised-to-grow.aspx

Federal Reserve Bank of New York. (2018). Quarterly Report on Household Debt and Credit in May 2018. Retrieved from https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2018Q1.pdf

Federal Reserve Bank of St. Louis. (2018). FRED Economic Data. Retrieved from https://fred.stlouisfed.org/

Financial Stability Board. (2017). *Financial Stability Implications from FinTech.* Retrieved from http://www.fsb.org/wp-content/uploads/R270617.pdf

Foo, J., Lim, L.-H., & Wong, K.-W. (2017). *Macroeconomics and Fintech: Uncovering Latent Macroeconomic Effects on Peer-To-Peer Lending.* Retrieved from https://www.stat.uchicago.edu/~lekheng/work/fintech.pdf

French, K. R. (2018). Data Library US Research Returns. Retrieved from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

Hodge, N. (2017). *Challenges of FinTech.* Retrieved from Enterprise Risk: https://enterpriseriskmag.com/wp-content/uploads/2017/06/ER_Fintech_Summer_17.pdf

Hull, J. C. (2012). *Risk Management and Financial Institutions* (3 ed.). Wiley.

Institute of Risk Management. (2018). *Institute of Risk Management*. Retrieved from Cyber risk and risk management: https://www.theirm.org/knowledge-and-resources/thought-leadership/cyber-risk/

International Organisation of Securities Commissions. (2017). *IOSCO Research Report on Financial Technologies (Fintech).* Retrieved from https://www.iosco.org/library/pubdocs/pdf/IOSCOPD554.pdf

Investing.com. (2018). *Market Data*. Retrieved from https://uk.investing.com

KPMG & H2 Ventures. (2017). *2017 Fintech100 - Leading Global Fintech Innovators.* Retrieved from https://assets.kpmg.com/content/dam/kpmg/de/pdf/Themen/2017/h2-fintech-innovators-2017.pdf

KPMG. (2018). *The Pulse of Fintech Q4 2017.* Retrieved from https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2018/02/pulse_of_fintech_q4_2017.pdf

Kremers, J., & Schoenmaker, D. (2015). Financial stability and proper business conduct - Can supervisory structure help to achieve these objectives? In R. H. Huang, & D. Schoenmaker, *Institutional Structure of Financial Regulation.* Routledge.

LendingClub. (2007-2018). *Loan Statistics.* Retrieved from https://www.lendingclub.com/info/download-data.action

LendingClub. (2015-2018). *Quarterly Earnings Release.* Retrieved from https://ir.lendingclub.com/QuarterlyResults.aspx?iid=4213397

LendingClub. (2018). *Annual Report 2017.* Retrieved from https://ir.lendingclub.com/Cache/1500109713.PDF?Y=&O=PDF&D=&FID=1500109713&T=&IID=4213397

Lin, M., Sias, R., & Wei, Z. (2017). *Institutional Investors in Online Crowdfunding.* Retrieved from http://www.fmaconferences.org/Boston/II_LSW.pdf

Menat, R. (2016). Why We're so Excited About FinTech. In S. Chishti, & J. Barberis, *The FinTech Book: The Financial Technology Handbook for Investors, Entrepreneurs and Visionaries.* Wiley.

Nicoletti, B. (2017). *The Future of Fintech.* Palgrave Macmillan.

Office for National Statistics. (2018). *Database*. Retrieved from www.ons.gov.uk

Office of Financial Research. (2017). *2017 Financial Stability Report.* Retrieved from https://www.financialresearch.gov/financial-stability-reports/files/OFR_2017_Financial-Stability-Report.pdf

Office of Financial Research. (2018). *The OFR Financial System Vulnerabilities Monitor.* Retrieved from https://www.financialresearch.gov/working-papers/files/OFRwp-18-01_Financial-System-Vulnerabilities-Monitor.pdf

Omarini, A. (2015). *Retail Banking: Business Transformation and Competitive Strategies for the Future.* Palgrave Macmillan UK.

Organisation for Economic Co-Operation and Development. (2010). *Policy Framework for Effective and Efficient Financial Regulation.* Retrieved from https://www.oecd.org/finance/financial-markets/44362818.pdf

People's Bank of China. (2017). *Financial Stability Report 2017.* Retrieved from http://www.pbc.gov.cn/english/130721/3390064/index.html

PwC. (2015). *Peer pressure: How peer-to-peer lending platforms are transforming the consumer lending industry.* Retrieved from https://www.pwc.com/us/en/consumer-finance/publications/assets/peer-to-peer-lending.pdf

Reserve Bank Australia. (2017). *Has the Way We Look at Financial Stability Changed Since the Global Financial Crisis?* Retrieved from Reserve Bank of Australia: https://www.rba.gov.au/speeches/2017/sp-ag-2017-03-14.html

Saunders, A., & Millon Cornett, M. (2017). *Financial Institutions Management: A Risk Management Approach.* McGraw-Hill.

Schueffel, P. (2016). Taming the Beast: A Scientific Definition of Fintech. *Journal of Innovation Management*, 32-54.

SGH Warsaw School of Economics. (2008). *Critical Values for the Dickey-Fuller.* Retrieved from SGH Warsaw School of Economics: web.sgh.waw.pl/~mrubas/EP/TabliceStatystyczneDF.doc

Sharpe, N. R., De Veaux, R., & Velleman, P. (2012). *Business Statistics.* Pearson.

Sironi, P. (2016). *FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification.* Wiley.

Tian, W. (2017). *Commercial Banking Risk Management: Regulation in the Wake of the Financial Crisis.* Palgrave Macmillan.

United States Department of Labor. (2018). Labor Force Statistics from the Current Population Survey. Retrieved from https://data.bls.gov/pdq/SurveyOutputServlet

Williams-Grut, O. (2016). *After Firing Its CEO, Lending Club Is Facing a Crisis*. Retrieved from Inc.: https://www.inc.com/business-insider/inside-lending-club-scandal.html

Yahoo Finance. (2018). *Yahoo Finance*. Retrieved from https://finance.yahoo.com/

Yeoh, P. (2016). Innovations in Financial Services: Regulatory Implications. *Business Law Review, 37*(5), 190-196.

Zinkin, J. (2014). *Rebuilding Trust in Banks.* Wiley.

Zopa. (2005-2018). *Loan Statistics*. Retrieved from https://www.zopa.com/public-loan-book

Zopa. (2018). *About Us*. Retrieved from Zopa Website: www.zopa.com/about

Appendix

Appendix 1: FinTech Origin

The three tables list the origins of companies on the FinTech100 list and its two subgroups Leading50 and Emerging50 (KPMG & H2 Ventures, 2017).

FinTech100

Origin	# of Companies
US	18
Australia	10
China	9
UK	9
Canada	6
France	5
Germany	5
India	4
Ireland	3
Israel	3
New Zealand	3
Sweden	3
Brazil	2
Mexico	2
Netherlands	2
Nigeria	2
Poland	2
Singapore	2
Belgium	1
Finland	1
Italy	1
Japan	1
Kenya	1
Korea	1
Malta	1
Switzerland	1
Taiwan	1
Turkey	1

Leading50

Origin	# of Companies
US	13
China	9
Australia	3
Canada	3
Germany	3
UK	3
Brazil	2
New Zealand	2
Sweden	2
Finland	1
France	1
India	1
Ireland	1
Israel	1
Korea	1
Mexico	1
Netherlands	1
Poland	1
Switzerland	1

Emerging50

Origin	# of Companies
Australia	7
UK	6
US	5
France	4
Canada	3
India	3
Germany	2
Ireland	2
Israel	2
Nigeria	2
Singapore	2
Belgium	1
Italy	1
Japan	1
Kenya	1
Malta	1
Mexico	1
Netherlands	1
New Zealand	1
Poland	1
Sweden	1
Taiwan	1
Turkey	1

Appendix 2: Objectives of Financial Regulation

This table shows the objectives of financial regulation mentioned in relevant literature. One publication is displayed per row and its mentioned objectives are clustered by the 4 defined main objectives used in this study.

Publication (# of Objectives) / Objective	**Financial Stability**	**Soundness of Financial Institutions**	**Investor / User Protection**	**Orderly and well-functioning markets**	**Not considered**
Principles of Financial Regulation (Armour, et al., 2016) (6 Objectives)	x		x	x	
Financial stability and proper business conduct (Kremers & Schoenmaker, 2015) (4 Objectives)	x	x	x	X	*Monetary (Price) Stability
Policy Framework for Effective and Efficient Financial Regulation (Organisation for Economic Co-Operation and Development, 2010) (6 Objectives)	x	x	x	x	
Commercial Banking Risk Management (Tian, 2017) (1 Objective)	x				
Rules, discretion and macro-prudential policy (Agur & Sharma, 2015) (1 Objective)	x				

Appendix 3: Risk Framework

This table shows the risks occurring in financial markets mentioned in relevant literature. One publication is displayed per row and its mentioned risk are matched to the risk framework developed for this thesis.

Publication / Risk	Systemic				Idiosyncratic							Not Considered
	Contagion	Procyclicality	Systemic Importance	Investor Confidence	Credit Risk	Liquidity Risk & Maturity Mismatch	Insolvency Risk	Business Model Risk	Cyber Risk	Third-party Reliance	Legal Risk	
Financial Stability												
Principles of Financial Regulation (Armour, et al., 2016)	x	x	x	x								*Public Good
2017 Financial Stability Report (Office of Financial Research, 2017)	x		x		x	x	x		x			*Macro Risk *Market Risk
Financial Institutions												
Financial Institutions Management (Saunders & Millon Cornett, 2017)					x	x	x	x	x			*Macro Risk *Market Risk
Global Systemically Important Banks (Bank for International Settlements, 2013)	x		x			x	x					
FinTech												
FinTech Credit (Bank for International Settlements & Financial Stability Board, 2017)	x	x	x	x	x	x	x	x	x	x	x	
IOSCO Research Report on Financial Technologies (International Organisation of Securities Commissions, 2017)				x	x	x		x	x		x	*Macro Risk
The Opportunities and Challenges of Fintech (Board of Governors of the Federal Reserve System, 2016)					x	x			x	x	x	
Real-Time Risk: What Investors Should Know About FinTech, High-Frequency Trading, and Flash Crashes (Aldridge & Krawciw, 2017)								x	x			
Guide to assessments of fintech credit institutions licence applications (European Central Bank, 2017)					x	x		x	x	x		
Financial Stability Implications from FinTech (Financial Stability Board, 2017)	x	x	x		x	x	x	x	x	x	x	*Excess Volatility
Challenges of FinTech (Hodge, 2017)				x	x	x		x			x	*Market Risk

Appendix 4: Data Tests Analysis I

ADF Test Results

The (*) indicates the presence of a unit root in the variable. For a model with N=50 and a constant and trend, the test statistic is critical at a 5% significance level when it is lower than -3.5 (SGH Warsaw School of Economics, 2008).

With taking the first difference, all unit roots were removed.

Variable	Level		Difference	
	tau2	Unit Root	tau2	Unit Root
LoanVolume	- 2.340	*	- 8.896	
GDP	- 4.606		- 3.964	
UNEMP	- 5.485		- 4.325	
CPI	- 3.665		- 8.797	
Credit	- 2.270	*	- 3.915	
ConsumerLoans	- 2.340	*	- 4.918	
Debt	- 0.452	*	- 4.795	
MDebt	0.143	*	- 4.925	
CDebt	- 0.297	*	- 5.374	
DDSP	- 0.364	*	- 4.211	
CDSP	- 1.644	*	- 3.719	
MDSP	0.588	*	- 3.972	
RealDSP	- 2.635	*	- 4.362	
FODSP	- 0.323	*	- 4.290	
TY36	- 1.926	*	- 6.517	
TY60	- 2.190	*	- 5.145	
LCRate	- 1.592	*	- 4.611	
LCSpread	- 1.554	*	- 5.872	
AFSpread	- 2.187	*	- 4.577	
Default	- 2.081	*	- 7.827	
StressIndex	- 2.503	*	- 5.402	
VIX	- 4.573		- 6.054	
FinTech	- 2.557	*	- 4.545	
SP500	- 4.613		- 6.926	
Mkt-RF			- 4.599	
SMB			- 5.842	
HML			- 6.138	

**tau2< -3.5*

Two Samples t-Test Results:

In order to test whether there is a significant difference in means between two subgroups, a two-samples t-test is used. The tables show the test results for comparing the subgroups to all other loan volume observations not defined to be in the subgroup. For the purpose t-test, the subgroups are also compared amongst each other. Only Q4 is found to have a significant difference in means at a 10% significance level.

Quarter:

		Loan Volume	
Subgroup	**Observations**	**Difference in Means**	**P-Value**
Q1	10	0.100	0.615
Q2	9	0.109	0.596
Q3	10	0.157	0.428
Q4	10	0.065	0.065 °

*** p<0.001; **p<0.01; *p<0.05; °p<0.1

Purpose:

		Loan Volume		Credit Card	
Subgroup	**Observations**	**Difference in Means**	**P-Value**	**Difference in Means**	**P-Value**
Debt Consolidation	39	- 0.049	0.744	0.049	0.738
Credit Card	39	- 0.001	0.995		

*** p<0.001; **p<0.01; *p<0.05; °p<0.1

Appendix 5: Descriptive Statistics Analysis I

Variable	Mean	Min	Max	SD
ΔLoanVolume	0.294	-0.631	4.759	0.771
ΔGDP	0.008	-0.020	0.017	0.007
ΔUNEMP	-0.005	-0.071	0.204	0.059
ΔCPI	0.004	-0.028	0.017	0.008
ΔTY36	0.022	-0.506	0.632	0.227
ΔTY60	0.013	-0.383	0.654	0.203
ΔFinTech	0.188	-0.667	3.598	0.711
ΔCredit	0.004	-0.018	0.016	0.008
ΔConsumerLoans	0.016	-0.033	0.368	0.060
ΔDebt	0.001	-0.014	0.021	0.010
ΔMDebt	-0.001	-0.018	0.019	0.011
ΔCDebt	-0.001	-0.046	0.043	0.024
ΔFODSP	-0.002	-0.026	0.040	0.011
ΔDDSP	-0.005	-0.029	0.039	0.012
ΔCDSP	0.000	-0.030	0.055	0.015
ΔMDSP	-0.011	-0.043	0.022	0.012
ΔRealDSP	0.005	-0.040	0.028	0.011
ΔStressIndex	0.139	-1.177	2.692	0.682
ΔVIX	0.032	-0.342	1.137	0.312
ΔSP500	0.021	-0.255	0.149	0.073
ΔMkt-RF	0.028	-0.224	0.164	0.082
ΔSMB	0.004	-0.077	0.059	0.033
ΔHML	-0.001	-0.146	0.168	0.060
ΔLCRate	0.004	-0.116	0.100	0.041
ΔLCSpread	0.008	-0.123	0.202	0.064
ΔAFSpread	0.028	-0.041	0.144	0.039
ΔDefault	0.030	-0.237	0.726	0.163

Appendix 6: Correlation Matrix Analysis I

	ΔLoan Volume	*ΔCPI*	*ΔGDP*	*ΔLC Spread*	*ΔSP500*	*ΔReal DSP(-1)*	*ΔCredit*	*ΔHML (-1)*	*ΔMkt.RF*	*ΔTY36*	*ΔUNEMP (-1)*	*ΔVIX*	*ΔStress Index*	*ΔUNEMP*	*Scandal4 (Dummy)*
ΔLoanVolume	1.000														
ΔCPI	-0.733	1.000													
ΔGDP	-0.625	0.510	1.000												
ΔLCSpread	0.545	-0.348	-0.394	1.000											
ΔSP500	-0.584	0.567	0.550	-0.635	1.000										
ΔRealDSP(-1)	-0.395	0.307	0.365	-0.246	0.146	1.000									
ΔCredit	-0.404	0.162	0.374	-0.134	0.135	0.211	1.000								
ΔHML(-1)	0.397	-0.190	-0.001	0.182	-0.102	-0.198	-0.097	1.000							
ΔMkt.RF	-0.451	0.335	0.407	-0.497	0.882	0.185	0.138	-0.184	1.000						
ΔTY36	-0.372	0.359	0.156	-0.600	0.472	0.096	0.205	0.070	0.363	1.000					
ΔUNEMP(-1)	0.390	-0.192	-0.692	0.217	-0.208	-0.267	-0.500	-0.161	-0.095	-0.138	1.000				
ΔVIX	0.384	-0.321	-0.243	0.229	-0.652	-0.258	-0.243	0.188	-0.795	-0.264	0.044	1.000			
ΔStress Index	0.389	-0.233	-0.214	0.114	-0.248	-0.111	-0.109	0.057	-0.113	-0.189	0.035	-0.020	1.000		
ΔUNEMP	0.412	-0.259	-0.700	0.403	-0.464	-0.159	-0.516	-0.085	-0.348	-0.305	0.790	0.152	0.087	1.000	
Scandal4(Dummy)	-0.163	0.123	0.101	0.010	0.103	-0.036	0.272	0.297	0.068	0.157	-0.057	-0.126	0.032	-0.049	1.000
Q4(Dummy)	0.280	-0.544	-0.070	-0.078	-0.042	-0.244	-0.032	0.174	0.084	-0.074	0.039	0.018	-0.005	-0.053	-0.005

Appendix 7: Data Tests Analysis II

ADF Test Results

The (*) indicates the presence of a unit root in the variable. For a model with N=50 and a constant and trend, the test statistic is critical at a 5% significance level when it is lower than -3.5 (SGH Warsaw School of Economics, 2008).

With taking the first difference, all unit roots were removed.

	Dataset 1				Dataset 2			
Variable	Level		Difference		Level		Difference	
	tau2	Unit Root	tau2	Unit Root	tau2	Unit Root	tau2	Unit Root
LoanVolume	- 1.526	*	- 4.699		- 0.458	*	- 10.030	
GDP	- 5.046		- 4.458		- 1.199	*	- 4.019	
UNEMP	- 3.525		- 3.858		- 1.147	*	- 3.505	
CPI	- 1.264	*	- 3.757		- 0.891	*	- 3.798	
Credit	- 2.018	*	- 5.204		- 2.639	*	- 5.667	
Debt	- 1.916	*	- 4.295			*		
DDSP	- 6.124		- 7.958		- 2.232	*	- 3.893	
DSP	- 1.881	*	- 3.553		- 2.466	*	- 3.516	
TY12	- 2.254	*	- 5.416		- 1.626	*	- 6.093	
TY24	- 2.121	*	- 4.366		- 1.702	*	- 5.095	
TY36	- 1.988	*	- 4.050		- 1.799	*	- 4.766	
TY48	- 2.227	*	- 3.941		- 2.099	*	- 4.771	
TY60	- 2.276	*	- 4.281		- 2.345	*	- 5.055	
ZopaSpread	- 2.388	*	- 5.953		- 2.256	*	- 5.957	
Default	- 0.389	*	- 6.858			*		
StressIndex	- 2.443	*	- 6.601		- 2.366	*	- 6.593	
FTSE100.VIX	- 4.008		- 5.993		- 2.803	*	- 6.664	
FinTech	2.035	*	- 6.590			*		
FTSE250	- 3.236	*	- 5.740		- 2.064	*	- 4.416	
Mkt-RF			- 5.354				- 6.164	
HML			- 5.581				- 6.153	

**tau2< -3.5*

Two Samples t-Test Results:

In order to test whether there is a significant difference in means between two subgroups, a two-samples t-test is used. The tables show the test results for comparing the subgroups to all other loan volume observations not defined to be in the subgroup. Only in dataset 1, Q1 and Q4 are found to have a significant difference in means at a 5% significance level.

Quarter:

	Dataset 1				Dataset 2		
Sub-group	**Obser-vations**	**Difference in Means**	**P-Value**		**Observations**	**Difference in Means**	**P-Value**
Q1	10	- 0.285	0.002	**	13	- 0.233	0.217
Q2	9	0.118	0.251		12	0.242	0.211
Q3	10	- 0.031	0.753		13	0.143	0.450
Q4	10	0.207	0.032	*	13	- 0.140	0.461

**** p<0.001; **p<0.01; *p<0.05; °p<0.1*

Appendix 8: Descriptive Statistics Analysis II

	Dataset 1				Dataset 2			
Variable	**Mean**	**Min**	**Max**	**SD**	**Mean**	**Min**	**Max**	**SD**
ΔLoanVolume	0.147	- 0.194	1.167	0.267	0.217	- 0.242	3.842	0.582
ΔGDP	0.007	- 0.016	0.025	0.009	0.008	- 0.016	0.025	0.008
ΔUNEMP	- 0.006	- 0.074	0.109	0.044	- 0.002	- 0.074	0.109	0.042
ΔCPI	0.005	- 0.007	0.016	0.005	0.006	- 0.007	0.021	0.005
ΔTY12	0.068	- 0.855	1.523	0.483	0.057	- 0.855	1.523	0.425
ΔTY24	0.065	- 0.756	1.819	0.501	0.056	- 0.756	1.819	0.441
ΔTY36	0.045	- 0.718	1.340	0.454	0.040	- 0.718	1.340	0.400
ΔTY48	0.020	- 0.629	1.011	0.374	0.022	- 0.629	1.011	0.331
ΔTY60	0.011	- 0.577	1.111	0.344	0.015	- 0.577	1.111	0.305
ΔFinTech	0.204	0.002	1.682	0.359				
ΔCredit	0.012	- 0.012	0.054	0.015	0.014	- 0.012	0.054	0.014
ΔDebt	- 0.012	- 0.369	0.024	0.073				
ΔDDSP	0.009	- 0.002	0.014	0.004	0.009	- 0.002	0.014	0.004
ΔDSP	- 0.007	- 0.069	0.023	0.014	- 0.003	- 0.069	0.034	0.016
ΔStressIndex	0.149	- 0.786	2.670	0.687	0.184	- 0.786	2.670	0.666
ΔFTSE100VIX	0.029	- 0.405	1.331	0.334	0.042	- 0.405	1.331	0.303
ΔFSTE250	0.023	- 0.194	0.233	0.086	0.023	- 0.194	0.233	0.083
ΔMkt-RF	0.007	- 0.138	0.191	0.073	0.001	- 0.138	0.191	0.069
ΔHML	0.001	- 0.127	0.206	0.073	- 0.003	- 0.172	0.206	0.072
ΔZopaSpread	0.023	- 0.180	0.529	0.144	0.048	- 0.663	1.059	0.256
ΔDefault	0.198	- 0.696	3.712	0.715				

Appendix 9: Correlation Matrix Analysis II

Dataset 1

	Δ Loan Volume	*Δ UNEMP*	*Δ CPI*	*Δ DDSP*	*Δ Mkt-RF*	*Δ Default (-1)*	*Δ GDP (-1)*	*Δ TY12 (-1)*	*Δ FTSE250 (-1)*	*Δ Mkt.RF (-1)*	*LC4*	*Q1*	*Q4*
Δ LoanVolume	1.000												
Δ UNEMP	0.310	1.000											
Δ CPI	-0.370	0.158	1.000										
Δ DDSP	-0.510	-0.461	0.189	1.000									
Δ Mkt-RF	-0.567	-0.014	0.152	0.389	1.000								
Δ Default(-1)	0.590	0.399	-0.372	-0.632	-0.378	1.000							
Δ GDP(-1)	-0.300	-0.716	0.229	0.413	0.033	-0.423	1.000						
Δ TY12(-1)	-0.271	-0.149	0.349	0.103	0.144	-0.347	0.123	1.000					
Δ FTSE250(-1)	-0.356	-0.353	0.259	0.233	-0.048	-0.348	0.274	0.156	1.000				
Δ Mkt.RF(-1)	0.291	0.156	-0.345	-0.243	0.034	0.201	-0.121	-0.420	-0.525	1.000			
LC4	-0.094	-0.208	0.092	0.251	-0.002	0.046	0.216	-0.018	-0.019	0.040	1.000		
Q1	0.473	-0.033	-0.400	-0.267	-0.178	0.257	-0.135	-0.286	-0.004	0.161	-0.050	1.000	
Q4	-0.344	0.048	0.115	0.053	0.158	-0.187	0.053	-0.093	0.018	-0.013	-0.050	-0.345	1.000

Dataset 2

	Δ Loan Volume	*Δ UNEMP*	*Δ FTSE250*	*Δ Mkt-RF*	*Δ Zopa Spread*	*LC4*
Δ LoanVolume	1.000					
Δ UNEMP	0.386	1.000				
Δ FTSE250	0.237	-0.113	1.000			
Δ Mkt-RF	-0.446	-0.103	-0.532	1.000		
Δ ZopaSpread	-0.428	-0.112	-0.248	0.416	1.000	
LC4	-0.053	-0.166	0.027	0.002	-0.005	1.000