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THE EVOLUTION OF FINANCIAL TECHNOLOGY AND ITS IPMACT ON CREDIT LENDING

Ph.D. Thesis

Evangelia G. Avgeri

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Abstract

The rise of peer-to-peer (P2P) lending presents a significant challenge to traditional banking systems globally, offering an alternative channel for accessing financial services. This thesis investigates various aspects of P2P lending within the United States, exploring its expansion, impact on financial inclusion within the mortgage market, and defaults rates.

The research questions guiding this study include the factors driving P2P lending expansion, the influence of P2P lending on Federal Housing Administration (FHA) mortgage loans, and the determinants of default in the P2P lending industry.

The innovation of this study lies in three key aspects: firstly, the introduction of the Economic Freedom Index and its sub-indices to explain the development of P2P lending; secondly, the exploration of P2P lending dynamics in circumventing mortgage supply constraints by providing loans to marginal borrowers, thereby promoting financial inclusion and sustainability; and thirdly, the incorporation of specific macroeconomic indicators to explain defaults in P2P lending.

The empirical study is mainly based on hand-collected data from LendingClub, the largest online lender in the U.S. and worldwide, spanning from 2007 until 2020. Panel data techniques and logistic regression models were employed for analysis.

The empirical findings reveal that P2P lending activities are influenced by economic freedom levels, market concentration, and demographic factors, underscoring the role of institutional variables in shaping the credit market landscape. Moreover, P2P lending serves as an alternative source of financing for marginal borrowers, facilitating access to mortgage loans and promoting financial inclusion. The analysis also demonstrates a causal relationship between P2P lending and an increase in FHA loan volume, highlighting its positive impact on mortgage financing accessibility.

Furthermore, the introduction of macroeconomic indicators enhances the predictive accuracy of default models in the P2P lending industry, with higher levels of economic indicators associated with lower delinquency rates.

The implications of these findings are significant for policymakers, investors, and financial regulators. Policymakers are urged to consider measures that enhance economic freedom, promote financial inclusion, and implement regulatory frameworks to mitigate risks associated with P2P lending. Investors can benefit from a better understanding of borrowers' creditworthiness and loan performance, while authorities can utilize forecasting models to address credit risk and prevent adverse effects on the economy. Overall, this thesis offers valuable insights into the complex dynamics of P2P lending, with implications for shaping policies aimed at fostering economic growth, financial stability, and sustainable development.

Περίληψη

Η άνοδος του peer-to-peer (P2P) δανεισμού αποτελεί σημαντική πρόκληση για τα παραδοσιακά τραπεζικά συστήματα παγκοσμίως, προσφέροντας ένα εναλλακτικό κανάλι για πρόσβαση σε χρηματοοικονομικές υπηρεσίες. Η παρούσα διατριβή μελετά διάφορες πτυχές του P2P δανεισμού στις Ηνωμένες Πολιτείες, διερευνώντας την επέκτασή του, τον αντίκτυπό του στη χρηματοοικονομική ένταξη στην αγορά στεγαστικών δανείων και τα ποσοστά αθέτησης.

Τα ερευνητικά ερωτήματα που καθοδηγούν αυτήν τη μελέτη περιλαμβάνουν τους παράγοντες που οδηγούν την επέκταση του δανεισμού P2P, την επίδραση του δανεισμού P2P στα στεγαστικά δάνεια της Ομοσπονδιακής Διοίκησης Στέγασης (FHA) και τους καθοριστικούς παράγοντες της αθέτησης πληρωμών στον κλάδο δανεισμού P2P.

Η καινοτομία αυτής της μελέτης έγκειται σε τρεις βασικές πτυχές. Πρώτον, η εισαγωγή του Δείκτη Οικονομικής Ελευθερίας και των επιμέρους δεικτών του για να εξηγηθεί η ανάπτυξη του δανεισμού P2P. Δεύτερον, η διερεύνηση της δυναμικής του P2P δανεισμού για την παράκαμψη των περιορισμών προσφοράς στεγαστικών δανείων παρέχοντας δάνεια σε οριακούς δανειολήπτες, προωθώντας έτσι τη χρηματοοικονομική ένταξη και βιωσιμότητα. Τρίτον, η ενσωμάτωση συγκεκριμένων μακροοικονομικών δεικτών για να εξηγηθούν οι αθετήσεις πληρωμών στον δανεισμό P2P.

Η εμπειρική μελέτη βασίζεται κυρίως σε δεδομένα από την LendingClub, τον μεγαλύτερο διαδικτυακό δανειστή στις ΗΠΑ και παγκοσμίως, που εκτείνονται από το 2007 έως το 2020. Για την ανάλυση χρησιμοποιήθηκαν τεχνικές δεδομένων πάνελ και μοντέλα λογιστικής παλινδρόμησης.

Τα εμπειρικά ευρήματα δείχνουν ότι οι δραστηριότητες δανεισμού P2P επηρεάζονται από τα επίπεδα οικονομικής ελευθερίας, τη συγκέντρωση της αγοράς και δημογραφικούς παράγοντες,

υπογραμμίζοντας το ρόλο των θεσμικών μεταβλητών στη διαμόρφωση του τοπίου της πιστωτικής αγοράς. Επιπλέον, ο δανεισμός P2P χρησιμεύει ως εναλλακτική πηγή χρηματοδότησης για τους οριακούς δανειολήπτες, διευκολύνοντας την πρόσβαση τους σε στεγαστικά δάνεια και προάγοντας έτσι τη χρηματοοικονομική ένταξη. Η ανάλυση καταδεικνύει επίσης μια αιτιώδη σχέση μεταξύ του δανεισμού P2P και της αύξησης του όγκου δανείων FHA, υπογραμμίζοντας τον θετικό αντίκτυπό του πρώτου στην προσβασιμότητα στη χρηματοδότηση στεγαστικών δανείων. Επιπλέον, η εισαγωγή μακροοικονομικών δεικτών ενισχύει την προγνωστική ακρίβεια των μοντέλων αθέτησης στον κλάδο του δανεισμού P2P, με υψηλότερα επίπεδα οικονομικών μεταβλητών να συνδέονται με χαμηλότερα ποσοστά αθέτησης.

Οι επιπτώσεις αυτών των ευρημάτων είναι σημαντικές για τους υπεύθυνους χάραξης πολιτικής, τους επενδυτές και τις ρυθμιστικές αρχές. Οι υπεύθυνοι χάραξης πολιτικής καλούνται να εξετάσουν μέτρα που ενισχύουν την οικονομική ελευθερία, προάγουν τη χρηματοοικονομική ένταξη και να εφαρμόζουν ρυθμιστικά πλαίσια για τον μετριασμό των κινδύνων που σχετίζονται με τον δανεισμό P2P. Οι επενδυτές μπορούν να επωφεληθούν από την καλύτερη κατανόηση της πιστοληπτικής ικανότητας των δανειοληπτών, ενώ οι αρχές μπορούν να χρησιμοποιούν μοντέλα πρόβλεψης για την αντιμετώπιση του πιστωτικού κινδύνου και την πρόληψη δυσμενών επιπτώσεων στην οικονομία. Συνολικά, η παρούσα διατριβή προσφέρει πολύτιμες γνώσεις για την περίπλοκη δυναμική του P2P δανεισμού, με επιπτώσεις στη διαμόρφωση πολιτικών που στοχεύουν στην ενίσχυση της οικονομικής ανάπτυξης, της χρηματοπιστωτικής σταθερότητας και της βιώσιμης ανάπτυξης.

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Introduction

Motivation

Peer-to-peer (P2P) lending, also known as crowdlending or marketplace lending, emerged as a disruptive financial innovation shortly after the 2007-2008 global financial crisis and has since experienced significant growth in subsequent years. This alternative lending model, facilitated by online platforms, offers individuals and businesses direct access to funding by connecting them with investors willing to lend money. P2P lending platforms act as intermediaries, matching borrowers with lenders, thereby bypassing traditional financial institutions. Since its inception, P2P lending has experienced rapid growth, driven by technological advancements, changing consumer preferences, and a desire for greater financial inclusivity.

Marketplace lending is very attractive for borrowers because of its convenient online accessibility, rapid funding and more lenient lending criteria as a result of its comparatively relaxed regulation. Crowdlending offers to borrowers with limited credit history an easy access to credit without the need for collateral. Investors, on the other hand, are generally rewarded with high returns, which makes P2P lending a popular opportunity that attracts yield-seeking investors

The dynamic nature of P2P lending is characterized by its ability to challenge conventional banking systems and enhance access to finance. However, the P2P lending landscape is not without challenges, including regulatory uncertainties, credit risk management, and concerns over platform sustainability.

Given this context, this thesis explores the diverse landscape of P2P lending in the United States, aiming to investigate three main research questions:

1. What are the determinants driving the expansion of P2P lending platforms?

2. How does P2P lending influence Federal Housing Administration (FHA)-insured mortgages?
3. What factors contribute to default rates in P2P lending?

These inquiries serve as the cornerstone of our investigation, directing our exploration into the drivers, impacts, and risk factors linked with P2P lending.

Many studies have analyzed the expansion of crowdlending, primarily focusing on financial, economic, and demographic variables, as evidenced by Oh and Rosenkranz (2020) and Cornelli et al. (2021); however, our study stands out by introducing economic freedom as a driver that affect the growth of crowdlending.

Our analysis concerning the relationship between the volume of FHA mortgages and P2P lending, is directly related to the concept of sustainability, as we demonstrate that P2P lending can contribute to a country's sustainable development goals, mainly through the financial inclusion.

The probability of default is the most crucial issue when the performance of P2P loans is assessed. Previous studies on marketplace default risk, such as those by Möllenkamp (2017) and Serrano-Cinca et al. (2015), have predominantly focused on loan and borrower characteristics as factors of delinquency. In our research, we examine the default determinants, introducing specific macroeconomic indicators, which constitutes the novelty of our study.

Through theoretical and empirical examination, the aim of this thesis is to shed light on the dynamics of P2P lending and its implications on the credit and housing market, thus revealing its wider influence on financial inclusion and strategies for risk management. To investigate the above-mentioned research questions, this thesis adopts a mixed-methods approach across three distinct chapters. Each chapter employs thorough empirical analysis, drawing on comprehensive datasets and employing advanced statistical techniques.

Structure of the thesis

The goal of the present thesis is to conduct a comprehensive exploration of the multifaceted landscape of P2P lending in the U.S. states, aiming to provide a thorough understanding of its dynamics and implications on both micro and macro levels. Specifically, it investigates the factors of P2P lending expansion, its impact on FHA-insured mortgages, and the determinants contributing to default. To effectively research these topics, the dissertation is organized into three essays, each one consisting a separate chapter, accompanied by relevant theoretical and empirical reviews.

The first chapter investigates the determinants of P2P lending evolution, with particular attention to analysing the impact of economic freedom levels across U.S. states from 2007 to 2020. To ensure a comprehensive analysis, various other financial, economic, and demographic variables are integrated to examine their influence on the P2P lending market. This study introduces the Economic Freedom Index and its sub-indices as an innovative approach, driven by the hypothesis that economic freedom can positively influence P2P lending volume. This hypothesis stems from the notion that economic freedom is interconnected with institutional variables that have the potential to shape the dynamics of the credit market.

For the empirical analysis, we utilize data from the LendingClub platform and the Economic Freedom Index of North America. We perform a panel data analysis to explore the relationship between the expansion of crowdlending and the degree of economic freedom, along with other significant variables. Our findings provide strong evidence that economic freedom significantly influences the dynamics of P2P lending, affecting diverse aspects such as regulatory environments, market competitiveness, and financial stability. In particular, high levels of the sub-indices relative to credit market regulation, business regulation, and sound money are positively related with crowdlending growth.

The second chapter studies the influential factors of FHA mortgage loans, with a specific focus on P2P lending, which serves as an alternative financing source enabling marginal borrowers to meet increased mortgage down payment requirements, thereby potentially impacting mortgage volumes through its ability to circumvent loan-to-value cap policies. Consequently, P2P lending can be viewed as a mechanism through which "rationed" borrowers gain market access, mitigating disparities and fostering financial inclusion, ultimately contributing to the attainment of Sustainable Development Goals. For the empirical analysis, we utilize data encompassing FHA mortgages, P2P loans, and various economic indicators across all 50 U.S. states from 2007 to 2017, employing panel data techniques for analysis. Research demonstrates a causal relationship between P2P lending and a notable rise in FHA loan originations, suggesting a positive influence of P2P lending on FHA loan activity. Our evidence clearly demonstrates that, in addition to financial benefits, crowdlending also creates social impact by providing financial resources to underserved individuals who have limited or no access to traditional banking systems. This contributes to the potential reduction of poverty and inequalities, while fostering sustainable development characterized by social and economic equity.

The third chapter explores various aspects concerning borrower default crowdlending within the United States. This study is driven by the hypothesis that both P2P loan information and macroeconomic factors play a role in loan performance. We identify a range of loan and borrower characteristics, as well as macroeconomic variables, that are significant in determining the likelihood of default. These factors should be considered when evaluating credit risk in P2P lending market. The empirical analysis utilizes a dataset comprising 1,863,491 loan records issued through LendingClub from 2007 to 2020Q3, and employs a logistic regression model to forecast loan defaults. Consistent with previous studies, our findings indicate that several contractual loan features, including loan credit grade, loan purpose, loan maturity, annual income, and length of employment, are predictive of loan defaults. The novelty of this research lies in its incorporation of macroeconomic indicators to explain defaults within the P2P lending sector. Our research suggests that integrating macroeconomic variables with loan data substantially enhances the predictive accuracy of default models. Overall, our findings reveal a considerable positive impact of unemployment rates and an adverse effect of GDP growth rates on P2P loan default rates. Additionally, empirical results indicate that a higher percentage change in the House Price Index, Consumer Sentiment Index, and S&P500 Index correlates with a decreased likelihood of delinquency.

Overall, the empirical analysis conducted in this thesis offers valuable insights into important aspects of P2P lending dynamics within the U.S. Through the examination of the determinants driving P2P lending expansion, the impact of P2P lending on FHA-insured mortgages, and the factors influencing default rates, a comprehensive understanding of the complexities within the P2P lending landscape is achieved.

The implications of our findings are significant for researchers and policymakers. By identifying the factors driving P2P lending expansion, highlighting the potential impact of P2P lending on FHA-insured mortgages, and clarifying the determinants of default rates, this thesis offers valuable insights for shaping policies aimed at fostering economic freedom and promoting financial inclusion and sustainable development. Additionally, policymakers should consider implementing a regulatory framework to mitigate potential risks associated with the crowdlending market and protect the interests of both investors and borrowers. The integration of macroeconomic indicators into default prediction models underscores the importance of considering broader economic trends when assessing credit risk in the P2P lending industry, thereby facilitating the implementation of robust risk management practices. Finally, the findings of the empirical analysis also provide a foundation for future research in the field of P2P lending market.

Chapter 1 - Determinants of peer-to-peer lending expansion: The role of Economic Freedom Index

The global rise of P2P lending is posing a challenge to the worldwide banking system. This research explores the key factors affecting the development of P2P lending, with a specific focus on examining the influence of economic freedom levels in U.S. states from 2007 to 2020. The study is motivated by the hypothesis that economic freedom can positively influences P2P lending volume, given its connection to institutional variables that can shape the dynamics of the credit market. For this analysis, we employ hand-collected data from LendingClub platform and Economic Freedom Index of North America. Various other financial, economic and demographic variables from all 50 U.S. states are incorporated to investigate their impact on P2P lending market. Panel data techniques are employed for the empirical analysis.

Our results, in line with prior research, show that P2P lending activities penetrates areas with higher market concentration and financial development, as well as fewer bank branches. Moreover, economic variables and demographic determinants play a crucial role in the expansion of crowdlending.

The innovation of this study is the introduction of the Economic Freedom Index and its sub-indices in order to explain the development of P2P lending. The analysis revealed significant positive correlation between P2P lending expansion and economic freedom at the state level. In particular, high levels of the sub-indices relative to credit market regulation, business regulation, and sound money are positively related with crowdlending growth. However, the freedom to trade internationally do not appear to have a significant influence on this market.

1.1 Introduction

P2P online platforms facilitate various types of credit, including consumer and business lending, as well as financing for investments and mortgages. This alternative source of lending encompasses a wide range of both borrowers and lenders, contributing to its exponential expansion. The success of P2P lending can be mainly attributed to technological innovation and enhanced accessibility, on the one hand, and its role as bridge in addressing gaps within the financial landscape on other hand. Given the rapid expansion of Financial Technology (FinTech) credit and its increasing economic significance, there is an immediate need for a thorough evaluation of this phenomenon.

In this study we explore the main drivers contributing to the rapid growth of crowdlending. While many studies analyzing the expansion of P2P lending focus on data from the market's early years (see e.g., Jagtiani and Lemieux, 2018; Mariotto, 2016), we specifically examine P2P loans originated during the period 2007-2020 - the most extensive period under consideration - utilizing data from LendingClub, the largest online lender in the U.S. and globally. The main emphasis in the relevant literature is to examine how the macroeconomic environment, credit market characteristics, and financial development influence the entry and expansion of marketplace lending (see, e.g., Oh and Rosenkranz, 2020; Cornelli, et al., 2021). Many researchers explore how socio-demographic factors, such as gender, age and education affect the increased trend of participation in the P2P lending market, either as lenders or as borrowers (see, e.g., Ichwan and Kasri, 2019; Havrylchyk et al., 2020). An underinvestigated aspect in the literature on the FinTech environment is the connection between economic freedom and P2P lending. The impact of Economic Freedom Indices, or their constituent components, on the economic growth of countries have been extensively studied and documented (e.g., Brkić et al., 2020; Tran, 2019; Hussain and Haque, 2016). Furthermore, many researchers explore the association between economic freedom and the expansion and sustainability of Microfinance Institutions (e.g., Anwar et al., 2021; Lebovics et al., 2016). While numerous researchers have investigated the impact of economic freedom on the banking and financial environment (e.g., Nguyen et al., 2022; Sufian and Habibullah, 2010; Ghosh, 2018; Gohmann et al., 2013), there has been relatively limited exploration into the impact of the degree of economic freedom on the expansion of FinTech credit.

This study aims to investigate the significance and characteristics of economic freedom in relation to the expansion of crowdlending, utilizing an extensive dataset covering 50 U.S. states from 2007 to 2020. To the best of our knowledge this is the first study that examines the link between economic freedom and marketplace lending.

Typically, economies with high economic freedom display minimal government intervention, open markets, protection of property rights, and a regulatory framework that supports free enterprise. A higher Economic Freedom Index can positively impact P2P lending expansion by fostering a more favorable regulatory environment, encouraging entrepreneurship, and increasing access to capital. We employ Economic Freedom Index of North America at the state level within the U.S. during the analyzed period. Utilizing a context focused on a single country aids in reducing the likelihood of confounding factors contaminating our findings. Furthermore, there is substantial variation in economic freedom among the U.S. states, and this diversity plays a meaningful role in shaping how the level of economic freedom impacts economic outcomes in the U.S.

To provide more thorough evidence regarding the correlation between local economic freedom and P2P expansion we broaden our analysis to include the following components of the Index: Regulation of Credit Markets, Business Regulations, Sound Money and Freedom to Trade Internationally. In this regard, economies possessing a high level of economic freedom exhibit a less restrictive regulatory framework in both business and credit markets, fewer restrictions on international trade, along with a stable monetary system. All these components have significant implications for the performance of firms and financial institutions. Hence, it is likely that the Economic Freedom Index’s components could have effect on all forms of credit, including P2P lending.

In addition, in our study we use a set of control variables to consider their potential effect on crowdlending development and to isolate the specific impact of economic freedom on the expansion of P2P lending. The selection of these variables is determined based on a review of previous relevant studies. Consequently, among the factors included are financial market variables (the Herfindahl-Hirschman Index, the number of bank branches per capita, the Financial Development Index), economic variables (Unemployment rate, GINI Index and Personal Income per capita), and state demographic variables (including the share of young population, educated individuals, and racial minorities).

This study, therefore, performs a panel data analysis to investigate the relationship between the expansion of P2P lending and the degree of economic freedom, along with the aforementioned variables, within the U.S. from 2007 to 2020.

To preview our empirical results, this study finds a positive and statistically significant relationship between economic freedom and P2P lending expansion. Our findings from the components’ analysis show that the sub-indices relative to credit market regulation, business regulation and sound money are positively associated with crowdlending growth. However, the freedom to trade internationally exerts no significant influence on this market. Our analysis confirms that financial market factors and economic variables affect the increase of loan origination. Moreover, demographic determinants, indicating borrower characteristics, play a crucial role in the expansion of crowdlending.

This study makes notable contributions to the expanding body of literature on P2P lending in two significant ways. Firstly, it sheds light on the connection between economic freedom and the expansion of P2P lending within an economy. This is unique, as most existing literature predominantly explores the effects of economic freedom on several economic outcomes, whether at the macroeconomic level, within firms or in the financial sector. Furthermore, prior research examining the growth of crowdlending focused on macroeconomic variables, factors within the financial market, and borrowers' characteristics. This study represents the initial comprehensive investigation into the positive impact of economic freedom on P2P loan originations. Secondly, our findings from the analysis of the explanation of P2P expansion are more robust and up-to-date compared to previous studies, as we utilize a more comprehensive dataset of P2P origination determinants spanning 14 years, from 2007 to 2020.

The remainder of this chapter is organized as follows. Section 2 covers the literature review of the major studies in the field. Section 3 provides information about data and variables and describes the methodology. Section 4 discusses the empirical results. Conclusion and policy implications of the study are presented in Section 5.

1.2 Literature Review

The main focus in the literature on FinTech credit has primarily revolved around explaining the emergence and expansion of crowdlending.

The effect of competition between P2P lenders and banks for loans are thoroughly documented. Mariotto (2016) comparing the two leading P2P lending platforms in the U.S., LendingClub and Prosper, concludes that they are substitutes with one another and that they are frontally competing, while P2P lending is transitioning from being a complement to potentially being a substitute of bank's consumer lending. Balyuk (2018) shows that traditional banks provide and increase credit to borrowers who have obtained loans from on line lending platforms. Wolfe and Yoo (2018) show that a substantial fraction of P2P loan volume substitutes for small commercial bank personal loan volume, while Tang (2019) shows that the P2P lending market serves as both substitutes and complements to the traditional banking system.

Several papers explore the determinants of entry and expansion of FinTechs. Rau (2020) examines the drivers of the development of crowdfunding, including P2P lending, at the global level. The findings indicate that the introduction of explicit legal framework significantly boosts crowdfunding. Financial development and ease of internet access are positively related to crowdfunding volume, while the ease of doing business is negatively associated.

Jagtiani and Lemieux (2018) document that LendingClub platform penetrates into areas where traditional financial institutions are underserved (few numbers of bank branches per capita) and the portion of the loans increases in areas where the local economy is not performing well.

Havrylchyk et al. (2020) investigate the drivers of P2P lending expansion by testing three hypotheses: the global financial crisis, the nature of banking in regards to barriers to entry and the learning costs. They find that online lenders have expanded into counties that were more affected by financial crisis, as well as countries with a poor branch network and lower bank concentration.

Similarly, Oh and Rosenkranz (2020) examine the role of financial development and literacy as determinants of marketplace lending expansion. They prove that financial institutions' efficiency, financial literacy, lower branch and ATM penetration, and high new business density are positively related with the expansion of P2P lending.

Furthermore, Cornelli et al. (2020) investigate the determinants of FinTech credit and discover that it is more developed in countries with higher GDP per capita and fewer bank branches per capita. In addition, in nations where banking regulation is less stringer, the ease of doing business is greater, and the bond and equity markets are more developed, FinTech credit tends to exhibit greater development. Le et al. (2021) review the connections between the expansion of FinTech loans and the effectiveness of financial institutions. The findings indicate a two-way relationship. A negative link between bank efficiency and FinTech credit suggests that FinTech credit is more developed in countries with less efficient banking systems. Conversely, a positive impact of FinTech credit on banking system efficiency implies that FinTech credit may stimulate improvements in the banking system. Their findings further emphasize that FinTech credit is more developed in economies where explicit FinTech regulation is present.

Subroto et al. (2023) explore the link between FinTech credit and de facto measures of financial openness and utilizing panel data estimation models offer robust evidence that an increase in all main components of total external liabilities leads to an increase in FinTech credit volumes.

Cornelli et al. (2021) show that FinTechs raise more capital in countries with more innovation capacity, better regulatory quality and higher financial development. Kowalewski et al. (2021) find that the development of FinTech credit services is fostered by the strength of both primary institutions, like the rule of law, and credit-specific institutions, especially in terms of insolvency framework effectiveness. Moreover, they show that the FinTech credit market develops faster in countries characterized by high levels of societal distrust toward banks.

The present study is also related to the literature investigating the effects of economic freedom on economic outcomes. Extensive literature offers evidence that regions with high levels of economic freedom experience heightened growth, increased productivity, higher income levels and improved economic outcomes (see, e.g., Bennett, 2021; Bregh and Bjornskov, 2021; Liu and Feng, 2022; Wu, 2011; Xu, 2019). Government intervention may increase the operational expenses of businesses, encompassing administrative and labor costs (Nikolaev et al. 2018). Consequently, economic freedom, characterized by minimal government interference in the economy, allows firms to encounter fewer distortions in their business decisions.

Tran (2019) examines the impact of economic freedom on economic growth using data of ASEAN countries over the period of 2000-2017 and finds that higher economic and labor freedom lead to higher economic growth. Brkić et al. (2020) investigate the influence of economic freedom on economic growth across a panel of European countries and conclude that elevated levels of economic freedom are associated with increased economic growth.

Hussain and Haque (2016) also find a positive correlation between the growth rate and the Economic Freedom Index. The study encompasses sub-indices such as trade freedom, financial freedom, business freedom and labor freedom, and found that each of these factors positively influences economic growth. Özyilmaz (2022) examines the impact sub-components of economic freedom analyzing data in 155 countries. He finds that trade freedom, financial health, business freedom, financial freedom, property rights, government integrity, and monetary freedom positively affect the economic growth but government spending affects it negatively.

Sooreea-Bheemul et al. (2020) examining the impact of economic freedom in 40 countries in Sub-Saharan Africa on foreign direct investment suggest that, regulatory efficiency (at a decomposed level of business, labor and monetary freedom), fiscal freedom and market openness economic freedom hold greater significance in attracting foreign direct investment than the overall economic freedom.

Several empirical studies, such as Demirgüç-Kunt, et al. (2004) and Sufian and Habibullah (2010), explore the effects of economic freedom on the banking sector. Ghosh (2018) observes that a higher level of economic freedom enhances bank competition in developing countries. Conversely, strict government supervision is found to suppress the growth of the banking industry. Shaddady and Moore (2019) find that increased supervision appears to have a negative impact on bank stability.

Many researchers explore the correlation between bank spreads and the degree of economic freedom (e.g., Fernandes-Maciel et al., 2022; Lu et al., 2023; Nguyen et al., 2022) and conclude that a higher the economic freedom leads to a lower degree of financial regulation, thereby contributing to reduced bank loan spreads. Nguyen et al. (2022) specifically identify freedom from government spending and taxation as key components driving this relationship, with labor market freedom also playing a role in reducing loan spreads.

Sufian and Zulkhibri (2015) discover a negative relationship between business freedom and banks' efficiency. Increased business freedom tends to lower barriers to competition in the banking industry. More competition in the banking sector undermine the efficiency of banks.

Several studies have explored the correlation between economic freedom and Microfinance Institutions (MFIs), focusing mainly on how economic freedom effects the efficiency of MFIs, examining its influence on both financial and social efficiency (Lebovics et al., 2016; Wijesiri et al., 2015; Louis et al., 2013). Anwar et al. (2021) study the effect of regulatory efficiency and market openness on the financial and social efficiency of MFIs in Thailand and Philippines and find that different freedoms result in different outcomes and significantly influence MFIs’ financial and social efficiency. They suggested that monetary freedom and financial freedom have statistically significant positive relationships with financial efficiency. However, investment freedom (a component of market openness) has a statistically significant negative relationship with both financial and social efficiency.

Crabb (2008) investigates the relationship between the success of microfinance institutions and the degree of economic freedom in their host countries. The findings indicate that MFIs predominantly operate in countries with a relatively low degree of overall economic freedom, and various economic policy factors play a significant role in sustainability. Finally, Ricci (2020) explores relationships between Bitcoin exchange activities among countries and national levels of economic freedom. The study demonstrates a strong connection between high levels of freedom to trade internationally and the diffusion of FinTech development.

1.3 Data and Research Methodology

1.3.1 Variables and data

The research question in this study is to identify the essential explanatory variables that are significant in determining the surge in P2P loan originations. To explain the increase of crowdlending we consider a set of variables, with economic freedom being anticipated as one of the most pivotal among them. We employ annual data spanning from 2007 to 2020 for all U.S. states. Thus, we consider a panel with 50 cross-sectional units and 14 time-series observations per unit. We assemble a hand-collected database containing P2P loan originations and examine eleven factors that are considered as crucial in influencing the crowdlending market.

We use P2P loan data from LendingClub's consumer platform, leveraging the publicly accessible nature of their data. Given that LendingClub is the largest lender in this market, the findings from this analysis are expected to have broader relevance and applicability. The data set comprises 700 observations, representing a total of 3.4 million funded loans with a cumulative value of $52.4 billion, spanning from 2007 to 2020. Table A.1 displays the distribution of total P2P loan volumes and numbers across every state.

Our specification takes into account a significant number of factors that could influence P2P lending, hypothesizing that marketplace lending expansion is closely linked to various drivers on both the demand and supply sides. The incorporated drivers align with previous relevant studies (see, e.g., Adams and Amel, 2016; Havrylchyk et al., 2020; Cornelli et al., 2020; Le et al., 2021; Jagtiani and Lemieux, 2018; Kowalewski et al., 2021), and are further enriched by the inclusion of the Economic Freedom Index and its components.

1. *Economic freedom measurement*

Economic freedom is a factor that can impact the growth of marketplace lending as it is linked to institutional variables that have the potential to influence the dynamics of the credit market. To explore the effects of economic freedom on P2P lending we employ the state-level Economic Freedom of North America Index obtained from the Fraser Institute. The Index is measured on a scale of 0 to 10, where a higher value indicates a greater level of economic freedom and its degree varies among states. Table A.2 presents the sample mean of the overall Economic Freedom Index by state. A quick examination of the table highlights the diversity in economic freedom among the U.S. states included in our sample.

To offer a comprehensive perspective on the influence of economic freedom on crowdlending, this study extends beyond analyzing the overall level of economic freedom and recognizes that a single measure may not capture the complexity of the economic environment. Consequently, we explore specific types of economic freedom measures crucial for P2P expansion.

The evaluation of different components of economic freedom has been conducted using a set of indicators sourced from Fraser Institute database. The Index encompasses six distinct areas, comprising government size, taxation, credit markets regulation, labor market and business regulations, legal system and property rights, sound money, and freedom to trade internationally. We have chosen the following four components for our analysis as they are hypothesized to be suitable for achieving our research objectives: Regulation of Credit Markets, Business Regulations, Sound Money and Freedom to Trade Internationally.

The Credit Market Regulation component assesses the level of restrictions, regulations, and interventions imposed by the government on credit-related transactions, lending practices, and financial institutions. Less stringent credit market regulations may encourage innovation in P2P lending models, lower entry barriers for P2P lending platforms and enhance access to credit for a broader range of borrowers. This can foster a more competitive and diverse lending landscape.

The Business Regulations component reflects the extent to which the government regulates various aspects of business activities, encompassing factors like the ease of business startup and license acquisition. This component may influence the ease of establishing and operating financial services, including P2P lending platforms. Less restrictive regulations can facilitate the entry of new platforms, fostering a competitive environment. Cornelli et al. (2020) find that FinTech credit is more developed in countries with less stringer banking regulation, leading to greater ease of doing business, while Le et al. (2021) indicate that FinTech credit is more developed in economies where explicit FinTech regulation is present.

The provision of sound money is crucial for economic freedom because, in its absence, the ensuing high rate of inflation operates as a concealed tax on consumers. The sound money focuses on the price stability in the exchange process. Its value is determined by the government policies that maintain low inflation rates and the freedom to use alternative currencies. De Haan and Sturm (2000) show that monetary freedom has a positive relationship with economic growth, while Anwar et al. (2021) indicate a statistically significant positive correlation between monetary freedom and the financial efficiency of MFI’s. The anticipation is that a stable currency reduces uncertainty in financial transactions and inflation-related risks, making P2P lending more attractive to both lenders and borrowers.

The importance of the freedom to trade internationally lies in its capacity to enhance individuals' ability to participate in voluntary exchanges, promoting the creation of wealth. Given that the international trade freedom not only encourages investments and international commerce (Berggren, 2009) but also stimulate the FinTech growth (Ricci, 2020), we except that the absence of trade restrictions or barriers could encourage the adoption of marketplace lending, enhancing fund availability and contributing to market expansion.

2. *Financial market variables*

Abundant empirical evidence indicates that market entry is lower in more concentrated banking markets and in markets with an extensive branch network. To explore credit market structure in the U.S., we utilize two variables as indicators of entry barriers: the Herfindahl-Hirschman Index (HHI) and the number of bank branches.

The HHI is a common measure of market concentration and is used to determine lending market competitiveness. The U.S. Department of Justice characterizes a market as highly concentrated if it has an HHI above 2500, as unconcentrated if the HHI is below 1500, and as moderately concentrated if the HHI is between 1500 and 2500. We anticipate that banking concentration impacts the presence and lending volume of LendingClub in a state from the supply side. The data for this analysis is sourced from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits.

In addition, we explore the effect of the number bank branches per capita. A reduced number of branches may serve as a proxy for the magnitude of the credit gap, potentially contributing to the expansion of marketplace lending. Data on branches from all FDIC-insured institutions, organized by U.S. state, is gathered from the FDIC Summary of Deposits database.

Moreover, in order to estimate how developed financial institutions and markets are, we employ the Financial Development Index (FDI). The Index is multidimensional, being a composite of the Financial Institutions Index and Financial Markets Index, with potential diverse impacts on various forms of credit, including P2P lending. We expect positive relationship between financial development and crowdlending volumes. Data for FDI is collected from International Monetary Fund (IMF).

3. *Economic and demographic variables*

Alongside financial market variables, this study examines the impact of economic and demographic factors as potential explanatory variables for the expansion of P2P lending. The factors considered encompass the Unemployment rate, Gini Index, Personal Income per capita, the share of the young population, educated individuals, as well as Hispanic and Black minorities.

The Unemployment rate can impact the demand for P2P loans, influencing the dynamics of marketplace lending. During periods of high unemployment, individuals facing financial strain due to job loss may turn to P2P lending platforms as an alternative source of funding. Data of unemployment rates by U.S. state during the period under study are available at US Bureau of Labor Statistics.

The Gini Index, a measure of income inequality, is expected to positively influence the demand for P2P loans in the U.S. The greater income disparities associated with a higher Gini Index may lead individuals facing financial constraints or lacking access to traditional financial services to seek funding from crowdlending platforms. The GINI coefficient spans from 0, representing a perfectly equal economy, to 1, indicating a perfectly unequal one. Each U.S. state is assigned a Gini Index, and we utilize data from the US Bureau of Labor Statistics to incorporate this information into our analysis.

The impact of Personal Income per capita on crowdlending expansion is generally expected to be negative. Higher per capita personal income tends to be associated with a potential decrease in participation in P2P lending, as individuals with elevated income levels may have access to alternative financial resources, reducing their reliance on such lending platforms. We utilize data from U.S. Bureau of Economic Analysis to compute the volume of Personal Income per capita for each U.S. state over the period 2007-2020.

Finally, we account for the impact of state demographic characteristics, encompassing the proportion of young population, educated individuals, and racial minorities. We anticipate that states with higher educational attainment and a higher proportion of young residents will exhibit increased levels of marketplace lending penetration. Additionally, we foresee the potential widespread adoption of this alternative lending market among Hispanic and Black minorities, given their exclusion from traditional credit markets due to discriminatory practices. To measure socio-demographic characteristics of the population, we rely on 1-year estimates from the American Community Survey released by the U.S. Census Bureau, the only data available at the state level.

1.3.2 Empirical Model

We use all the afore-mentioned variables as the determinants of crowdlending expansion and estimate a baseline model using this set of variables as regressors. Therefore, the development of P2P lending market can be described through the following equation:

$$P2P_{it} = \beta_0 + \beta_1 EF_{it} + \beta_2 \text{Financial Market}_{it} + \beta_3 \text{Economic}_{it} + \beta_4 \text{Demographic}_{it} + u_{it} \quad (1)$$

Among them, i identifies a particular state, t denotes time (year), $P2P_{it}$ is the P2P loan volume of state i in time t, β_0 is the constant, β_1 to β_4 are the coefficients of the independent variables and u_{it} is the unobserved error terms.

The dependent variable is the log of P2P loan volume per capita (per 10,000 population). EF_{it} represents the level of economic freedom in the 50 U.S. states at a specific point in time, represented by year t. Financial Market $_{it}$ refers to financial market control variables, including the Herfindahl-

Hirschman Index, the number of bank branches per 10,000 population and the Financial Development Index. Economic $_{it}$ represents a set of control variables for economic conditions at year t (Unemployment rate, the GINI Index and Personal Income per capita). Demographic $_{it}$ implies the vector of demographic characteristics (the share of young population, educated individuals, and Hispanic and Black minorities) which could capture demand for P2P lending.

In the following stage we decompose the Economic Freedom Index into sub-indices that have been theorized to be crucial factors influencing crowdlending. The general model in equation (1) can be defined by Economic Freedom components, and a more specific econometric model is being estimated:

$$P2P_{it} = \beta_0 + \beta_1 \text{EF\_area3B}_{it} + \beta_2 \text{EF\_area3C}_{it} + \beta_3 \text{EF\_area5}_{it} + \beta_4 \text{EF\_area6}_{it} + \beta_5 \text{Financial Market}_{it} + \beta_6 \text{Economic}_{it} + \beta_7 \text{Demographic}_{it} + u_{it} \quad (2)$$

where EF_area3B $_{it}$ and EF_area3C $_{it}$ are two components within Area 3 of Economic Freedom Index, assessing the extent of regulation and restrictions imposed on credit markets and business, respectively. EF_area5 $_{it}$ corresponds to the Sound Money sub-index evaluating the stability and reliability of a state's currency, while EF_area6 $_{it}$ assesses the freedom to trade internationally. The remaining variables are the same as in the baseline model (1). Table A.3 presents the definition of the variables used in this article, as well as their sources.

1.3.3 Descriptive statistics

Table 1.1 provides descriptive statistics for the variables used in our empirical model. Their number, mean and extreme values are reported. The overall Economic Freedom Index has a mean score of 8.023, with a minimum of 7.631 and a maximum of 8.493. The Economic Freedom component with the highest average score is sound money, registering at 9.717, and it is followed by the regulation of credit markets, which scores 8.706 on average.

The average number of bank branches per 10,000 people is nearly 3. The mean HHI for all states over the analyzed period is 1,189, indicating an unconcentrated market. The Index reached its peak values, surpassing 5,000, for a span of three years (2011-2014) in the state of South Dakota, indicating a notably concentrated financial market.

Regarding the Unemployment rate, the average stands at approximately 6%, reaching a maximum value of 14% in 2009, notably following the recent Great Recession in 2008. The Gini Index varies between 0.4 and 0.5, signifying a moderate degree of income inequality. On average, the percentages of young individuals, those with a bachelor's degree, and individuals who are Hispanic or Black are 20%, 29%, 11% and 10%, respectively.

Table 1.1: Descriptive statistics

Variables	**Observaitons**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Dependent variable					
P2P	700	4.417	1.133	0.66	5.677
Economic Freedom Index					
EF_overall	700	8.023	0.141	7.631	8.493
EF_area3B	700	8.706	0.691	7.312	9.520
EF_area3C	700	8.181	0.155	8.030	8.608
EF_area5	700	9.717	0.094	9.514	9.856
EF_area6	700	7.960	0.163	7.765	8.329
Financial market variables					
HHI	700	1,189.07	947.312	169.06	6,249.75
Branches	700	2.967	1.092	0.0419	6.341
FDI	700	0.909	0.011	0.875	0.921
Economic and demographic variables					
UR	700	5.953	2.244	2.4	14.05
GINI	700	0.459	0.02	0.4	0.515
PIpercapita	700	4.649	0.0808	4.468	4.888
Young	700	20.231	1.235	16.8	25.2
Bachelor	700	29.416	5.391	17.1	46.9
Hispanic	700	11.239	10.126	1	49.3
Black	700	10.227	9.41	0.3	37.9

1.4 Empirical findings

1.4.1 Baseline results

Panel data estimation is employed to capture the impact of all explanatory variables on the explained variable, P2P loan originations. Table 1.2 reports the baseline results when estimating equation (1). Two panel data analysis techniques, namely the fixed effects (FE) model and random effects (RE) model, are used for the estimation. The choice between these models is determined through the Hausman test, with the results indicating the preference of FE model across all specifications. Robust standard errors, year effects, and state effects are incorporated into each regression model to address the issues of heteroscedasticity, time effects, and country effects.

We start with a simple model that includes only economic freedom and P2P loan originations (Model 1). The results show a positive association between economic freedom and P2P lending expansion. This finding aligns with our hypothesis that higher economic freedom exerts a positive impact on crowdlending development. This consistency persists when we control for financial market variables in Model 2 and economic and demographic characteristics in Model 3.

We employ Akaike's information criterion (AIC) to compare the three models and determine which one is the best fit for the data. The AIC values, along with considerations of R-squared and F-statistics, consistently indicate that the full model, including all the variables, fits the data better. The majotity of independent variables in Model 3 are statistically significant in explaining the P2P lending expansion and have the expected association (positive or negative) with the dependent variable.

Beginning with economic freedom, we observe that a one-point increase in the Economic Freedom Index lead to a 0.59% increase in P2P loan originations. The reasoning behind the positive correlation is that a high Economic Freedom Index creates a more favorable regulatory environment, fosters a climate supportive of financial innovation, and enhances access to capital. These factors collectively contribute to the expansion of marketplace lending. Our results are in line with many previous studies emphasizing the positive impact of economic freedom on economic growth (e.g., Brkić et al., 2020; Tran, 2019), the growth of Microfinance Institutions (e.g., Kendo and Eboue, 2016) and the development of FinTech (Ricci, 2020).

Regarding financial market variables, the statistically significant and positive effect of the HHI on P2P lending expansion implies that loan origination activities are more pronounced in states characterized by a highly concentrated lending market. This finding is in accordance with the study of Jagtiani and Lemieux (2018) who also find that more P2P credit provided in areas that have a higher HHI (e.g., HHI >2500). Moreover, in line with earlier research (e.g., Havrylchyk et al., 2020; Le et al., 2021) there is an observed trend indicating that the growth of crowdlending is more rapid in states with a lower number of bank branches per capita. Hence, the presence of bank branches has an adverse effect on P2P lending, aligning with the notion that P2P lending platforms attract customers who are underserved by traditional banks.

A positive relationship between financial development and P2P lending volumes could signal that crowdlending can expand in economies characterized by a higher degree of development in financial institutions and markets. This confirms the findings of Oh and Rosenkranz (2020) and Le et al. (2021). Consistent with this viewpoint, Cornelli et al. (2021) highlight that FineTechs raise more capital in countries with higher financial development.

The positive and highly significant estimated coefficient of the GINI Index suggests a substantial impact of income inequality in driving the expansion of marketplace lending. This implies that as the GINI Index increases, signaling higher levels of income inequality, there is a notable and meaningful increase in marketplace lending expansion. Many research (e.g., Demir et al., 2022; Hodula, 2023) explore the interrelationship between FinTech and the GINI Index, revealing that rise of FinTech credit is associated with a reduction in income inequality facilitated by increased financial inclusion.

As expected, there is a positive correlation between the proportion of P2P loans in a state and unemployment rates, and a negative with Personal Income per capita. A higher unemployment rate positively influence P2P lending, as individuals facing job loss turn to these platforms as an alternative source of funding during financial strain. Increasing personal income, on the other hand, lead to a decline in engagement with P2P lending, as individuals with higher income levels might have alternative financial options and reduced reliance on such lending platforms. These findings are consistent with prior studies such as Jagtiani and Lemieux (2018).

With respect to demographic variables, the study identified a positive influence of high educational attainment and the presence of young population on the demand of P2P lending. These two factors reflect a greater inclination toward adopting new technologies, enhancing the understanding and utilization of P2P lending. This correlation aligns with the findings of Havrylchyk et al. (2020) and Ichwan & Kasri (2019). The accelerated growth of P2P lending in states with a higher percentage of Black minorities may suggest an increased demand from these regions, potentially driven by a need to overcome discrimination within traditional credit markets. However, there is no significant evidence indicating that Hispanic minorities have an impact on crowdlending volumes.

Table 1.2: Economic freedom and P2P loan originations: Baseline models

Dependent variable:	**Model 1**	**Model 2**	**Model 3**
Constant	2.4277***	-11.2139**	-72.7738***
	(0.2576)	(6.5285)	(8.1236)
EF_overall	0.2487***	0.1839***	0.5921***
	(0.0291)	(0.0395)	(0.0523)
HHI		0.0009***	0.0002***
		(0.0002)	(0.0001)
Branches		-2.5941***	-0.2576*
		(0.4586)	(0.1927)
FDI		23.1143***	3.5637*
		(5.2353)	(1.9891)
UR			0.2135***

			(0.0243)
GINI			16.5268***
			(5.3162)
PIpercapita			-12.5946***
			(5.4586)
Young			0.0491*
			(0.0281)
Bachelor			0.0836*
			(0.0379)
Black			0.0246*
			(0.1298)
Hispanic			0.0075
			(0.0715)
Observations	700	700	700
Number of states	50	50	50
R-squared	0.0172	0.434	0.7949
F-statistics	70.841**	151.21***	186.59***
Year effect	Yes	Yes	Yes
State effect	Yes	Yes	Yes
Hausman test (p-value)	0.0000	0.0000	0.002
Akaike's Information Criterion (AIC)	1,936.21	1,523.23	926.69

*Note: The table reports the impact of economic freedom on P2P lending in the U.S. over the period 2007-2020 using fixed effects method. The use of fixed effects method is justified by the Hausman test. Model 3 is the baseline of Eq. (1), which includes economic freedom, financial market variables and economic and demographic variables. The dependent variable is log of P2P loan volume per 10,000 population. All independent variables are defined in Appendix Table A.3. ***, ** and * indicate significant levels at 1%, 5%, and 10%, respectively. Robust standard errors are in parenthesis.*

1.4.2 Economic Freedom components and P2P lending

To enhance our understanding of the influence of economic freedom on crowdlending growth, we delve deeper into four constituent components of the Economic Freedom Index: Regulation of Credit Markets, Business Regulations, Sound Money, and Freedom to Trade Internationally. Table 1.3 reports the results when estimating equation (2).

Models 1 to 4 concentrate on the isolated effects of each component, whereas Model 5 incorporates all four components to examine the consistency of the effects of economic freedom on the P2P lending market.

Models 1 to 4 each focus on one economic freedom indicator along with the identical ten control variables as presented in Equation (1), and the estimation results are detailed in Table 1.3. In Model 5, four economic freedom sub-indices are combined with the control variables.

In Model 1 we find that freedom of regulation in credit market, characterized by a low level of restrictions and government interventions in lending practices, exhibits a positive and significant at 1% level impact on P2P loan originations. This result is in line with the reasoning that less stringent credit market regulations foster innovation in P2P lending, reduce entry barriers for P2P lending platforms, and improve access to credit for a more diverse range of borrowers. Our results are in line with cited findings of Le et al. (2021) and Cornelli et al. (2020) who demonstrate that stringent banking regulation is negatively associated with FinTech credit development.

Similarly, Model 2 and 5 show robust evidence that the higher the sub-Index relative to business regulations the higher the P2P loan originations. The positive relationship is statistically significant at 1% level. This implies that in states with fewer regulatory constraints, there is a more conducive environment for the establishment and growth of P2P lending platforms. Ricci (2020) indicate that FinTech business development is facilitated by low values of regulatory barriers in conducting business activities.

With respect to sound money, in our analysis we find strong evidence that this sub-Index is positively linked to P2P loan issuance. A higher Sound Money Index positively impact the expansion of P2P lending by promoting monetary stability and reducing the risk of inflation, fostering a more reliable financial environment for both lenders and borrowers. Consequently, this encourages increased participation in P2P lending platforms. Recent study of Anwar et al. (2021) indicate a statistically significant positive correlation between monetary freedom and the financial efficiency of MFI's, while De Haan and Sturm (2000) show that monetary freedom has a positive relationship with economic growth.

Nevertheless, we do not find evidence supporting the idea that freedom to trade internationally is a determinant of P2P lending expansion, as the relationship is not statistically significant.

The results of control variables remain consistent with those reported in the baseline model, demonstrating similar parameter estimates and significance levels.

Table 1.3: Economic freedom and P2P loan originations: Economic freedom components

Dependent variable: P2P loan volume	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Constant	-72.9139**	-79.2139**	-84.7738***	-74.7738***	-13.5138***
	(6.9376)	(8.5285)	(8.1236)	(7.7816)	(11.0436)
EF_area3B	0.5887***				0.5114***
	(0.0521)				(0.0641)
EF_area3C		7.3761***			9.661***
		(0.1146)			(0.1037)
EF_area5			5.2751***		3.9751***
			(0. 3254)		(0.5154)
EF_area6				4.8621	3.8621
				(0. 3193)	(0. 4113)
HHI	0.0012***	0.0022***	0.0001**	0.0012*	0.0022*
	(0. 0011)	(0. 0002)	(0. 0006)	(0. 0001)	(0.0002)
Branches	-0.3576*	-0.0476	-0.2276	-0.0247	-0.1776*
	(0. 2227)	(0.1697)	(0.1357)	(0.1297)	(0.1337)
FDI	3.1637*	4.8637*	8.3637**	9.3337**	11.3637**
	(1. 8875)	(2. 0485)	(2. 0145)	(1. 9845)	(2.0445)
UR	0.3135***	0.0844***	0.0454***	0.0854*	0.0337**
	(0. 1243)	(0. 1243)	(0. 0148)	(0. 1583)	(0.0243)
GINI	12.5268***	23.5268***	14.1128*	11.1268***	9.12687**
	(4. 3252)	(5. 9252)	(3. 2512)	(4. 1652)	(3.9652)
PIpercapita	-10.5941*	-11.4821*	-8.8221*	-6.6421	-5.5521**
	(4.5856)	(1.9036)	(1.6336)	(3.6336)	(1.4636)
Young	0.0551*	0.0332	0.0522*	0.0232*	0.0251*
	(0. 0331)	(0. 0448)	(0. 0223)	(0. 0458)	(0.0181)
Bachelor	0.1836*	0.2236*	0.1136*	0.0236*	0.0836***
	(0.0229)	(0.0383)	(0.0332)	(0.0433)	(0.0229)
Black	0.0332*	0.1047**	0.1387**	0.0947	0.0742**
	(0.1458)	(0.1247)	(0.0774)	(0.0757)	(0.0658)
Hispanic	0.0085	0.2112*	0.1322	0.0812	0.0089
	(0.0615)	(0.0647)	(0.0597)	(0. 0647)	(0. 0515)
Observations	700	700	700	700	700
Number of states	50	50	50	50	50
R-squared	0.7125	0.7932	0.8606	0.7594	0.8954
F-statistics	256.59***	272.77***	383.59***	280.37***	440.21***
Year effect	Yes	Yes	Yes	Yes	Yes
State effect	Yes	Yes	Yes	Yes	Yes
Hausman test (p-value)	0.001	0.001	0.000	0.000	0.000
Akaike's Information Criterion (AIC)	925.86	952.98	697.89	903.20	516.24

*Note: The table reports the impact of economic freedom's components on P2P lending in the U.S. over the period 2007-2020 using random effects method. The use of random effects method is justified by the Hausman test. Model 5 is the model of Eq. (2), which includes all economic freedom components used in this study, financial market variables and economic and demographic variables. The dependent variable is log of P2P loan volume per 10,000 population. All independent variables are defined in Appendix Table A.3. ***, ** and * indicate significant levels at 1%, 5%, and 10%, respectively. Robust standard errors are in parenthesis.*

1.5 Conclusion and policy recommendations

P2P lending is a dynamic financial phenomenon and holds immense significance in shaping the landscape of the financial market. As an innovative alternative to traditional banking, P2P lending has increasingly captured attention due to its potential to reshape how individuals and businesses access and provide financial resources. Examining its expansion is of great importance, since the results may reveal how technology and changing consumer habits are reshaping the entire financial sector.

This study examines the factors influencing the growth of crowdlending in the U.S., utilizing P2P loan volume data from LendingClub spanning from 2007 to 2020. Notably, this analysis covers the longest period compared to previous studies on the same field. Our comprehensive analysis considered an array of factors influencing the growth of P2P lending platforms, with a keen focus on economic freedom measures.

The results of our panel data analysis, consistent with previous studies, confirm that financial market characteristics play a crucial role in influencing the expansion of crowdlending. Specifically, our finding indicate that P2P loans are more prevalent in areas with highly concentrated lending market (high HHI) and a lower number of bank branches per capita. This suggests that borrowers residing in areas underserved by traditional banks they are more likely to turn to online lending. Moreover, we find that crowdlending can expand in economies characterized by a higher degree of development in financial institutions and markets.

Our study presents evidence that P2P lending expands in economies characterized by high GINI Index values and high levels of unemployment rates. Conversely, personal income per capita exerts a negative effect on P2P loan originations, since individuals with higher income levels may have access to alternative financial options, reducing their reliance on this kind of lending. Our documentation, also, reveals a positive impact of high educational attainment, a high percentage of the young population, and Black minorities on the demand for P2P lending.

The novelty of our study is that we introduce economic freedom as driver that explain the growth of crowdlending. While several studies have explored the effects of the Economic Freedom Index on various economic outcomes, to the best of our knowledge, this study is the first to establish a connection between economic freedom and the expansion of P2P lending.

Consistent with theoretical predictions, we find robust evidence that economic freedom significantly contributes to the dynamics of P2P lending, impacting various aspects including regulatory environments, market competitiveness, and financial stability.

By decomposing Economic Freedom Index into sub-Indices, this study reveals significant positive impact of freedom of regulation in credit market on P2P lending. Our findings further emphasize that P2P lending is more developed in economies where business regulatory constraints are low, indicating higher levels of the relevant economic freedom component. Additionally, a higher degree of Sound Money Index can also positively impact the expansion of P2P lending. In contrast to findings of previous studies, Freedom to Trade Internationally sub-Index has no statistically significant explanatory power in our model.

To sum up, this study contributes to the growing literature by providing a deeper understanding of the determinants of P2P lending expansion. The empirical evidence show that alternative data should be utilized to explain the growth of this market. Economic freedom plays an important role in determining how this alternative financial market will ultimately take shape.

There are important implications of our findings for researchers and policymakers. The development of P2P lending presents an opportunity for fostering global economic growth, sustainable finance and economic inclusion in the coming years. To harness the potential benefits of P2P lending, increased levels of economic freedom is needed. Policymakers should consider measures that enhance economic freedom within their jurisdictions, promoting a regulatory environment conducive to financial innovation, reducing market entry barriers, and fostering competition. These key strategies are instrumental in facilitating the sustainable growth of P2P lending. Policymakers can further enhance financial literacy and inclusion, particularly in areas with limited access to traditional banking services, to capitalize on the potential benefits of P2P lending expansion.

Considering that crowdlending is regarded as a risky activity with implications for financial stability, policymakers should also consider implementing a regulatory framework that includes prudent oversight, risk management standards, and transparency requirements to mitigate the potential risks and protect both investors and borrowers.

An important direction for future research involves exploring additional factors influencing the pace of P2P lending expansion, not only in the U.S but also in other economies where varied regulations applied to P2P platforms. Moreover, there is a need to explore the factors contributing to the risks associated with crowdlending. Investigating how existing regulations and transparency measures impact risk management in crowdlending platforms can provide valuable insights into addressing challenges and enhancing the industry's resilience.

Chapter 2 - Peer-to-peer lending as a determinant of Federal Housing Administration-insured mortgages to meet Sustainable Development Goals

In this chapter we investigate the influential factors of Federal Housing Administration (FHA) mortgage loans, focusing our research interest on P2P lending, the most successful FinTech lending model. We consider P2P lending an alternative source of financing that marginal borrowers use to pay the increased mortgage down payment, making them eligible to receive a mortgage from conventional banks. In other words, we examine whether and to what extent P2P lending has a positive impact on the FHA loans volume by providing the ability to circumvent the loan-to-value (LTV) cap policy. As a result, P2P lending can be seen as a means for “rationed” borrowers to have access to the market by reducing inequalities and promoting financial inclusion, thus achieving Sustainable Development Goals (SDGs). We employ hand-collected data from FHA mortgages, P2P loans and other economic factors from all 50 U.S. states from 2007 - 2017 and use panel data techniques for this purpose. Research shows that P2P lending, GDP per capita, population growth, broad money growth rate, interest rate, unemployment rate, new housing units and consumer confidence Index produce effects on FHA loans. We show that P2P lending, a nonconventional determinant, is causally associated with a significant increase in the count and volume of FHA loans, implying that P2P lending has a positive impact on them. The ability of P2P to bypass mortgage supply constraints (tightened LTV caps) by providing small loans to borrowers to meet the increased down payment requirements is very important to policy makers, as it shows that constraining the volume of mortgage loans may be not achieved. Macroprudential tools designed to control credit growth may prove ineffective, as the use of alternative forms of lending helps circumvent them and ultimately leads to excessive household leverage with all the risks that it poses to the financial system.

2.1 Introduction

After the housing crisis of 2007-2009 and the subsequent recession, the availability of mortgages decreased and lending standards tightened. This credit crunch drove borrowers to search for alternative sources of finance, such as P2P lending, which is considered the most successful FinTech lending model.

The aim of our study is to investigate whether P2P lending acted as a credit channel, bypassing the restrictions imposed by banks on mortgage lending, and can be considered a means to reduce inequalities and to facilitate the economic inclusion of borrowers in the mortgage market. In our paper, we show that the increase in volume of FHA mortgages, as it is fueled by P2P lending, among other factors, can be viewed as a path to financial inclusion for underserved borrowers, thus achieving the objective of equal access to financial resources, which is the main goal of sustainability. In that sense, P2P lending creates social impact by providing access to credit for individuals that are excluded or underserved by traditional financial institutions. In other words, this form of social lending aims to make mortgage financing and investing more accessible to all borrowers.

We focus on the Federal Housing Administration (FHA) mortgages because the FHA is considered the closest substitute for private subprime lending, thus representing the riskiest category of mortgages. Post crisis, subprime lending was almost eliminated, and riskier potential borrowers struggled to obtain a mortgage loan. FHA facilitated loan originations to low and moderate income borrowers, gaining market share, which peaked at 37% of overall home purchase mortgage market in 2009, while the corresponding percentage in 2007 was 7%[1].

While regulators did not explicitly impose mandatory loan-to-value (LTV) ratios on residential mortgages, the FHA increased its caps. In 2008, the Housing and Economic Recovery Act (HERA) increased the minimum cash down payment requirement on FHA loans to 3.5%. The down payment for FHA loans was as low as 3% for forty-three years (1965-2008). Almost half of FHA mortgage originations in the period from 2002 - 2006 had an LTV ratio above 97%. In the following years, the origination of risky loans gradually declined, reaching an all-time low of 1.23% in 2017. Since fiscal year 2010, over 50% of issued loans were within the LTV ratio of 95%-97%[2].

Historically, the statutory cap on LTV was a commonly used borrower-based macroprudential policy to limit the risks, to curb the real estate boom, and to ensure safety in the economy. The effectiveness of the LTV policy was examined by studies such that of Morgan et al., 2019; Araujo et al., 2020 and Wong et al., 2011. More precisely, Forster and Sun (2022) by performing a counterfactual policy analysis found that the dangerous expansion in the U.S. housing sector could have been effectively offset if authorities had followed a maximum LTV ratio policy.

One issue with implementing LTV limits is that there are ways to bypass the restrictions. In the U.S. during the housing boom, piggyback loans grew rapidly. They were used to help pay down payments on a property or to avoid paying private mortgage insurance (PMI). With piggyback mortgages, borrowers could obtain a secondary loan, usually from a different lender, to fund a fraction, or even the whole amount, of the down payment required for a home purchase. As a result, in many cases,

[1] U.S. Department of Housing and Urban Development (HUD). A Look at the FHA's Evolving Market Shares by Race and Ethnicity **2011**. Available online: https://www.huduser.gov/portal/periodicals/ushmc/spring11/ch1.pdf (accessed on 29 June 2021).

[2] U.S. Department of Housing and Urban Development (HUD). Fiscal Year 2018 Independent Actuarial Review of the Mutual Mortgage Insurance Fund: Cash Flow Net Present Value from Forward Mortgage Insurance- In-Force **2018**. Available online: https://www.hud.gov/sites/dfiles/Housing/documents/ActuarialMMIFForward2018.pdf (accessed on 29 June 2021).

the down payment was as low as zero (Crowe et al., 2013). In our paper, we evaluate the ability of P2P lending, a lightly regulated channel of FinTech credit, to provide funds to potential borrowers to meet the increased down payment for a house purchase. P2P lenders are generally regulated by the U.S. Consumer Financial Protection Bureau, the Federal Trade Commission, and state regulators rather than by the Federal Reserve. We investigate the increase in FHA loans within the framework of tight mortgage lending criteria attributed to, inter alia, the expansion of FinTech lending as a complementary channel to mortgage lending for marginal borrowers. Given that FHA loans mostly address subprime borrowers, who are borrowers with low credit scores and less available cash, it is important to examine how FHA loan originations were evaluated during a period of credit tightness and increased down payment requirements.

The rationale behind the regulatory change in 2008 was the belief that low down payment combined with falling house prices would lead to high rates of default. The maximum LTV ratio was reduced to 96.5% in order to limit the access of risky borrowers to mortgage credit and to prevent negative default externalities.

However, our results show that FHA-insured mortgages increased, since marketplace lending allowed subprime borrowers to ensure the necessary financing and bypass the imposed LTV-based policy.

Marketplace lending emerged after the global financial crisis and is now the leading alternative financing format globally. In the U.S., it is estimated that marketplace lenders currently supply 38% of all unsecured personal lending. According to PWC report (2015), the P2P loan origination volume in the U.S. increased by 84%, on average, since 2007. In 2015, P2P consumer lending was equivalent to 12.5% of traditional consumer lending (Wardrop et al., 2016). In 2017, consumer marketplace lending reached 46 billion USD in total, growing by 12.3 billion USD (36.5%) in 2017 alone.

Many researchers examined the risk related to marketplace lending (see e.g., Käfer, 2017; Durovic, 2017; Lenz, 2017 and Setyaningsih et al., 2019). Suryono et al. (2019) mention six core problems associated with P2P lending, namely information asymmetry, determination of borrower credit scores, moral hazard, investment decisions, platform feasibility, and immature regulations.

Our results show that FHA mortgage originations rapidly increased in the post-crisis period and this event is closely related to the emergence of P2P lending in the U.S. Moreover, the recovery of FHA loans observed from 2015 to 2017, after the big loss of its market share from 2011 through 2014, coincides with the sharp increase in P2P loans. The total volume of FHA mortgages issued in 2015 was 72% higher than the previous year, and the corresponding increase in P2P lending was 83%.

Our analysis highlights the dynamic of crowdlending to circumvent tightened LTV caps (mortgage supply constraints) by providing small loans to borrowers, who can in turn meet the increased down payment requirements, thus increasing the total volume of FHA loans. To our knowledge, this paper is the first that examines to what extent the LTV cap policy can be bypassed by the availability of P2P lending. Beyond financial advantages such as faster approval, flexibility, and higher returns for investors, this form of lending can also encourage financial inclusion and social impact by providing access to credit for underserved segments of the population. In this sense, it supports social and environmental causes, thus promoting sustainability. Financial inclusion is essential for reducing poverty, promoting economic growth, and increasing the economic social and environmental impact of investments on people's lives (OECD, 2020).

Several recent studies have examined the U.S. residential mortgage market in light of new technological achievements and show that traditional methods of lending may no longer be common practice. For example, Jayasuriya, Ayaz, & Williams (2023) study how the use of digital footprint is reshaping the mortgage market and shows that the number of lenders that use a borrower's digital footprint has remarkably increased, and that these users bear a significantly lower risk compared to nonusers. Buchak et al. (2018) and Fuster et al. (2019) show that FinTech lenders dramatically increased their market share of U.S. mortgage lending, suggesting that technological innovation has improved the efficiency of financial intermediation in the U.S. mortgage market.

A paper closely related to ours is that of Braggion et al. (2019), which is the first to examine the growth of Chinese P2P lending after the increase in LTV limits. Authors conclude that policy intervention in the real estate mortgage market caused an increase in the demand for peer-to-peer lending in China, as it acts, to some degree, as a credit channel that circumvents city-level LTV caps and the housing market macroprudential policy in China.

In addition to using U.S. data instead of Chinese data in our analysis, there are two key differences between this study and our paper. First, in addition to crowdfunding, we study the effect of other factors on the development of FHA mortgages, such as the GDP per capita and population growth, which, as empirical results show, have a significant impact on mortgage origination. Second, while they use a difference-in-differences setting to study changes in P2P lending after the change in the LTV policy, we use a panel data model to analyze the correlation between FHA mortgages and crowdlending from 2007 to 2017. The panel data technique is common in applied research and it uses all the data information available. The use of panel data may offer several advantages, such as control for heterogeneity across individual units (states in this study), support of a great number of variables, and less multicollinearity among independent variables.

Clearly, the volume of FHA-endorsed mortgages is affected by many factors. The most important ones are related to the prevailing economic conditions over the eleven-year period under review. Some of the most significant economic and financial factors that are incorporated in our model to examine their effect on the U.S. mortgage originations are interest rate, GDP per capita, unemployment rate, house price index, new residential housing units, population growth, broad money growth rate, and consumer confidence index.

The main goal of this study is to examine the correlation between FHA-endorsed mortgages and marketplace lending, taking into account other macroeconomic and financial factors as well.

Technically, we use panel data analysis for the period 2007–2017. We employ a state-level data set for all 50 U.S. states, and we test the correlation with FHA loans.

This study suggests that the evolution of FHA loans in the sample period 2007–2017 was influenced by many factors, among which was the boom of P2P lending, our main variable of interest. The study finds that the emergence of crowdlending is causally associated with a significant rise in the volume of FHA loans during the study period, implying that P2P lending has a positive impact on mortgage loans.

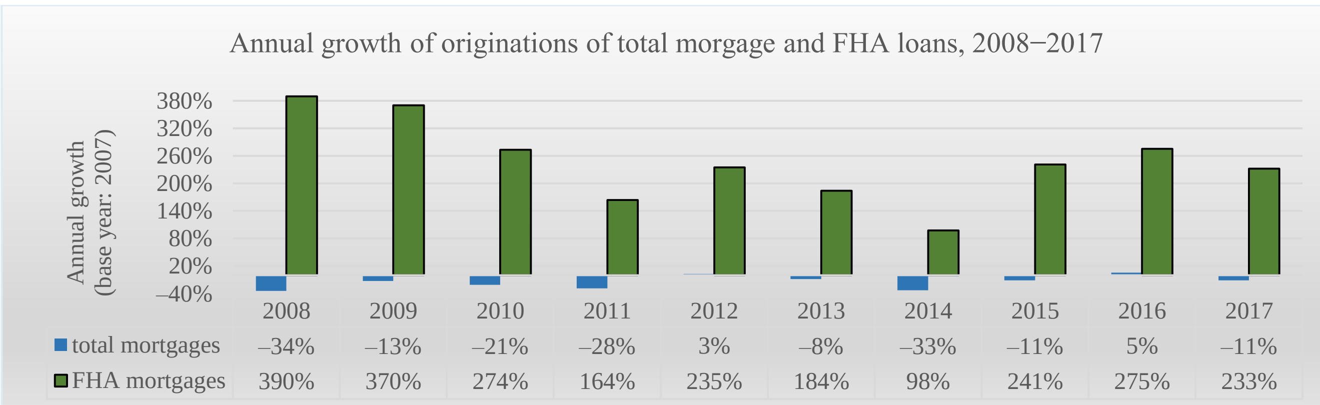
Furthermore, there is evidence for seven more determinants of FHA mortgage endorsements: GDP per capita, population growth, broad money growth rate, interest rate, unemployment rate, new housing units, and consumer confidence Index.

The rest of the chapter is organized as follows: Section 3.2 summarizes the growth in post-crisis FHA-insured mortgages and marketplace lending. Section 3.3 reviews the literature. Section 3.4 presents Holmstrom and Tirole's 1997 model, which allows us to formulate the hypothesis that P2P lending has a positive effect on FHA mortgage origination. Section 3.5 describes the data used and the methodology. Section 3.6 presents and discusses the empirical results. Finally, Section 3.7 concludes the chapter.

2.2 Loan origination behavior in the post-crisis period

We conducted a data analysis of FHA mortgages and P2P loans issued from 2007 to 2017, as after the housing market downturn mortgage endorsements were severely curtailed while FHA mortgage volume significantly increased. Figure 2.1 presents the percentage change in total mortgage originations versus the percentage change in total FHA loan originations during the period under review. The 2007 financial year, which was the beginning of the financial crisis, is used as the base year for comparison purposes.

Figure 2.1: Annual growth rate of total mortgage originations versus the annual growth rate of the FHA loan originations, 2008-2017 (base year: 2007)



During the entire period under review and especially the first four years (2008–2011), aggregate mortgage endorsements were severely curtailed while FHA mortgages skyrocketed, despite the reduction in the LTV ratio. A characteristic example is the year 2008, during which the total mortgage originations decreased by 34% compared to the base year 2007, while FHA loans increased sharply by 390%.

This remarkable trend reversal provides evidence that economic factors that lead to an increase in FHA mortgages may exist, despite the declining trend in mortgages (in general).

P2P lending started in the U.S. in February 2006 with the launch of Prosper Marketplace, followed by Lending Club. We use a data set from Lending Club, the largest (based upon issued loan volume and revenue) online lender in the U.S. and worldwide. Lending Club matches borrowers’ demand and lenders’ supply for funding, without the intermediation of traditional banks. It does not originate loans itself but relies on WebBank, an online bank whose main activity is to finance P2P lending platforms.

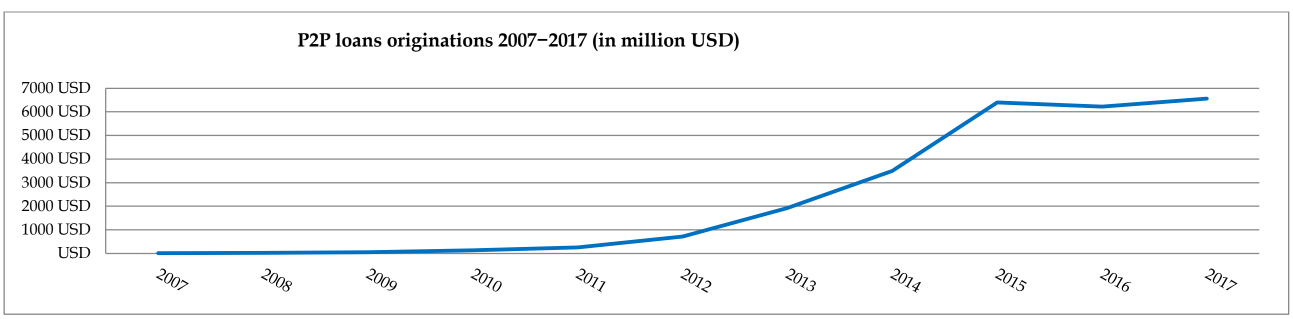
Loan amounts requested on Lending Club vary from 1000 to 40,000 USD, and borrowers may ask for a loan for different reasons, such as debt consolidation, large purchases, or credit card refinancing. Table 2.1 shows the total volume of funded P2P loans, the total number of loans approved, and the number of states that participated in the P2P process from 2007 to 2017.

Table 2.1: Lending Club dataset (P2P loan volumes, number of P2P loans and number of States)

Lending Club	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Volume (in million USD)	5	21	51	131	254	716	1918	3494	6401	6225	6559
No. of Loans	602	2286	5245	12,469	21,090	53,205	130,708	235,026	419,885	433,637	442,001
No. of States	37	46	42	43	44	45	48	48	48	49	49

For the period from 2007–2017, Lending Club facilitated more than 25.7 billion USD in loans (total number of loan originations: 1.8 million). The loan originations progressively increased until 2012, and from 2013 onward, they experienced exponential growth. Figure 2.2 depicts the growth in P2P loans over the period analyzed.

Figure 2.2: Yearly P2P loan volumes



Note: The figure above shows the aggregate loan volume in millions USD originating each year from P2P marketplace platform LendingClub Corporation.

Tables B.1 and B.2 in Appendix B show the loan volume (USD) and the number of mortgages and P2P loans, respectively, issued by each state for each year under study.

Examining the volume of FHA mortgage and the P2P loan origination in each of the U.S. states, we observe that there are ten states with the highest origination of P2P loans and FHA mortgages. More specifically, 50% of total endorsements of U.S. FHA mortgages are issued in these ten states with more than 60% of total P2P endorsements originated in the same states.

Table B.3 in Appendix B presents the percentages of the total FHA mortgage volume issued in each of these ten states during the eleven-year period in question. Table B.4 shows the corresponding percentages of the total P2P loan volumes issued in each of these ten states. Finally, Figure B.1 in Appendix B illustrates the evolution of P2P loans and FHA mortgages in each of these ten states over time (2007–2017).

The patterns followed by both types of loans in each of these states over time are remarkably similar, confirming our prediction that there is a positive correlation between the increase in P2P credit and the increase in FHA mortgages.

The diagrams illustrate the housing crisis of 2007–2009. The greatest fluctuations are observed in the first three years of the period analyzed (housing crisis period). Following the first three years, the patterns of the two types of loans become quite similar and smoother without remarkable deviations during the entire period in question.

2.3 Literature Review

The emerging literature on P2P lending is diverse and rapidly growing. Among the different studies investigating the significant impact of FinTech lending on the housing market, this is the first study, to our knowledge, to examine P2P as a source of credit to which borrowers resort to bypass tightened

LTV caps and obtain mortgages from conventional banks, thus ensuring equal opportunities to everybody. In this sense, our research contributes to three aspects of financial literature: residential mortgage lending, LTV policy, and P2P lending.

2.3.1 Changes in mortgage lending after crisis

In a broad sense, this study is related to the literature investigating the structural changes in residential mortgage lending in the U.S. in the aftermath of the financial crisis (see e.g., Bratton and Levitin, 2020; Goodman, Parrott and Zhu, 2014; D' Acunto and Rossi, 2022; Defusco et al., 2020).

Goodman (2017) measures the mortgage originations in order to quantify the tightness of mortgage credit post-crisis. The author finds that credit tightness resulted in more than one million fewer housing purchase loans per year than would have been originated with reasonable lending standards. Moreover, he assesses the policy actions taken by Federal Housing Finance Agency (FHFA) and FHA, concluding that the FHA still has some important actions to undertake.

Hwang, Miller and Van Order (2016) investigate the increased demand for FHA loans as a result of the expansion of loan limits in 2008. They find evidence that the boom in FHA led to a riskier pool of borrowers than would have existed in the absence of FHA loans.

Another study, Park (2017) using a seemingly unrelated regression model, examines the impact of FHA availability on the overall mortgage market and conventional lending. It shows that FHA endorsements in 2008 were associated with an increase in overall volume originations without substantially displacing conventional loans. In 2014, the FHA impact on overall lending was smaller, but the degree of substitution between FHA and conventional was greater (one-for-one).

2.3.2 Effectiveness of LTV cap policy

This paper is also related to a large body of research, which examines the effectiveness of LTV ratio as a macroprudential tool to constrain loan creation (see e.g., Morgan et al., 2019; Cerutti et al., 2017; Jimınez et al., 2017; Wang and Sun, 2013).

Using panel data methods from 46 countries, Morgan et al. (2019) find that the imposition of an LTV cap reduces credit by 5.9% one year after its implementation, whereas Claessens et al. (2013) find that macroprudential policies are much more effective in booms than in bust periods.

Based on data from 57 countries over three decades, Kuttner and Shim (2016) investigate the effect of LTV ceiling imposition on house prices and concludes that there are no significant effects of such a policy.

Araujo et al. (2020) examine the effects of a maximum LTV policy on the behavior of borrowers and finds that the imposition of a more conservative ceiling reduces both probability of arrears and the mean value of loans. Similarly, Wong et al. (2011) finds the LTV policy to be effective in reducing both household mortgage leverage and systematic risk associated with boom- and-bust cycles in property markets by reducing mortgage delinquency ratios.

Arena et al. (2020) show that the effectiveness of macroprudential measures in Europe has been limited by circumvention, particularly through nonbanks when nonbanks are subject to less stringent regulation. Cizel et al. (2019), similarly, shows evidence of leakages to the shadow banking sector. Using cross-country data, their results suggest that macroprudential policies lead to substitution from bank-based financial intermediation to nonbank intermediation.

2.3.3 Peer-to-peer lending in the US

Finally, this study falls into the rapidly growing literature on P2P lending marketplaces in the U.S. (see e.g., Havrylchyk et al., 2019; Mariotto, 2016; Di Maggio and Yao, 2021).

Jagtiani and Lemieux (2018) find that the Lending Club platform penetrates areas where traditional financial institutions are underserved (small number of bank branches per capita), and the portion of the loans increases in areas where the local economy is not performing well.

There are several studies that examine whether crowdlending platforms and traditional banks are substitutes or complements in the credit market. For instance, Cornaggia et al. (2018) show that a substantial fraction of the P2P loan volume substitutes the small commercial bank personal loan volume. Thus, small banks appear to lower their borrower quality threshold to curtail volume loss.

Tang (2019) shows that the P2P lending market both substitutes and complements the traditional banking system. Using a regulatory change to accounting standards (i.e., the implementation of FAS 166/167 in 2011), as an exogenous shock to bank credit supply, Tang (2019) finds that P2P lending is a substitute for bank lending in terms of serving inframarginal bank borrowers yet complements bank lending with respect to small loans.

Although Kim et al. (2020) examine the effect of P2P lending on the overall volume of small business loans issued by traditional lenders, in our study we investigate the link between marketplace lending and FHA-insured mortgages. Our results are consistent with the hypothesis that P2P platforms complement banks.

A segment of the existing emergent literature, that reviews financial technology, explores the rise of FinTech lending in the U.S. mortgage market.

Our paper is close to Buchak et al. (2018), which provides a detailed analysis of the growth of shadow banks, particularly FinTech shadow banks, in the residential lending market. It finds a shift in mortgage lending from banks to shadow banks in response to improved technology and post-crisis regulatory burdens on traditional banks.

Similarly, Fuster et al. (2019) show that FinTech lenders increased their market share of U.S. mortgage lending, as they process mortgage applications faster than other lenders, alleviating capacity constraints associated with traditional mortgage lending.

2.4 Holmstrom and Tirole's model in our analysis

The analysis is based on the framework of the Holmstrom and Tirole (1997) model, which allows us to formulate our key empirical prediction: the impact of P2P lending on the effects of changes in loan-to-value caps and mortgage down payment borrower requirements, as in Braggion et al. (2019). The rise in down payment requirements from traditional lenders is analogous to a "collateral squeeze", which restrains credit in Holmstrom and Tirole's model. We show that the availability of P2P lending allows borrowers to bypass the important LTV cap, neutralizing its effects such that the levels of new credit are not reduced. These results allow us to formulate the empirical prediction for our test.

We construct a principal–agent equilibrium model, based on the abovementioned model, which explains how loan provision and investments are affected by changes in the supply of capital. The fixed investment scale model has three types of agents: firms, intermediaries (banks), and individual (uninformed) investors. This paper examines the effect of firms' capital tightening (due to a collateral squeeze) on investment behavior and interest rates in the economy. The increase in down payment requirements in FHA-insured mortgages corresponds to this collateral squeeze.

Firstly, we analyze the possibility for financing a project (home purchase) by using indirect financing from banks ("the two-party contract").

Each firm (borrower) has an asset (down payment) that is pledged as collateral. If the project (I) costs more than the asset (A) available, the borrower must find external funds (I-A) to undertake the investment. The project yields R (success) or 0 (failure). The probability of success depends on whether the borrower exerts effort, after the project has received funding. A borrower needs to exert effort to raise the probability of success to pH. The borrower's private benefit (opportunity cost from managing the project diligently) from not exerting effort is B, which lead to pL, with pH - pL=Δp > 0. If the project fails, neither party obtains anything. If the project succeeds, the borrower is paid Rb > 0 and the bank is paid Rm > 0. If the borrower does not default, the distribution in returns is R = Rb + Rm.

The open market rate of return-on-investment capital is γ.

The participation constraint for the bank is

$$p_H R_m \geq \gamma\ (I - A) \qquad (1)$$

and for the borrower is: $p_H R_b \geq \gamma A$. The incentive constraint for the borrower is $p_H R_f \geq p_L R_b + B$, where R_F is the risk-free rate, i.e., the borrower must prefer to be diligent, so that $R_b \geq \frac{\boldsymbol{B}}{\boldsymbol{\Delta p}}$. The maximum expected income for banks must be

$$R_m = R - \frac{B}{\Delta p} \qquad (2)$$

Combining (1) and (2) constraints, we have

$$p_H\ (R - \frac{B}{\Delta p}) \geq \gamma\ (I - A) \qquad (3)$$

We rearrange (3) and have the following condition for the banks to originate a loan:

$$A \geq \overline{\boldsymbol{A(\gamma)}} = I - \frac{\boldsymbol{pH}}{\boldsymbol{\gamma}}\ (R - \frac{\boldsymbol{B}}{\boldsymbol{\Delta p}}) \qquad (4)$$

So, only borrowers with assets (down payment) A $\geq \overline{\boldsymbol{A(\gamma)}}$ can purchase a house using a residential mortgage issued by traditional banks.

The rise in down payment requirements that was imposed post-crisis on FHA-insured mortgages equals an increase in minimum required assets ($\bar{\boldsymbol{A}}$ +δ).

Holmstrom and Tirole in 1997 proved that when aggregate firm capital is reduced, investment will decrease and the minimum initial assets will increase. Consequently, poorly capitalized firms will be the first to lose their financing. Similarly, in our study, subprime borrowers, with less available cash, cannot afford the increased minimum down payment and will be excluded from the mortgage market, leading to a decrease in the FHA loan volume.

When we introduce P2P lending in the model, the outcome on the housing market is reversed. When a borrower fails to obtain a mortgage from a bank due to insufficient assets (down payment), they use P2P lending to cover the difference δ and the minimum required down payment ('the three-party contract").

The participation constraint for the P2P lender is

$$P_H R_{p2p} \geq (\bar{\boldsymbol{A}} + \delta) - A \tag{5}$$

The participation constraint for the banks becomes

$$P_H R_m \geq I - (\bar{\boldsymbol{A}} + \delta) - A \tag{6}$$

The incentive constraint for the borrower remains

$$R_b \geq \frac{B}{\Delta p} \tag{7}$$

The distribution of returns becomes

$$R = R_m + R_{p2p} + R_{b.} \tag{8}$$

Therefore, this analysis allows us to formulate the hypothesis that P2P lending has a positive effect on FHA mortgage origination, which is tested in section 3.5.

2.5 Data and description of variables and methodology

To explain the increase in FHA mortgages in the years during and after the financial crisis, we must consider both macroeconomic and financial factors. One of the most important factors is expected to be crowdlending.

We employ annual data over the period 2007–2017 for all 50 U.S. states. Thus, we consider a panel with 50 cross-sectional units and 11 time-series observations per unit. We assemble a hand-collected database containing FHA loan originations and examine nine factors that are considered as important determinants of the changes in the FHA mortgage market. The volume of FHA mortgage loans is the dependent variable in our model and the variables P2P lending, interest rate, GDP per capita, unemployment rate, house price Index, new residential housing units, population growth, broad money, and consumer confidence index are the independent variables.

The following regression model is used for the analysis:

$$FHA_{it} = \beta_0 + \beta_1 P2P_{it} + \beta_2 IR_{it} + \beta_3 GDP_{it} + \beta_4 UR_{it} + \beta_5 HPI_{it} + \beta_6 BM_{it} + \beta_7 NHU_{it} + \beta_8 POPUL_{it} + \beta_9 CCI_{it} + u_{it} \qquad (9)$$

Among them, $_i$ identifies a particular state, $_t$ denotes time (year), and FHA is the FHA-insured mortgage volume of state $_i$ in time $_t$. β_0 is a constant, β_1 to β_9 are the coefficients of the independent variables and u_{it} is the random error term. All the variables are summarized in Table 2.2.

Table 2.2: Selected variables

Variables	Notation	Source	Value
FHA mortgage loans volume (USD)	FHA	Federal Financial Institution Examination Council	USD, in logs
Peer-to-Peer loan volume	P2P	Lending Club	USD, in logs

Interest rate	IR	The Federal Reserve System	logs
GDP per capita (USD)	GDP	Bureau of Economic Analysis	USD, in logs
Unemployment rate	UR	U.S. Bureau of Labor Statistics	percentage points
House price index	HPI	U.S. Federal Housing Finance Agency	Index
Broad money (USD)	BM	The World Bank	USD, annual growth
New residential housing units	NHU	U.S. Census Bureau	logs
Population	POPUL	U.S. Census Bureau	logs
Consumer confidence Index	CCI	Organization for Economic Cooperation and Development (OECD)	Index

2.5.1 Dependent variable

The volume of FHA mortgage loans is the dependent variable in our model. Information on the majority of U.S. mortgage loans is available in the Home Mortgage Disclosure Act of 1975 (HMDA). The Federal Financial Institution Examination Council (FFIEC) requires financial institutions to maintain, report, and publicly disclose information about home-lending activity every year. Data include, among others, the year, state, loan amount, loan type, and the borrower's income, race, and ethnicity.

2.5.2 Explanatory variables

In the literature, various economic indicators have been proposed as factors that affect the endorsements of mortgages. In this study, we examine the economic and financial factors that may affect the FHA mortgage market. These are in accordance with previous studies, such as Mogaka et al. (2015), Morgan et al. (2019) and Tripathy (2020), but also enhanced with variables that emerge because of unusual economic conditions (financial crisis).

The P2P is the main variable of interest. Other factors equal, a positive association between FHA-insured mortgage loans and P2P lending is expected, since P2P loans may be used as a source of financing the increased mortgage down payment. This study uses data from Lending Club, the largest P2P platform in the U.S. The original dataset contains 1,756,154 borrowing records.

Many studies consider the interest rate and the GDP per capita as important economic factors that affect the mortgage market.

The interest rate reflects the conditions in the credit market. Higher interest rates increase the cost of borrowing, lowering the demand for houses (Igan et al., 2011; Bouchouicha and Ftiti, 2012; among others). In this study, we use the effective federal funds rates (EFFR).

GDP per capita is an indicator of economic development and standard of living. Adams and Füss (2010) noted that GDP growth has a positive impact on the housing market. High GDP per capita indicates high purchasing power and high demand for houses, increasing the mortgage uptake.

In the literature, the unemployment rate has been assessed as a factor that also affects mortgage endorsements. Demir et al. (2003) argue that the unemployment rate has an impact on the ability of potential borrowers to take up mortgages. Hardt (2000) claims that lack of job security affects the ability to access housing loans. Thus, we expect rising unemployment to reduce the demand for housing.

Many studies suggest that population growth is another factor that affects housing demand and explains the fluctuations in the housing market. For instance,.Pashardes and Savva, (2009) and Mankiw and Weil (1989) study the relationship between demographics and the housing market. We expect that an increase in population increases the demand for residential mortgage loans.

Another variable that is introduced in our model is the house price index. Based on this index, an increase in housing prices is expected to be negatively related to the volume of mortgages.

Two additional factors are also included in our study: broad money and residential housing units. Broad money represents the money supply in an economy. According to Liow, Ibrahim and Huang (2006), excessive money supply may lead to an inflationary environment and might affect investments and mortgage uptake. So, we expect that an increase in broad money has a negative effect on mortgage originations. Additionally, an excess supply of houses leads to a decrease in prices. So, new housing units are expected to be positively correlated to the demand for housing loans.

Finally, the consumer confidence index is another important economic indicator for investors and measures how optimistic consumers are regarding both their financial situation and the overall economic outlook. Confidence increases the willingness for house purchases and leads to an increase in new granted mortgages.

To determine the relevant factors that affect the FHA mortgages, this study employs the panel data model. Before proceeding to estimate the model, a multicollinearity test and correlation analysis was carried out.

2.6 Presentation and Discussion of Empirical results

Table 2.3 presents the descriptive statistics of the variables. Apart from the variables UR, HPI, CCI, and BM, all the other independent variables and the dependent variable are log-transformed to reduce data variability.

The higher the coefficient of variation (CV) is, the greater the level of dispersion around the mean. CCI, HPI, GDP per capita, POPUL, NHU, P2P loans, and FHA loans have a lower CV value. However, this is not the case for UR, IR, and BM growth rate.

Table B.5 in Appendix B lists the U.S. states along with the varying median across state variables (FHA mortgages, P2P loans, GDP per capita, unemployment rate, house price index, new residential housing units growth rate, and population growth) during the sample period. As can be observed, there are considerable differences in the values of these parameters across the states.

Although the panel data model can better solve the collinearity problem compared with cross-sectional and time-series models, there is also the possibility of intercorrelations and interassociations among the independent variables. A high degree of multicollinearity makes the model estimation of the coefficients unstable and significantly inflated the standard errors of the coefficients.

Table 2.3: Descriptive statistics of all variables

Variables	Obs.	Mean	Median	Std. Dev.	Min.	Max.	Coefficient of Variation (%)	Skewness	Kurtosis
FHA	550	9.372	9.405	0.524	7.700	11.144	5.60	−0.162	2.733
P2P	550	6.115	6.799	2.280	0.000	8.963	3.72	−1.635	5.042
IR	550	−0.525	−0.584	0.584	−1.046	0.720	−111.21	0.976	2.534
GDP per capita	550	4.693	4.688	0.088	4.493	4.915	1.88	0.258	2.519
UR	550	0.062	0.061	0.022	0.024	0.356	35.58	0.621	2.850
HPI	550	347.14	315.62	103.21	185.37	756.98	0.297	1.036	3.769
BM	550	5.064	4.902	3.352	−2.752	11.713	66.19	−0.383	4.193
NHU	550	7.040	7.084	0.469	5.845	8.247	6.67	−0.085	2.924
POPUL	550	6.586	6.647	0.439	5.728	7.595	6.67	−0.049	2.405
CCI	550	99.09	98.936	1.429	96.742	101.344	0.01	0.034	1.799

Thus, we tested multicollinearity using the variance inflation factor (VIF) method. Based on the results shown in Table 2.4, we can see that the VIF of all variables is below 10; therefore, there is no collinearity problem as there is no linear association among predictor variables. Moreover, the tolerance value (1/VIF) is greater than 0.10, indicating that variables are not correlated.

Table 2.4: Multicollinearity test

Variable	VIF	1/VIF
IR	1.98	0.506
UR	2.72	0.367
CCI	1.77	0.564
P2P	1.63	0.612
BM	1.61	0.623
NHU	6.78	0.148
GDP per capita	1.53	0.653
POPUL	7.82	0.128
HPI	1.40	0.715
Mean VIF	3.03	

Correlation analysis is also carried out to measure the strength of the relationship between the variables considered in the study. Pearson's moment correlation coefficient test is used to measure the degree of correlation between two variables with the correlation coefficient varying between +1 and -1. A value of ± 1 indicates a perfect correlation between the two variables. Table 2.5 shows the correlation among all the chosen variables.

Table 2.5: Correlation matrix of all variables

	FHA	P2P	IR	GDP per Capita	UR	HPI	NHU	BM Growth	POPUL	CCI
FHA	1									
P2P	0.3947 ***	1								
IR	−0.1304 ***	− 0.266 ***	1							
GDP per capita	0.1163 ***	0.2812 ***	−0.0693	1						
UR	0.3718 ***	0.0215	−0.4646 ***	−0.2687 ***	1					
HPI	0.0844 **	0.1748 ***	0.1643 ***	0.4670 ***	−0.1727 ***	1				
NHU	0.7559 ***	0.2778 ***	0.1290 ***	0.0219	−0.0240	−0.0377	1			
BM	−0.194 ***	− 0.2541 ***	0.5703 ***	−0.0855 **	−0.3201 ***	0.0631	0.0985 **	1		
POPUL	0.8704 *	0.3511 ***	−0.0092	0.0014	0.2729 ***	0.0687 *	0.3755 ***	−0.0094	1	
CCI	−0.0950 **	0.3480 ***	0.1526 ***	0.2782 ***	−0.5179 ***	0.1720 ***	0.1813 ***	−0.0469	0.0144	1

*Note: The level of significance is noted by * for 10%, ** for 5%, and *** for 1%.*

Our results show that there is a highly negative relationship between interest rate (IR) and unemployment rate (UR) and a highly positive correlation between IR and the broad money growth (BM). The inflationary pressure that the BM creates justifies this highly positive correlation with the IR variable i.e., a higher inflation rate explains a higher interest rate. On the other hand, job loss and the inability of people to save or borrow money may also justify this highly negative correlation with the interest rate i.e., the higher the UR the lower the IR.

Afterward, we observe a highly negative correlation between UR and the consumer confidence index (CCI) (-0.5179). A possible explanation is that when the unemployment rate increases, the optimism that the CCI captures decreases. Concerning the positive correlation between GDP per capita and house price index (HPI) (0.4670), it can be explained by the following: as GDP per capita increases, personal income increases as well, which means that the demand in the housing market may also rise, thus increasing house prices.

The panel data estimation is employed to capture the impact of the explanatory variables (P2P lending, interest rate, GDP per capita, unemployment rate, house price index, new residential housing units, population growth, broad money growth and consumer confidence index) on the explained variable (FHA mortgages). For the estimation, two techniques of panel data analysis are used: fixed effects model (FE) and random effects model (RE).

The difference between the FE and RE models is that in the RE model, unlike the FE model, the variation across entities is assumed to be random and not correlated with the predictor or independent variables of the model.

The selection between these two models is made using the Hausman test, with the preferred model being the RE model under the null hypothesis and the preferred model being the FE model under the alternative hypothesis.

The Hausman test gives a ch2 = 61.10 and p-value > chi2 = 0.000, p-value is less than 0.05, demonstrating that the hypothesis test is statistically significant, the null hypothesis is rejected, and the FE model is preferred. Table 2.6 below presents the estimation results from Equation (9) using the FE model.

Table 2.6: Summary of regression results using the FE model

Dependent Variable: FHA Mortg	**FEM regression results**	
Independent variables	Coefficient	Standard Error
P2P	0.0092*	0.0049
IR	0.0525**	0.0203
GDP per capita	0.8357**	0.3259
UR	-0.7008	0.8029
HPI	0.0003	0.0003
NHU	-0.2633***	0.0862
BM	- 0.0265***	0.0024
POPUL	4.6083***	0.8894
CCI	-0.0752***	0.0070
Constant	-15.562	5.4837
Observations	550	
Number of states	50	
R-squared	0.7831	
Adjusted R-squared	0.4256	
F-statistic	51.64	
P-value	0.0000	
Hausman test (p-value)	0.0000	
Modified Walt test (p-value)	0.0000	
Born and Breitung HR-test (p-va	0.0005	

*Note: The level of significance is noted by * for 10%, ** for 5%, and *** for 1%.*

The modified Walt test is used for groupwise heteroscedasticity in the residuals of the FE regression model. The results (p-value < 0.05) indicate that we must reject the null hypothesis of homoscedasticity. The heteroscedasticity robust HR-test introduced in Born & Breitung (2016) is used to identify serial correlation in the error term in our panel data model. The null hypothesis is no first order autocorrelation. The HR-test confirms a statistically significant correlation in the error term in the model (p-value < 0.05).

Because of the problems of heteroscedasticity and serial correlation, the Driscoll and Kraay standard errors (D-K Std. Err.) estimation model is used to manage these issues. This model proposes a nonparametric covariance matrix estimator that is spatially and temporally independent. Table 2.7 below presents the estimation results from Equation (9) using the D-K Std. Err. model.

Table 2.7 : Summary of regression results using the Driscoll and Kraay Std. Err. model.

Dependent variable: FHA	**Regression with Driscoll-Kraay Std. Err.**	
Independent variables	Coefficient	Standard Error
P2P	0.0778***	0.0078
IR	-0.0772*	0.0746
GDP per capita	0.9695***	0.0984
UR	-0.7180*	0.0823
HPI	-4.4232	0.0001

NHU	0.3752***	0.0306
BM	-0.0279*	0.0147
POPUL	0.5811***	0.0297
CCI	-0.0659**	0.0284
Constant	27.9458	2.5676
Observations	550	
Number of states	50	
R-squared	0.8509	
Adjusted R-squared	0.6753	
Residuals	Normally distributed (Shapiro − Wilk test, p = 0.156)	
F-statistic	83076.22	
P-value	0.0000	

Note: The level of significance is noted by * for 10%, ** for 5%, and *** for 1%.

The regression results with the D-K Std. Err. model show that the value of the adjusted R2 has increased in comparison with the adjusted R2 with the FE model (which was 0.4256) and is now significant. This adjusted R2 of the D-K Std. Err. model (0.67) shows that the independent variables included in the model can explain most of the variation in the dependent variable.

Furthermore, we checked the normality of residuals since it helps to ensure that the model's assumptions are met and that the data fits well to our model. The assumption is that the error terms are normally distributed; thus, the estimators are efficient and have desirable statistical properties such as minimum variance. To assess normality, we use the statistical test of Shapiro − Wilk. The results of the test indicate that the residuals are normally distributed because the p-value is greater than the conventional significance level of 0.05.

The estimated coefficients of the variables included in the model confirm our hypotheses about the signs of the coefficients. For example, the sign of the interest rate coefficient is now negative, as expected, (while with the FE model the sign is positive) and the sign of the new house units coefficient has a positive and statistically significant effect on FHA mortgages (while with the FE model this correlation was significantly negative). Moreover, the sign of the unemployment rate variable remains negative (as expected), but in the regression with the D-K Std. Err. model, it becomes statistically significant at the 10% level. The P2P, GDP per capita, and POPUL coefficients carry the expected sign and are significant at the 1% confidence interval. The coefficient of P2P lending is positive and

highly significant. This finding indicates that as more P2P loans are issued, the higher the volume of FHA mortgage origination. Therefore, the main hypothesis of our analysis is fulfilled (that an increase in P2P loans is strictly related to an increase in FHA mortgages).

The variable GDP per capita has a positive and statistically significant (at 1% level) effect on real FHA mortgages, as expected. Specifically, a 1% increase in GDP per capita is associated with about a 0.97% increase in FHA loans. The same holds between FHA mortgages and population with a 1% increase in the population leading to a 0.58% increase in FHA mortgages.

Finally, BM growth has to have a statistically significant (at 10% level) and negative impact on FHA mortgages, with a 1% increase in the variable leading to a 0.028% decrease in FHA mortgages.

2.7 Discussion of Results

The main aim of our study is to examine the relationship between the volume of FHA mortgages and P2P lending, considering various economic and financial factors, and the possibility of financial inclusion of underserved borrowers.

Indeed, based on our results, the initial hypothesis of our study, that there is a positive relationship between crowdlending and FHA mortgages, is verified. P2P lending has a positive and statistically significant (at the 1% level) impact on the volume of FHA mortgages, which is in line with the existing literature supporting that FinTech lending has a significant impact on the housing market. However, among the studies that investigate FinTech lending as a substitute for traditional mortgage lending (banks), this study is the first to examine P2P as a source of financing for subprime borrowers to obtain FHA mortgages from conventional banks. Based on our analysis, P2P lending can be a strong alternative for house buyers who do not fulfill the typical criteria required to obtain a FHA mortgage for their purchase. As a result, P2P reinforces the housing market and the economy as a whole, thus contributing to its sustainability.

Another result, also strictly related to sustainability, is the highly positive and statistically significant impact (coefficient 0.969) of the GDP per capita variable on FHA mortgages. This finding is in line with various studies in the literature, such as Mogaka et al. (2015) and Adams and Füss (2010), and shows that a unit increase in the GDP per capita drives a significant increase in the volume of FHA mortgage loans. "GDP per capita" is a crucial variable in our analysis and its in- crease is directly related to the sustainability of the economy concerning economic growth, higher income, and improvement in people's welfare that may also drive an increase in the housing demand.

Population growth is another important factor in our study that also has a positive and significant impact (coefficient +0.5811) on FHA originations and promotes sustainability in terms of economic growth, housing demand, and improvement in living conditions. This result is straightforward since the greater the population, the greater the housing needs, and is also shown in the existing literature, such as Pashardes and Savva (2009), the results of which are directly comparable to ours (coefficient +0.337).

A positive relationship is also observed between the volume of FHA mortgages and the new residential housing units. This result is strictly related to the law of supply and demand. If the market functions well, then an excess supply of houses lowers house prices, and boosts the housing market and the economy growth. So, we can safely conclude that if the market functions well, a positive relationship between FHA mortgages and new residential housing units contributes to the sustainability of the economy in terms of economic growth and welfare.

Other important variables in our analysis that also significantly affect the volume of FHA mortgage loans in a negative way are broad money growth, unemployment rate, and interest rate. Studies such as Liow, Ibrahim and Huang (2006) and Julius (2012) concerning money supply, Avery et al. (2006) concerning interest rate, and Demir et al. (2003) and Hardt (2000) concerning the unemployment rate, among others, indicate similar results to our study and show this negative relation between those variables and the volume of mortgages. An increase in these variables drives a significant decrease in the volume of FHA mortgages, which actually harms the sustainability of an economy. More specifically, an increase in the interest rate implies an increase in the cost of borrowing: an increase in the unemployment rate reinforces a sense of uncertainty, lowering people's willing to spend or to borrow, and the broad money growth increases inflationary pressures. An increase in these variables lowers the demand in the housing market, thus increasing poverty and the income discrepancies among segments of the population, and harming sustainability.

2.8 Conclusions

In this chapter, we set under examination the determinants of the FHA mortgage volume in the years following the financial crisis, where mortgage credit was tight and borrowers' creditworthiness particularly low. We examine all 50 U.S. states in the period from 2007 to 2017 and run a correlation analysis for various variables as determinants of FHA mortgages. The models used for the relationship analysis between FHA mortgage loans and crowdlending are the fixed effects and the Driscoll and Kraay standard errors models, which are used to address the problems of heteroscedasticity and serial correlation. The variables used in the analysis are interest rate, GDP per capita, unemployment rate, house price index, new residential housing units, population, broad money growth rate, and consumer confidence index.

Based on our results from the panel data analysis, we conclude that P2P lending, the GDP per capita, unemployment rate, interest rate, new residential housing units, population growth, broad money growth rate, and the consumer confidence index are significant determinants for the volume of FHA mortgages. More specifically, we show that there is a positive and significant relationship between the volume of FHA mortgages and P2P lending, GDP per capita, population growth, and new residential housing units, and a significant negative relationship with unemployment rate, interest rate, consumer confidence index and broad money growth rate.

An interesting result of our analysis is that we considered P2P lending as a factor of FHA loan volume, since P2P loans are used as a source for financing the increased down payment requirements. The empirical evidence of this study supports the hypothesis that an increased volume in P2P loans had a positive and significant impact on FHA mortgages for the period 2007–2017, in line with the SDGs for sustainable finance and economic inclusion, adopted by the United Nations.

P2P lending has various financial advantages such as flexibility, simplified process, speed, lower lending standards, and higher returns for investors. Beyond the financial advantages, P2P lending also creates social impact. In this context, crowdlending can provide financial resources to underserved people who have limited or no access to the traditional banking system due to their lack of credit history, lack of collateral, or other barriers. In this way, poverty, economic inequalities, and regional economic disparities may be reduced, and sustainable development with social and economic equity may be promoted.

In our paper, we show that P2P lending can contribute to a country's sustainable development goals, mainly through the financial inclusion. Thus, this analysis concerning the relationship between the volume of FHA mortgages and various economic and financial factors, with an emphasis on P2P lending, is directly related to the notion of sustainability.

Nonetheless, it is crucial to note that while crowdlending has the potential to contribute to sustainable growth, there are also associated risks, such as borrowers defaulting and regulatory complexities. Thus, it is recommended that policy decision-makers establish a regulatory framework for the crowdlending market, analogous to that of traditional banking system, and an effective mechanism for assessing and managing risks.

Based on our results, the policy intervention that imposes limits on LTV ratios as a tool to constrain mortgage lending has proved ineffective, since it is eluded via the P2P credit channel. Even if P2P loans concern small amounts, they drive an increase in household debt and mortgage lending. In light of this research, one potential approach to contain household leverage would be for macroprudential regulation to design additional tools, to monitor not only LTV but other indicators as well. With appropriate regulation, crowdlending can contribute to a more inclusive and resilient economy.

Chapter 3 - Factors determining default in P2P lending

The research documented in this study examines multiple factors related to borrowers' default in P2P lending in the United States. The empirical study is based on a total number of 1,863,491 loan records issued through LendingClub from 2007 to 2020Q3 and a logistic regression model is developed to predict loan defaults.

The innovation of this study is the introduction of specific macroeconomic indicators in order to explain the defaults in P2P lending industry. The study indicates that macroeconomic variables assessed alongside loan data can significantly improve the forecasting performance of default model. Our general finding demonstrates that higher percentage change in House Price Index, Consumer Sentiment Index and S&P500 Index is associated with a lower probability of delinquency. The empirical results also exhibit significant positive effect of unemployment rate and GDP growth rate on P2P loan default rates.

Our results have important implications for investors for whom it is of great importance to know the determinants of borrowers' creditworthiness and loan performance when estimating the investment in a certain P2P loan. In addition, the forecasting performance of our model could be applied by authorities in order to deal with the credit risk in P2P lending and to prevent the effects of increasing defaults on the economy.

3.1 Introduction

P2P credit allows direct matching of lenders' supply and borrowers' demand of funding, without the intermediation of traditional banking. In online marketplaces borrowers raise funding from multiple lenders (individuals or institutions). Despite the benefits of this new on-line lending channel, it remains a risky activity for lenders since the default risk in this lending market is still high. Consumer default should be examined further in order to conclude whether FinTech lending investment is an attractive opportunity. Consequently, the aim of this study is to find what determines marketplace loan performance, investigating multiple factors.

Credit risk stems from the possibility of the borrower defaulting payments, because of the inability or lack of willingness to pay them back. For investors it is essential to know the determinants of loan performance in order to focus on the most relevant influential factors when estimating whether a particular loan is worth an investment or not. Studying the default behavior is of great importance as the higher default rates in this market, compared to the corresponding rates in the banking system, may lead to financial stability disruptions and can evolve into a financial crisis, if the credit risk in the P2P market spread and contaminate the financial market.

Many studies that examine marketplace default risk use data of the earliest years of the operation of this market (see e.g. Carmichael, 2014; Möllenkamp, 2017; Serrano-Cinca et al., 2015). We examine 1,863,491 P2P loans with clear payment status outcome that were originated during the period 2007-2020Q3 (the longest analyzed period) via LendingClub, the largest (based upon issued loan volume and revenue) online lender in the US and worldwide.

Our analysis confirms that loan and borrower characteristics can indeed be used to predict probability of default. More specifically, our results show that characteristics explaining defaults are loan amount, loan maturity, number of delinquency incidences, recent credit inquiries, time since last delinquency and last public record, revolving credit utilization and number of open credit lines in borrower's credit file. Borrowers with low annual income, short employment length, high debt-to-income ratio and many charge-offs within 12 months exhibit higher likelihood of default. Loans intended to fund small businesses and borrowers who rent their apartment are positively correlated with the default rate. The most important factor of loan performance is the credit grade that is assigned by LendingClub. Higher credit grade loan is associated with lower default risk.

Our study aims to extend the P2P literature by investigating specific macroeconomic factors as determinants of default risk. Many papers in banking literature examine the influence of the macroeconomic environment on credit market and loan success. Incorporating this kind of exogenous features in our analysis allows us to draw conclusions on the effect of macroeconomic conditions on P2P borrowers' default. We specifically examine the impact of GDP growth rate, Unemployment rate, House Price Index (HPI), Consumer Sentiment Index (CSI) and S&P500 Index on borrowers' probability of default.

Our results confirm the theoretical predictions, i.e. macroeconomic factors play a crucial role in consumer default. The empirical evidence shows a positive relationship between Unemployment rate and an increase in delinquencies and between GDP growth rate and delinquencies. On the other hand, we find that the HPI, CSI and S&P500 Index are negatively correlated with the defaults. Our results are supported by the literature on banks and traditional financial services (see e.g. Skarica, 2014; Mateus, 2020; Crouk, 2012; Wadud et al., 2020; Fallanca et al., 2020; Ghosh, 2017). The findings of our empirical study reveal that the inclusion of these indicators improves model fit and prediction of default.

This study contributes to the growing literature on P2P lending in two important ways. Firstly, this study shed light on the association between specific macroeconomic indicators and the default risk from P2P lending within an economy, while the majority of the existing literature investigate loan and borrower information to evaluate credit risk of P2P loans and predict the likelihood of default. Secondly, our conclusions are more robust and updated since, unlike previous studies, a more comprehensive dataset of default determinants is used spanning 14 years (from 2007 to 2020).

The rest of this chapter is organized in the following order: Section 2 presents the literature review. Section 3 shows the statistical analysis for P2P loans. Section 4 provides empirical results for the determinants of loan default. The final section is outlying the conclusion and policy implications.

3.2 Literature Review

The majority of FinTech lending literature has mainly focused on the explanation of the emergence and expansion of P2P credit and on the P2P loan performance and default risk.

Balyuk and Davydenko (2018) document that marketplace lending has evolved from trading venues into credit intermediaries and the most P2P loans being funded by institutional investors, such as banks. Rau (2020) investigates the determinants of the crowdfunding development and finds that the quality of regulation, the financial system inefficiency and the ease of internet access all provide very robust links to crowdfunding volumes. Havrylchyk et al. (2020) examine the drivers of the expansion of P2P lending in the US and find evidence that counties that were more affected by financial crisis, with weak banking competition and higher population density have more P2P loans per capita. Oh and Rosenkranz (2020) find that financial institutions' efficiency, financial literacy and lower branch and ATM penetration are positively related with the expansion of P2P lending.

Jagtiani and Lemieux (2018) document that LendingClub platform penetrates into areas where traditional financial institutions are underserved (few numbers of bank branches per capita) and the portion of the loans increases in areas where the local economy is not performing well.

Mariotto (2016) comparing the two leading P2P lending platforms in the US, LendingClub and Prosper, concludes that they are substitutes with one another and that they are frontally competing, while P2P lending is transitioning from being a complement to potentially being a substitute of bank's consumer lending.

There are several studies that examine whether crowdlending platforms and traditional banks are substitutes or complements in the credit market. For instance, Kim et al. (2020) find that the entry of P2P platforms reduced small business loans issued by traditional lenders, in particular, in the low- or moderate- income tracts. Balyuk (2018) shows that traditional banks provide and increase credit to borrowers who have obtained loans from on line lending platforms. Wolfe and Yoo (2018) show that a substantial fraction of P2P loan volume substitutes for small commercial bank personal loan volume, while Tang (2019) shows that the P2P lending market serves as both substitutes and complements to the traditional banking system. The interaction between bank lending and lending via P2P lending platforms in Germany is examined by De Rute et al. (2016) and in China by Zhang et al. (2019).

Many researchers examine the risk related to the marketplace lending (see e.g., Käfer, 2018; Durovic, 2017; Lenz, 2017 and Setyaningsih et. al, 2019). Suryono et al. (2019) mention six core problems associated to P2P lending, namely information asymmetry, determination of borrower credit scores, moral hazard, investment decisions, platform feasibility and immature regulations. Zhao et al. (2021) discuss the credit risk contagion of P2P lending and find that the platform correlations, the susceptible immune rate, the elimination rate of the P2P platforms by regulatory agencies, the saturation coefficient and other factors affect the risk contagion in the internet financial market.

Di Maggio and Yao (2021), using a consumer credit panel dataset, document that FinTech borrowers are more likely to default and exhibit higher indebtedness than borrowers from traditional financial institutions. Chava et al. (2019) show that, in the short run, P2P borrowers who are in debt (from traditional banks) benefit from an improvement in credit score and laxer credit constraints after obtaining a loan from P2P, because they use the funds from the platforms mainly to consolidate their credit card debts. In the long run, though, these improvements cause an increase in credit card limits, which for subprime borrowers ultimately translate into higher default rates.

Lots of studies in the FinTech literature focus on the determinants of P2P loan default by examining the performance of these loans. Most of these studies explore loan and borrower characteristics to evaluate credit risk of P2P loans and predict the likelihood of default (see e.g. Carmichael, 2014; Möllenkamp, 2017). Serrano-Cinca et al. (2015), using a sample of 24,449 loans, issued through LendingClub from 2008 until 2014 find that factors that best explain default are loan purpose, annual income, current housing situation and indebtedness. They conclude that credit grade has the highest predictive probability, but their model can be improved by including other factors. Similarly, Jagtiani and Lemieux (2019) find that the assigned rating grades perform well in predicting loan performance over the two years after origination. Emekter et al. (2015) indicates that credit score, debt-to-income (DTI) ratio and FICO score play an important role in loan defaults. Durovic (2017) analyzes two loan characteristics, loan term length and loan purpose and finds that longer term loans are riskier than the shorter term ones and the least risky loans are those used for credit card payoff.

Polena and Regner (2017) define four loan risk classes (based on the assigned credit grade) and find that the borrower's and loan's information that identified as determinants for default in previous studies are only significant in specific loan classes. Canfield (2018) investigates determinants of loan defaults in the Mexican P2P market and analyzes the effect of gender on delinquent behavior. He notes that female lenders have better default behavior than men, as measured by loan survival times.

Chen et al. (2022) use transaction data from LendingClub originated from 2015 until 2018 to estimate the gross rate of return (ROR) on an individual loan base and their results reveal that that borrowers' credit rating, loan interest rate, loan status, and paid-month are the most critical factors to influence investors' ROR.

Lots of studies in banking literature show that economic conditions play a crucial role in consumer delinquency and thus should be taken into consideration when assessing loan performance. Louzis et al. (2012) investigating the determinants of non-performing loans in Greek banking system show that GDP, unemployment, interest rate and public debt have a strong effect on the level of NPLs in all loan categories. Similar study on the Italian banking system was conducted by Foglia

(2022). Their empirical findings show that GDP and public debt have a negative impact on NPLs and unemployment rate and domestic credit a positive one. Wadud et al. (2020) provide evidence on the determinants of household loan delinquency for mortgages, credit card and auto loans in the US. They report positive effect of unemployment rate on delinquency rates and adverse effect of current consumer sentiment and per capita income. Research of Mateus (2019) demonstrates that consumer sentiment and the S&P 500 index impact negatively on delinquency and default. Bofondi and Ropele (2011) examine the macroeconomic determinants of banks' loan quality in Italy and find that the growth rates of GDP, the stock prices index and house price index are negatively correlated with probability of defaulting on loans.

Recent studies are beginning to expand the research on loan default in P2P lending industry by investigating factors, other than loan and borrower characteristics. Nigmonov et al. (2022), utilizing a probit regression analysis, investigate the macroeconomic factors that influence default risk and show that a higher interest rate and inflation increase the probability of default in P2P lending. Croux et al. (2020) by including in their model, aside from the data provided by LendingClub, variables such as GDP growth, VIX Index and Russell 2000 Index, show that macroeconomic conditions also impact the likelihood of P2P loan default.

3.3 Preliminary analysis of P2P loans

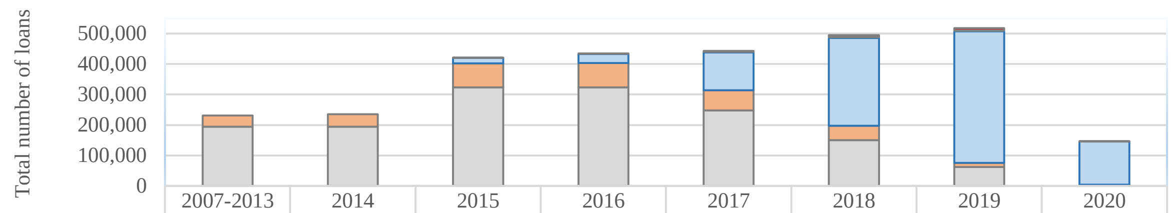
3.3.1 Data selection

This study uses data from the LendingClub consumer platform. Our data set contains information about 2,925,440 loans issued between June 2007 and September 2020[3]. Over the loan origination study period LendingClub lent around $45 billion to borrowers. The loans in our data set have seven different statuses: Fully Paid, Charged Off, Current, Default, Late (31–120 days), Late (16–

[3] Yash. 2020. LendingClub 2007-2020Q3. Kaggle. https://www.kaggle.com/ ethon0426/lending-club-20072020q1?select=Loan_status_2007-2020Q3.gzip. Date accessed: 2022-5-13.

30 days) and In Grace Period. Figure 3.1 shows the number of loans in each loan status per year (during the first seven years the volume of originated loans was not that significant, thus we summed up the observations of these years).

Figure 3.1: Distribution of loan statuses



	2007-2013	2014	2015	2016	2017	2018	2019	2020
Late			464	714	3,349	6,518	7,243	576
In Grace Period			290	467	1,795	3,093	3,695	689
Current			17,504	30,120	124,067	288,448	431,741	141,162
Charged Off	36,102	41,748	79,708	79,083	66,246	47,226	13,564	58
Fully Paid	194,614	193,870	323,123	324,022	248,119	149,945	61,837	4,228

Only the loans with exact ending resolution of the payment are useful, in order to distinguish between 'good' and 'bad' loans and estimate the probability of occurrence of a loan default. Thus, we have removed the categories Current, Default, Late (31–120 days), Late (16–30 days) and In Grace Period, since they include loans that do not yet have a clear payment status outcome (for example, 60-month loans funded in 2018 have not reached their maturity yet and their outcome is still unknown).

Our final sample consist of funded loans whose outcome is known, i.e. "Charged Off" or "Fully Paid". A loan is characterized as "Fully Paid" when the whole funded amount plus the interest rate were paid back. A loan with status "Charged Off" is a loan where a borrower defaulted on the loan and the loan will never be paid back.

3.3.2 Statistical analysis

Table 3.1 reports the loan temporal distribution of the selected sample and presents statistics on the total number and amount of funded loans with known outcome across time, the status outcomes of these (fully paid or charged off) and the corresponding loan default rate per year (default rate is given by dividing the defaulted loans by total number of matured loans).

From the selected 1,863,491 loans, 363,826 defaulted and 1,499,759 repaid fully. The fully paid status has the largest share (80.5% of issued loans on average over the period 2007-2020Q3), while the percentage of default status increasingly grows every year, from 15.6% in 2007-2013 to 24% in 2018. The decline in the volume of defaulted loans in the last 2 years is attributed to the fact that we do not yet have mature loans (only 2 years have passed from loan issuance). Thus, the reduced default rates in 2019 and 2020 is fairly biased given that it has generally been observed that the default rate is increasing with the maturity.

Overall, the ratio default per total loans is 19.5% with total amount of defaulted loans $ 5.8 billion (out of the total of $ 27.2 billion). The highest rate of default was recorded in 2018 (24 %) with total losses of $ 812 million.

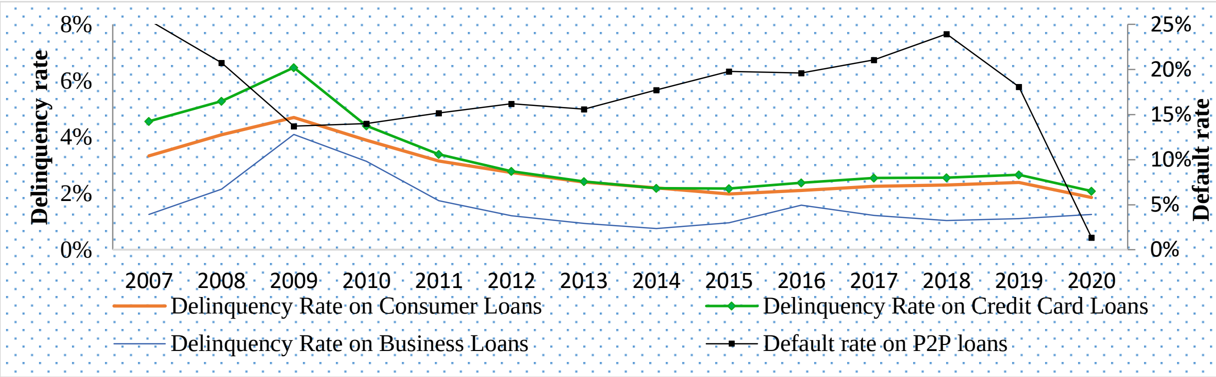
Table 3.1: Loan temporal distribution

Year	2007-2013	2014	2015	2016	2017	2018	2019	2020	Total
Total number of loans	230,716	235,618	402,831	403,103	314,367	197,171	75,401	4,286	**1,863,491**
(percentage)	*12.4%*	*12.6%*	*21.6%*	*21.6%*	*16.9%*	*10.6%*	*4.0%*	*0.2%*	***100.0%***
Amount of loans (000s)	3,172,878	3,503,640	6,048,843	5,761,210	4,474,635	3,023,308	1,126,882	59,130	**27,170,525**
(percentage)	*11.7%*	*12.9%*	*22.3%*	*21.2%*	*16.5%*	*11.1%*	*4.1%*	*0.2%*	***100.0%***
Number of charged off loans	36,102	41,748	79,708	79,081	66,247	47,226	13,564	58	**363,734**
(percentage)	*9.9%*	*11.5%*	*21.9%*	*21.7%*	*18.2%*	*13.0%*	*3.7%*	*0.0%*	***100.0%***
Amount of charged off loans (000s)	533,271	652,172	1,269,502	1,229,651	1,051,285	812,509	228,968	1,057	**5,778,414**
(percentage)	*9.2%*	*11.3%*	*22.0%*	*21.3%*	*18.2%*	*14.1%*	*4.0%*	*0.0%*	***100.0%***
Number of fully paid loans	194,614	193,870	323,123	324,022	248,120	149,945	61,837	4,226	**1,499,757**
(percentage)	*13.0%*	*12.9%*	*21.5%*	*21.6%*	*16.5%*	*10.0%*	*4.1%*	*0.3%*	***100.0%***
Amount of fully paid loans (000s)	2,639,607	2,851,468	4,779,341	4,531,559	3,423,350	2,210,799	897,913	58,073	**21,392,111**
(percentage)	*12.3%*	*13.3%*	*22.3%*	*21.2%*	*16.0%*	*10.3%*	*4.2%*	*0.3%*	***100.0%***
Loan default rate	**15.6%**	**17.7%**	**19.8%**	**19.6%**	**21.1%**	**24.0%**	**18.0%**	**1.4%**	**19.5%**

Source: Authors' calculations based on LendingClub database.

Figure 3.2 presents a comparison of the default rate of P2P loans and delinquency rates on consumer loans, credit card loans and business loans over the time under consideration. The pattern followed by the default rates of P2P loans and the three types of loans of traditional lending is reversed. Namely, the trend in P2P is clearly rising while in traditional banking loans downward. Default rates in P2P lending are reflected over time at higher levels compared to traditional loans (average default rate 17.3% vs 2.78%) and peak in 2018, while the corresponding rate of traditional lending peaks in 2009.

Figure 3.2: Comparison of the level of default rates on P2P loans and delinquency rates on loans at all US commercial banks



Source: Authors' calculations based on data provided by Board of Governors of the Federal Reserve System (US) and LendingClub.

Table 3.2 presents the self-reported loan purpose default statistics. It indicates that the loans that are supposed to be used for debt consolidation and credit card debts are the most frequent (57.1% and 22.2% of all funded loans respectively), whereas the loans funded for wedding, renewable energy and vacation contribute less than 1% of total loans. The highest default rate is observed in loans for small business funding (28.7%), followed by loans regarding house buying (22.2%) and loans for moving purposes (22.1%). The less risky loan purpose for lenders is wedding loans and car purchase (repayment rate 87.6% and 85.8% respectively).

Table 3.2: Loan distribution by loan purpose

Loan purpose	**Total loans**		**Charged off loans**		**Fully paid loans**	
	Number	***percentage of the total***	***Number***	***Default rate***	***Number***	***Repayment rate***
car	20,286	1.1%	2,871	14.2%	17,415	85.8%
credit card	413,270	22.2%	69,725	16.9%	343,545	83.1%
debt consolidation	1,064,797	57.1%	220,047	20.7%	844,750	79.3%
educational	424	1.3%	88	20.8%	336	79.2%
home improvement	124,100	5.4%	21,428	17.3%	102,672	82.7%
house	11,152	1.0%	2,481	22.2%	8,671	77.8%
major purchase	41,880	2.0%	7,742	18.5%	34,138	81.5%
medical	22,640	1.1%	4,635	20.5%	18,005	79.5%
moving	13,249	1.8%	2,932	22.1%	10,317	77.9%
other	114,039	4.9%	22,894	20.1%	91,145	79.9%
renewable energy	1,263	0.2%	275	21.8%	988	78.2%
small business	20,682	1.1%	5,940	28.7%	14,742	71.3%
vacation	13,355	0.6%	2,382	17.8%	10,973	82.2%
wedding	2,354	0.1%	293	12.4%	2,061	87.6%
Total	**1,863,491**	**100.0%**	**363,733**	**19.5%**	**1,499,758**	**80.5%**

Source: Authors' calculations based on LendingClub database.

LendingClub evaluate borrowers' riskiness to default and classifies them in credit grades from A (low risk borrowers) to G (high risk borrowers). The grades are used to assign the interest rate of the funded loan (borrowers in grade G exhibit higher likelihood of delinquency and thus they are charged higher interest rate). Table 3.3 shows loans temporal distribution among the seven credit grades. For each category of loan grade, it is presented the total number of P2P loans issued, the number of defaulted loans and the corresponding default rate over the period spanning from 2007 to 2020Q3. The majority (29.4% of total loans) of issued loans belong to grade B, closely followed by credit grade C (28.4%). A small number of total loans (48,251 out of 1,863,491) originated for borrowers who classified in grades F and G, which are expected to bear the highest credit risk.

Credit grade G, as expected, presents the highest default rate (48.8%). The second worst loan performance is observed in F-graded loans (44.3% default rate), which are accompanied with the second highest credit risk. Finally, all loan categories reached their peak during the issued year 2018 (A: 9.18%, B: 19.4%, C: 29.7%, D: 38%, E: 43.8%, F: 52.2% and G: 54.4%). Only 6.5% of total loans stem from credit grade A defaulted. Comparatively low default rates is also found in grades B (13.5%).

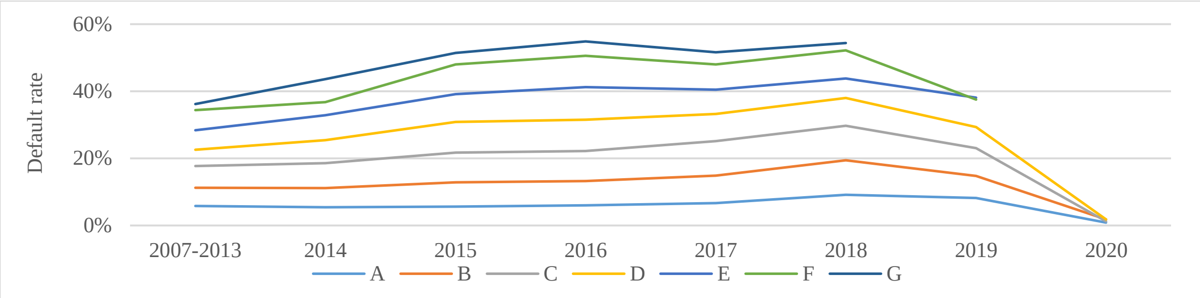
Table 3.3: Temporal distribution by credit grade

Grade		**2007-2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**total**
A	*Total loans*	38,763	36,108	72,728	69,348	57,111	49,591	21,293	1,503	346,445 (18.6%)
	Charged off loans	2,230	1,954	4,035	4,122	3,780	4,525	1,730	13	22,389 (6.2%)
	Default rate	**5.8%**	**5.4%**	**5.5%**	**5.9%**	**6.6%**	**9.1%**	**8.1%**	**0.9%**	**6.5%**
B	*Total loans*	75,012	61,934	113,304	127,321	94,190	53,736	20,419	1,154	547,070 (29.4%)
	Charged off loans	8,406	6,875	14,524	16,813	13,997	10,424	3,007	21	74,067 (20.4%)
	Default rate	**11.2%**	**11.1%**	**12.8%**	**13.2%**	**14.9%**	**19.4%**	**14.7%**	**1.8%**	**13.5%**
C	*Total loans*	58,749	66,563	113,999	119,800	99,212	51,193	18,468	906	528,890 (28.4%)
	Charged off loans	10,372	12,369	24,738	26,529	24,891	15,215	4,255	11	118,380 (32.5%)
	Default rate	**17.7%**	**18.6%**	**21.7%**	**22.1%**	**25.1%**	**29.7%**	**23.0%**	**1.2%**	**22.4%**
D	*Total loans*	33,908	42,987	59,015	53,399	40,830	30,952	13,955	723	275,769 (14.8%)
	Charged off loans	7,646	10,920	18,205	16,834	13,572	11,750	4,093	13	83,033 (22.8%)
	Default rate	**22.5%**	**25.4%**	**30.8%**	**31.5%**	**33.2%**	**38.0%**	**29.3%**	**1.8%**	**30.1%**
E	*Total loans*	15,638	20,118	32,503	22,690	15,289	9,585	1,243	0	117,066 (6.3%)
	Charged off loans	4,443	6,610	12,715	9,350	6,192	4,199	473	0	43,982 (12.1%)
	Default rate	**28.4%**	**32.9%**	**39.1%**	**41.2%**	**40.5%**	**43.8%**	**38.1%**		**37.6%**
F	*Total loans*	7,009	6,223	9,200	8,259	4,940	1,715	16	0	37,362 (2.0%)
	Charged off loans	2,412	2,285	4,420	4,178	2,373	896	6	0	16,570 (4.6%)
	Default rate	**34.4%**	**36.7%**	**48.0%**	**50.6%**	**48.0%**	**52.2%**	**37.5%**		**44.3%**
G	*Total loans*	1,637	1,685	2,082	2,286	2,793	399	7	0	10,889 (0.6%)
	Charged off loans	593	735	1,071	1,255	1,441	217	0	0	5,312 (1.5%)
	Default rate	**36.2%**	**43.6%**	**51.4%**	**54.9%**	**51.6%**	**54.4%**	**0.0%**		**48.8%**

Note: The numbers in parentheses are the percentages of each loan category to the total number of loans. The numbers are from authors' calculations based on LendingClub database.

As Figure 3.3 illustrates, grade A borrowers are steadily capable of payed their loans as their default rates are the lowest during the period under examination. Overall the rate of default gradually increases as loan grade deteriorates (most of the defaulters are presented in the riskiest categories), which is proof that the assessment method is used by LendingClub is accurate and reliable and reduces the information asymmetry problem in the platform.

Figure 3.3: Average default rate on each credit grade for each originated year.



Source: Authors' calculations based on LendingClub database.

3.4 The empirical study

3.4.1 Variables and model

The research question in this study is to find the significant explanatory variables that are essential in determining the probability of default for LendingClub loans. We employ binary logistic regression to assess the capability of determinants analyzed to predict the loan default.

1. Dependent variable

Since two outcomes are possible, the dependent variable is binary (or dichotomous) and presents the status of loan payment "Charged Off". The variable takes the value of one (1) if the borrower defaulted on the loan and the value of zero (0) if the loan was fully paid.

2. Independent variables

The factors that usually predict the repayment of a loan or its default are expected to be loan and individual borrower characteristics. There are more than 100 variables in the data set of LendingClub, but not all are of interest for our analysis. Our variables were selected based on the results of previous studies on P2P default behavior and have been proved to play essential role in borrower solvency. Table C.1 in Appendix C summarizes the P2P variables explanation. The independent variables are categorical or continuous. Except for term, grade, employment length, home ownership and loan purpose, all the other variables are continuous.

We expect that loan performance not only depends on the borrower and loan information but also on the overall state of the economy. Based on the theory and results of the relevant banking literature we consider the following factors, reflecting the health of general economy, as potential explanatory variables: real GDP growth rate, Unemployment rate, House Price Index, S&P500 Index and Consumer Sentiment Index.

A lot of studies (e.g. Croux et al., 2020; Louzis et al., 2012 and Skarica, 2014) suggest that an increase in Gross Domestic Product (GDP) positively affects loan quality and decreases the likelihood of default. Thus, we expect real GDP growth to have a negative effect on default rate (low GDP growth rates, during periods of economic recession, decrease the ability of borrowers to repay their loans).

The unemployment rate, which is linked to the uncertainty regarding future income, is an important indicator for signaling borrower solvency and is commonly used to interpret the default rate. Rise in unemployment rates, can be expected to increase the hazard (delinquency risk). Louzis et al., 2012 argue that unemployment is an important factor that affects consumer NPLs in the Greek banking sector, implying that an increase in unemployment levels has a negative impact on borrowers' ability to settle their obligations. A lot of studies find strong positive correlation between unemployment and consumers' delinquency (Mateus, 2020; Tobbak et al., 2014; Bellotti et al., 2009; Agarwal and Liu, 2003; among others).

In the literature the House Price Index (HPI) has been assessed as a factor that negatively affect non-performing loans4. Usually, a positive shock in house prices results in a fall in delinquency volume. Ghosh (2015) finds that a rise in housing price reduces NPLs. Crouk (2012) concludes

[4] We use the FHFA House Price Index (FHFA HPI), which is a broad measure of the movement of single-family house prices based on data from all 50 states and over 400 American cities that extend back to the mid-1970s.

that the greater the fall in house prices, the greater the increase in delinquent debt and Wadud et al. (2020) show that house prices have an adverse and significant impact on mortgage delinquency rate.

P2P default probability may be affected by the performance of the US equity market. The impact of such Indices on loan delinquencies was assessed, for example, by Altman et al., (2005), Ghosh (2017) and Fallanca et al. (2020). A decrease in financial wealth is expected to increase the borrowers' probability of defaulting on loans, since the ability to service debts also decreases. We use historical data from S&P 500 Index[5], which reflects the overall return characteristics of the stock market as a whole, as a measure of changes in financial wealth.

Consumer Sentiment Index (CSI) is another important economic indicator and measures how optimistic consumers are about their financial situation and the overall economic outlook[6]. The effect of CSI is expected to be ambiguous. Increased households' optimism is likely to cause less loan defaults, but high consumer optimism may be expected to increase the demand for loans and, as a consequence, an increasing debt may lead to high levels of loan delinquencies. Wadud et al. (2020) show the impact of current and expected consumer sentiment and other independent variables on delinquencies with respect to mortgage, credit cards, automobile and student loans. Mateus (2020) reports that an increase in consumer sentiment causes delinquency and default to decrease in auto loans, credit cards, mortgages and student loans in the US.

Table C.2 in Appendix C presents the macroeconomic variables, their sources and the expected signs.

We use all the afore-mentioned variables as the determinants of P2P default and estimate a baseline model using this set of variables as regressors. Therefore, the probability of default for a P2P loan can be described through the following equation:

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[5] The S&P 500 index measures the value of the stocks of the 500 largest corporations by market capitalization listed on the New York Stock Exchange or Nasdaq.

[6] In this study we use the Michigan Consumer Sentiment Index (MCSI). MCSI is a monthly survey of consumer confidence levels in the United States conducted by the University of Michigan. The survey is based on telephone interviews that gather information on consumer expectations for the economy.

$D = \beta_0 + \beta_1$ loan_amnt $+ \beta_2$ term $+ \beta_3$ grade $+ \beta_4$ emp_length $+ \beta_5$ home_ownership $+ \beta_6$ annual_inc $+ \beta_7$ purpose $+ \beta_8$ dti $+ \beta_9$ delinq_2yrs $+ \beta_{10}$ inq_last_6mths $+ \beta_{11}$ mths_since_last_delinq $+ \beta_{12}$ mths_since_last_record $+ \beta_{13}$ open_acc $+ \beta_{14}$ revol_bal $+ \beta_{15}$ revol_util $+ \beta_{16}$ hargeoff_within_12_mths $+ \beta_{17}$ GDP $+ \beta_{18}$ HPI $+ \beta_{19}$ UR $+ \beta_{20}$ S&P500 $+ \beta_{21}$ CSI $+ \varepsilon$ (1)

Here, D is a binary variable and represents probability of default (1 if the funded loan has been defaulted and 0 otherwise). Equation (1) analyzes the determinants of probability of default. All the macroeconomic variables are in growth values, except the unemployment rate. The values of the individual variables obtained from LendindClub are reported in Table C.1 in Appendix C.

3.4.2 Descriptive Statistics

Table 3.4 reports the summary statistics for all variables used in this study. Their number, mean, extreme values and median are reported. On average 60% of the time applicant has less than 10 years of work experience. Borrowers have an average income of $ 77,360, an average dti ratio of about 18.6 % and an average of 0.31 incidences of delinquency in their credit file within the last two years. On average, the size of a typical loan $14,580 and 75% of all loans issued have maturity of 36 months (25% have a repayment period of 60 months). The average credit grade of an applicant is 2.7, which corresponds to credit category between B and C.

Regarding the macroeconomic variables, average GDP growth rate for US during the study period is 2.24 % and the unemployment rate 5.25%. The average annual change in House Price Index, S&P 500Index and CSI is 4.79%, 9.79% and 4.72% respectively.

Table 3.4: Descriptive statistics of all variables.

Variables	Number of observations	Mean	Std. Dev.	Min.	Max.	Median
loan_amnt	1,863,491	14,580.44	8,969.92	500	40,000	12,000
annual income	1,863,491	77,360.57	117,753.9	0	1.10e+08	65,000
dti	1,863,491	18.561	13.086	-1	999	17.71
grade	1,863,491	2.691	1.271	1	7	3
delinq_2yrs	1,863,491	0.313	0.875	0	42	0
inq_last_6mths	1,863,491	697.658	32.705	610	845	690
mths_since_last_delinq	1,863,491	701.658	32.705	614	850	694
mths_since_last_record	1,863,491	0.618	0.918	0	33	0

open_acc	916,981	34.427	21.907	0	226	31
revol_bal	1,863,491	11.604	5.575	0	90	11
revol_util	1,863,491	0.208	0.589	0	86	0
chargeoff_within_12_mths	1,863,491	4.652	3.196	0	64	4
employment length over 10 years (Y/N)	1,863,491	0.328	0.469	0	1	0
employment length under 10 years (Y/N)	1,863,491	0.605	0.488	0	1	1
term (maturity 36 months)	1,863,491	0.749	0.433	0	1	1
GDP	1,863,491	2.239	0.575	-3.4	2.92	2.28
HPI	1,863,491	4.794	1.688	-5.61	5.57	5.11
UR	1,863,491	5.251	1.231	3.6	9.55	4.9
S&P500	1,863,491	9.797	10.743	-38.49	29.6	9.54
CSI	1,863,491	4.724	5.353	-18.3	28.19	5.63

Note: Credit grade "1" is the loan category of A, which is the least risky class of loans. Credit grade "7" is the loan category of G (high risk borrowers).

Table C.3 in Appendix C shows the correlation matrix table (Pearson's correlation coefficients) of all non-categorical variables. The largest correlation (0.553) can be found between the number of open credit lines and the number of delinquencies for the past 2 years. The second highest linear relationship is obtained between GDP and CSI (0.538). Although, the rest of coefficients are not high. So, the chosen independent variables are not highly correlated to each other and multicollinearity problems do not arise. Finally, the most correlated variable with default is the number of charge-offs within 12 months with a correlation of 0.094.

3.4.3 Empirical results

We first carry out non-parametric test in order to examine if there are differences in the chosen variables between two subsamples of loan status ("Charged off" and "Fully paid"). The Mann–Whitney U (Wilcoxon rank sum) test is used for comparing the two groups, where the null hypothesis is that the two samples come from identical populations (i.e. have the same median). Alternative hypothesis assumes that observations in one sample tend to be larger than observations in the other.

Table C.4 in Appendix C shows the results of the non-parametric test and summarizes the differences between defaulted and fully paid loans. Examining the selected variables, we see that the significance levels of all variables are less than 0.01, which means that there are statistically significant differences between two groups and thus the null hypothesis is rejected. More specifically, loan amount, dti, credit grade and loan maturity are higher on defaulted loans, while annual income and employment length are smaller. The borrowers of defaulted loans tend to have lower declared income and credit grade but higher revolving line utilization and dti ratio.

To further determine the exact effect of one of each variable on the probability of a P2P loan to default, we perform 3 logistic regression models[7]. The estimation results of the models are reported in Table 3.5. Model 1 uses the variables provided by LendingClub (individual borrower and loan characteristics), model 2 contains only the macroeconomic variables (exogenous economic factors) and the overall model 3 uses all the explicative variables.

Firstly, we use goodness-of-fit measures by means of the Hosmer-Lemeshow test and the method of Akaike information criterion (AIC) to compare the 3 models and determine which one is the best fit for the data. Hosmer-Lemeshow test shows that the model 3 is the most adequate in explaining the status loans with a p-value of 0.736. The AIC, similarly, indicates that the full model, including all the variables, fits the data better (the model with the smallest AIC is a better-fitting model). Consequently, the inclusion of variables related to macroeconomic conditions clearly improves our model.

Table 3.5: Binary logistic regression results of loan default.

Dependent variable: Defaulted loans	**Model 1**		**Model 2**		**Model 3**	
Variables	**Odds Ratio**	**Robust Std. Err**	**Odds Ratio**	**Robust Std. Err**	**Odds Ratio**	**Robust Std. Err**
_cons	1.8361***	0.1024	1.2023	8.9308	2.5198***	3.9348
loan_amnt	1.0001***	3.6145			1.0001***	3.6155
dti	1.0065***	0.0005			1.0064***	0.0005
delinq_2yrs	1.0215***	0.0027			1.0206***	0.0028
inq_last_6mths	0.9947***	0.0001			0.9948***	0.0001
mths_since_last_delinq	1.0002***	0.0001			1.0002**	0.0001
mths_since_last_record	1.0590***	0.0032			1.0625***	0.0032
revol_bal	0.9938***	0.0006			0.9939***	0.0006
revol_util	1.0297***	0.0043			1.0268***	0.0043
chargeoff_within_12_mths	1.0502***	0.0010			1.0492***	0.0010
term (maturity 36 months)	0.5944***	0.0042			0.5979***	0.0042
Credit Grade A (Y/N)	0.1939***	0.0061			0.1898***	0.0060

[7] Results are reported for the whole sample period. We tested splitting the data into two subsamples, subperiod 1: the first 4 years (2007-2010) of operation of P2P lending industry in the US, which coincide with the financial crisis and subperiod 2: time period from 2011 to 2020 and we found that the estimates from the regressions were very similar (in terms of coefficients and statistical significance of the variables) and didn't deviate from the overall sample.

Credit Grade B (Y/N)	0.3294***	0.0097			0.3241***	0.0094
Credit Grade C (Y/N)	0.4910***	0.0140			0.4843***	0.0138
Credit Grade D (Y/N)	0.6406***	0.0183			0.6324***	0.0180
Credit Grade E (Y/N)	0.7893***	0.0229			0.7751***	0.0225
Credit Grade F (Y/N)	0.9123***	0.0286			0.9068***	0.0285
employment length over 10 years (Y/N)	0.8993***	0.0107			0.9007***	0.0107
HS:ANY	1.1023	0.1522			1.1367	0.1297
HS: NONE	1.3155	0.4561			1.3339	0.6733
HS: OTHER	0.5426	0.2864			0.5351	0.4009
HS: OWN	0.5426***	0.1114			0.5336***	0.0108
HS: RENT	1.4337***	0.0088			1.4330***	0.0091
annual income	0.8065***	0.0144			0.8061***	0.0143
LP: car	0.8537***	0.0275			0.8541***	0.0275
LP: credit_card	0.9704***	0.0127			0.9694***	0.0127
LP: debt_consolidation	1.0231**	0.0120			1.0220**	0.0119
LP: home_improvement	1.0367***	0.0156			1.0328***	0.0120
LP: house	1.0323	0.0357			1. 0296	0.0356
LP: major_purchase	0.0394*	0.0227			1.0382*	0.0227
LP: medical	1.1206***	0.0297			1.1198***	0.0296
LP: moving	1.1210***	0.0365			1.1198***	0.0365
LP: renewable_energy	1.1292	0.1143			1.1179	0.1159
LP: small_business	1.4581***	0.0369			1.4569***	0.0379
LP: vacation	0.9704	0.0343			0.9687	0.0344
LP: wedding	0.8567***	0.0146			0.9213***	0.1125
open_acc	0.9999***	0.0001			0.9990***	0.0001
GDP			1.1242***	0.0059	1.1273***	0.0111
HPI			0.9872***	0.0017	0.9472***	0.0049
UR			1.1915***	0.0025	1.1835***	0.0102
S&P500			0.9981***	0.0002	0.9949***	0.0003
CSI			0.9928***	0.0005	0.9880***	0.0009
Observations	**1,812,335**		**1,863,491**		**1,812,335**	
Pseudo R2	**0.0773**		**0.0031**		**0.1815**	
Year effect	**Yes**		**Yes**		**Yes**	
US States effect	**Yes**		**Yes**		**Yes**	
Log Likelihood	**- 418,817.16**		**-917,037.65**		**- 413,800.34**	
Akaike's information criterion (AIC)	**1,635,466**		**1,834,087**		**1,617.106**	
Hosmer and Lemeshow's test (p-value)	**0.034**		**0.000**		**0.736**	

Note: Coefficients and standard errors are reported as odds ratios. All models' specifications employ robust standard errors in order to handle potential heteroscedasticity or model's misspecification. Year and US States effects are incorporated in each regression model to address the problems of period effects and state-level effects respectively.
*The base value of model for credit grade is Credit Grade G (Grade G is the loan category with the highest assigned credit risk). HS stands for Home Status and the base value for homeownership is Mortgage. LP stands for Loan Purpose and the educational purposes was taken as the base group. The base value for loan maturity (term) is 60 months and for employment length is less than 10 years. The definitions of the variables are in Table C.1 and C.2 in Appendix C. The levels of significance is noted by * for 10%, ** for 5% and *** for 1%.*

The majority of independent variables in model 3 are statistically significant at 1% level in explaining the probability of a loan default and indicate the expected association (positive or negative) with the dependent variable. Based on the results, the delinquency probability for a typical P2P loan can be determined using the Odds ratio reported. With the Odds ratio, the probability of loan success (fully paid) is set in relation to the probability of loan default.

Credit grade is an important factor determining loan performance and default likelihood. As expected, consistent with the statistical analysis in section 3.2, the lower the credit grate, the riskier the loan. The results show a descending order from A (low risk borrowers) to G (high risk borrowers). The estimated exponentiated coefficients for each credit grade are significant at the 1% level. The variable with the highest predictive capability of all in the study is one reporting whether a borrower was assigned with grade A. Going up from grade B to grade A is associated with a decrease of almost 80% in the odds of becoming a defaulted loan.

Another important factor determining the loan outcome is the self-recorded loan purpose. The default probability is high in loans used for small business funding, medical and moving purposes, while loans for wedding expenditures, car purchase and credit card bear lower default risk, with the odds ratio being 0.9213, 0.8541 and 0.9694 respectively.

The loan amount is positively correlated with loan default. The higher the loan amount the higher the probability of default on a P2P loan. However, the influence of this factor seems to be quite low. This finding is similar to results in Polena and Ranger (2016) study.

The annual income positively and significantly affects the probability of a loan success. Borrowers with high annual income are less likely to default. The odds ratio is 0.8061, suggesting that for one unit increase in the annual income we expect to see a decrease of about 20% in the odds of defaults.

Debt-to-income (dti) ratio and number of 30+ days past-due incidences of delinquency in the last two years are positive determinants of the likelihood of borrowers' default. These results are consistent with Croux et al, (2020), who also find that borrowers with higher dti or with a higher number of credit inquiries are more likely to default.

One more open credit line in the borrower's credit file reduces the loan default probability, with odds ratio being 0.99 (1% percent reduction in the odds ratio). The coefficient of the number of inquiries in past 6 months are interpreted on the same basis. This is in accordance with the study of Möllenkamp (2017), although in the conclusion of his analysis the influence of the two variables were even stronger.

The factor number of charge offs during last year has a positive and statistically significant impact on default. The higher the number of charge offs within 12 months, the higher the likelihood of a P2P loan default.

Revolving credit utilization rate has been found to be a significant determinant of P2P loan default. One more $US of credit borrower is using from the available revolving credit increases the odds of default likelihood by 2.6%.

The housing situation is a significant predictor for borrowers' default. The indicator of whether a borrower is a homeowner show high economic significance and decreases the odds of delinquent behavior. On the contrary, borrowers who rent their home have a higher risk of default. This result agrees with Croux et al. (2020) and Polena and Ranger (2016) findings.

Study's results also show that short-term loans (36 months) are associated with a lower likelihood of default. This finding is in congruence with the study of Durovic (2017) who also found positive relation between loan maturity and default risk. In contrast, as the employment length of the borrower increases the odds of loan success.

The macroeconomic variables, that this research mainly focuses on, are statistically important and strongly impact the likelihood of loan being default.

The most important macroeconomic determinant for increasing the odds of loan default is unemployment rate. A positive increase of about 18% in the odds of becoming a loan defaulted is expected when the proportion of the population in unemployment increases one percent. The finding of a strong negative impact of unemployment rate on P2P loan quality is consistent with the existing financial literature (e.g. Carmichael, 2014; Fallanca et al., 2020).

The coefficient of GDP growth rate is statistically significant but, surprisingly, it indicates positive relationship with loan defaults, implying that an improvement in the growth of GDP results in a higher likelihood of delinquency. Our findings contradicts, apparently, several empirical results, such as those in the study of Croux et al. (2020), who indicates a negative relationship between GDP growth rate and delinquency of P2P loans. Louzis et al. (2012), also, show that consumer and mortgage NPLs are negatively related to the GDP growth rate. The finding of our study in the light of the above could be attributed to the explanation that the high economy growth may be increase the demand for P2P loans and an increasing debt in the economy may lead to high default rates in the long run.

Our study is the first in the marketplace lending market studies that examine the impact of HPI, CSI and S&P500 Index on default probability of P2P loans.

Changes in HPI seems to have impact on default. The higher the growth rate of HPI at the time a loan is originated the lower the likelihood of a borrower to default. A 1% increase in HPI is associated with a 0.06 percentage points reduction in the odds of loan default. This magnitude is comparable to a previous result from Bofondi and Ropele (2011). They explore the macro factors affecting household and business loans in Italy and find that an increase in HPI by 1% is associated with a decrease of 0.27% in new bad loans ratio.

Consistent with previous studies in traditional finance, the results of model 3 show that there is a negative relationship between CSI and likelihood of default. Mateus (2020) examining the factors impact the delinquency rates of auto loans, credit cards, mortgages and student loans in the United States, finds that consumer optimism has significant and negative effect on loan quality, with the stronger effect on mortgage delinquency rates and the least significant on credit card default. Wadud et al (2020), find that consumers' sentiment in the American states reduces mortgages and automobile delinquencies, whereas raises credit card loan defaults. Fuinhas et al. (2019) claims, however, that there is a positive relationship between consumers' sentiment and the proportion of student borrowers in delinquency or default.

Finally, the S&P500 Index is negatively associated with defaults. Although the magnitude is not strong this finding indicates that the positive percentage change in the annual returns of the Index lowers the likelihood the P2P borrower will default. This finding falls in line with the study of

Mateus (2020) who argue that the S&P500 is statistically significant and has a negative effect on delinquency of credit cards. A similar negative relation for the real estate loans has been found in the empirical work of Fallanca et al. (2020), but with slight statistical significance.

3.5 Concluding Remarks

The probability of default, as a cornerstone of credit risk, is the most central issue when the performance of P2P loans is assessed. Information asymmetry between lenders and borrowers remains an important problem existing in marketplace lending. Analysis of the determinants of loan default can significantly help investors make more accurate assessment for borrowers' credit riskiness and may resolve the issues of adverse selection and moral hazard.

This research examines the default determinants of P2P loans using an extended dataset of almost 2 million loans with clear ending resolution issued through the LendingClub from 2007 to 2020Q3, the longest analyzed period compared to previous corresponding studies. We investigate the impact of loan and borrower characteristics together with macroeconomic factors on P2P loan delinquencies utilizing logistic regression analysis. A binary logistic model of a total of 21 explanatory variables is proposed to predict loan default.

Our results, consistent with previous studies, confirm that loan and borrower information can indeed predict the likelihood of loan default.

For explaining default we find the following characteristics significant: loan amount, loan maturity, number of delinquency incidences, recent credit inquiries, time since last delinquency and last public record, revolving credit utilization and number of open credit lines in borrower's credit file. Our regression results also reveal that borrowers with low annual income, short employment length, high debt-to-income ratio and many charge-offs within 12 months exhibit higher likelihood of default.

Self-reported loan purpose is among the most significant independent variables. Borrowers utilizing P2P loans to fund small businesses experience higher default probability. Whereas, loans for wedding expenses and car purchase bear low credit risk. Current housing situation is also a determinant explaining default: Borrowers who rent their apartment have higher risk of default, while homeowners are less risky. Finally, the most relevant determinant of loan performance is the credit grade that is assigned by LendingClub. Higher credit grade loan is associated with lower default risk.

Except from loan and borrower's characteristics, research interest during the last few years has begun to turn to exogenous economic conditions. Recent studies include macroeconomic factors to explain the reasons that lead P2P borrowers to default. Empirical evidence show that default is influenced by factors such as inflation, interest rate, GDP growth, Unemployment rate and VIX Index. Our findings, in line with existing studies, show that the Unemployment rate positively and significantly influence loan default. Higher unemployment rates are linked to higher default rates. However, the novelty of our study is that we introduced HPI, S&P Index and CSI as drivers that explain the defaults in P2P lending market. A number of studies in banking literature indicate that higher HPI, S&P Index and CSI decrease loan delinquencies and hence NPLs. To the best of our knowledge this study is the first to relate these three variables to the probability of P2P default. Consistent with theoretical predictions of traditional financial market literature, our findings reveal significant impact of HPI, CSI and S&P500 Index on likelihood of P2P default. Higher percentage change in HPI, CSI and S&P500 Index in the year of a loan issued seems to be associated with a lower probability of delinquency.

To sum up, this study contributes to the growing literature by providing a deeper understanding of the predictors of loan default. The empirical findings reveal that alternative data should be utilized to identify borrowers' creditworthiness. Macroeconomic factors play an important role in borrowers' delinquency and should be taken into consideration when assessing credit risk. There are important implications of our findings for researchers, lenders and policy makers.

When evaluating borrowers' riskiness to default, data on the country's economic situation should also be used so that the lender can identify good borrowers from subprime ones and make profitable credit decisions. This study can encourage further research in the field of P2P lending credit risk regarding the investigation of additional macroeconomic variables as possible determinants, not only in the US but also in other countries with developed online lending market.

Chapter 4 - Conclusions

The research presented in this thesis sheds light on various aspects of crowdlending, elucidating its role as a dynamic financial phenomenon that significantly impacts the landscape of the financial market. P2P lending has emerged as an innovative alternative to traditional banking, capturing attention for its potential to reshape how individuals and businesses access financial resources. This thesis explores the factors driving the expansion of P2P lending, its impact on financial inclusion within the mortgage market, and the determinants of defaults in this market. The empirical investigation is based on meticulously gathered data from LendingClub spanning the period from 2007 until 2020. Panel data techniques and logistic regression models were employed to analyze the datasets.

The first study examines the factors influencing the growth of crowdlending in the U.S. Notably, this analysis covers the longest period compared to previous studies on the same field. The study introduces the Economic Freedom Index and its sub-indices as drivers to explain the development of P2P lending. Economic freedom emerges as a significant driver of crowdlending expansion, with robust evidence indicating its pivotal role in shaping regulatory environments, market competitiveness, and financial stability. Additionally, various financial, economic, and demographic variables are considered, and the results confirm that financial market characteristics play a crucial role in influencing the expansion of crowdlending.

The second study focuses on the interplay between P2P lending and Federal Housing Administration (FHA) mortgage volume, particularly in the aftermath of the financial crisis. The analysis reveals a positive and significant relationship between P2P lending and FHA mortgages, emphasizing the role of alternative lending channels in promoting economic inclusion and sustainable finance. Despite the financial advantages offered by P2P lending, such as flexibility and simplified processes, policymakers are urged to address associated risks through effective regulatory frameworks. The study underscores the need for macroprudential regulation to monitor emerging forms of lending and mitigate systemic risks in the housing market.

Lastly, the research investigates the determinants of loan default in P2P lending market. The research provides a comprehensive insight into the factors predicting defaults, encompassing a wide range from loan and borrower attributes to macroeconomic indicators. Notably, the analysis introduces novel drivers such as House Price Index, S&P Index, and Consumer Sentiment Index, shedding light on their impact on P2P loan delinquencies. The findings underscore the importance of leveraging alternative data and considering macroeconomic conditions when assessing credit risk, offering valuable insights for lenders, policymakers, and researchers.

In conclusion, this thesis contributes to the growing body of literature on P2P lending by providing a comprehensive understanding of its expansion, impact on mortgage markets, and risk management strategies. The findings underscore the transformative potential of P2P lending in fostering economic inclusion and sustainable growth. Policymakers should consider measures that enhance economic freedom, promote financial inclusion, and implement regulatory frameworks to mitigate potential risks and protect investors and borrowers. Future research directions should include the exploration of additional variables as determinants of P2P lending expansion and credit risk, both in the U.S. and other economies with developed online lending markets.

References

Adams, R. M., & Amel, D. F. (2016). The Effects of Past Entry, Market Consolidation, and Expansion by Incumbents on the Probability of Entry in Banking. Review of Industrial Organization, 48(1), 95–118.

Adams, Z., & Füss, R. (2010). Macroeconomic determinants of international housing markets. Journal of Housing Economics, 19(1), 38-50.

Agarwal, S., & Liu, C. (2003). Determinants of Credit Card Delinquency and Bankruptcy: Macroeconomic Factors. Journal of Economics and Finance, 27 (1), 75-85.

Altman, E., Brady, B., Resti, A., & Sironi, A. (2005). The Link between Default and Recovery Rates: Theory, Empirical Evidence and Implications. The Journal of Business, 78 (6), 2203-2228.

Anwar N. A. M., Hussain H. I., Kamarudin F., Sufian F., Zainal N., & Wong C. M. (2021). Impact of regulatory efficiency and market openness to social and financial efficiency: empirical evidence from microfinance institutions. Society and Business Review, 16(3), 374-397.

Araujo, D. K. G., Barroso, J. B. R. B., & Gonzalez, R. B. (2020). Loan-to-value policy and housing loans: effects on constrained borrowers. Journal of Financial Intermediation, 42, 100830.

Arena, M., Chen, T., Choi, S. M., Geng, N., Gueye, C. A., Lybek, T., Papageorgiou, E., & Zhang, Y. S. (2020). Macroprudential policies and house prices in Europe. IMF Policy Paper 2020/004. Available online: https://www.imf.org/en/Publications/Departmental-Papers-Policy-Papers/Issues/2020/02/20/Macroprudential-Policies-and-House-Prices-in-Europe-48627 (accessed on 29 June 2021).

Avery, R.B., Brevoort, K.P., & Canner, G.B. (2006). High-priced home lending and the 2005 HMDA data. Federal Reserve Bulletin, 8, 123–166.

Balyuk, T. & Davydenko, S. (2018). Reintermediation in FinTech: Evidence from online lending, Working paper, University of Toronto.

Balyuk, T. (2018). Financial Innovation and borrowers: Evidence from Peer-To-Peer Lending. Rotman School of Management Working Paper, (2802220).

Bellotti, T., & Crook, J. (2009). Credit scoring with macroeconomic variables using survival analysis. Journal of the Operational Research Society, 60(12), 1699-1707.

Bennett, D. (2021). Local economic freedom and creative destruction in America. Small Business Economics, 56(1), 333–53.

Berggren, N. (2009). The Benefits of Economic Freedom: A Survey. The Independent Review, 8, 193–211.

Bergh, A., & Bjørnskov, C. (2021). Does economic freedom boost growth for everyone? Kyklos, 74(2), 170-186.

Bofondi, M., & Ropele, T. (2011). Macroeconomic Determinants of Bad Loans: Evidence from Italian Banks. Bank of Italy Occasional Paper, No. 89.

Born, B., & Breitung, J. (2016). Testing for serial correlation in fixed-effects panel data models. Economic Review, 35, 1290-1316.

Bouchouicha, R., & Ftiti, Z. (2012). Real estate markets and the macroeconomy: A dynamic coherence framework. Economic Modelling, 29, 1820–1829.

Braggion, F., Manconi, A., & Zhu, H. (2019). Can Technology Undermine Macroprudential Regulation? Evidence from Peer-to-Peer Credit in China. Journal of Financial Economics, 138, 295–315.

Bratton, W., & Levitin, A. (2020). A Tale of Two Markets: Regulation and Innovation in Post-Crisis Mortgage and Structured Finance Markets. Faculty Scholarship at Penn Carey Law. Available online: https://scholarship.law.upenn.edu/faculty_scholarship/2096 (accessed on 29 June 2021).

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks. Journal of Financial Economics, 130(3), 453-483.

Brkić, I., Gradojević, N., & Ignjatijević, S. (2020). The impact of economic freedom on economic growth? New European dynamic panel evidence. Journal of Risk and Financial Management, 13(2), 26.

Canfield, C. (2018). Determinants of default in p2p lending: the Mexican case. Independent Journal of Management & Production. 9. 001. 10.14807/ijmp.v9i1.537.

Carmichael, D. (2014). Modeling Default for Peer-to-Peer Loans. SSRN Electronic Journal, doi: 10.2139/ssrn.2529240.

Cerutti, E., Claessens, S., & Laeven, L. (2017). The use and effectiveness of macro-prudential policies: new evidence. Journal of Financial Stability, 28, 203–224.

Chava, S., Paradkar, N., & Zhang, Y. (2019). Winners and losers of marketplace lending: Evidence from borrower credit dynamics. Georgia Tech Scheller College of Business Research Paper 18-16.

Chen, P., Lo, S., & Tang, H. (2022). What if borrowers stop paying their loans? Investors' rates of return on a peer-to-peer lending platform. International Review of Economics & Finance, 77, 359-377.

Cizel, J., Frost, J., Houben, A., & Wierts, P. (2019). Effective Macroprudential Policy: Cross-Sector Substitution of Price and Quantity Measures. Journal of Money, Credit and Banking, 51(5), 1209-1235.

Claessens, S., Ghosh, S.R., & Mihet, R. (2013). Macro-prudential policies to mitigate financial system vulnerabilities. Journal of International Money and Finance, 39, 153–185.

Cornaggia, J., Wolfe B., & Yoo W. (2018). Crowding Out Banks: Credit Substitution by Peer-To-Peer Lending. SSRN Working paper, 3000593. Available online:

https://www.fdic.gov/analysis/cfr/bank-research-conference/annual-17th/papers/13-wolfe.pdf (accessed on 29 June 2021).

Cornelli, G., Doerr, S., Franco, L., & Frost, J. (2021). Funding for FinTechs: patterns and drivers. Bank for International Settlements Quarterly Review, 31-43.

Cornelli, G., Frost, J., Gambacorta, L., Rau, R., Wardrop, R., & Ziegler, T. (2020). Fintech and Big Tech Credit: A New Database, Bank for International Settlements Working Paper, No. 887.

Crabb, P. (2008). Economic freedom and the success of microfinance institutions. Journal of Developmental Entrepreneurship, 13(2), 205-219.

Crook, J., & Banasik, J. (2012). Forecasting and explaining aggregate consumer credit delinquency behavior. International Journal of Forecasting, Elsevier, 28(1), 145-160.

Croux, C., Jagtiani, J., Korivi, T., & Vulanovic, M. (2020). Important factors determining Fintech loan default: Evidence from a LendingClub consumer platform. Journal of Economic Behavior & Organization, 173, 270–296.

Crowe, C., Dell' Ariccia, G., Igan, D., & Pau Rabanal, P. (2013). How to deal with real estate booms: Lessons from country experiences. Journal of Financial Stability, 9, 300-319.

D' Acunto F., & Rossi A. (2022). Regressive Mortgage Credit Redistribution in the Post-crisis Era. Review of financial studies, 35(1), 482-525.

Defusco, A., Johnson, S., & Mondragon J. (2020). Regulating Household Leverage. The Review of Economic Studies, 87(2), 914–958.

De Haan, J., & Sturm, J.E. (2000). On the relationship between economic freedom and economic growth. European Journal of Political Economy. 16(2), 215-241.

Demir, A., Pesque-Cela, V., Altunbas, Y., & Murinde, V. (2022). Fintech, financial inclusion and incomeinequality: A quantile regression approach. The European Journal of Finance, 28(1), 86–107.

Demir, H., Kurt, V., & Hagdas, V. (2003). Housing Finance in Turkey. In Proceedings of the2nd FIG Regional Conference, Marrakesh, Morocco, 2-5 December 2003.

Demirgüç-Kunt, A., Laeven, L., & R. Levine, R. (2004). Regulations, market structure, institutions, and the cost of financial intermediation. Journal of Money, Credit and Banking, 36(3b), 593–622.

De Roure, C., Pelizzon L. & Tasca P. (2016). How does P2P lending fit into the consumer credit market? Deutsche Bundesbank Discussion Paper No 30/2016.

Di Maggio, M., & Yao, V. W. (2021). Fintech borrowers: Lax-screening or cream-skimming? Working Paper. Review of Financial Studies, Society for Financial Studies, 34(10), 4565-4618.

Durović, A. (2017). Estimating Probability of Default on Peer to Peer Market – Survival Analysis Approach. Journal of Central Banking Theory and Practice, 6(2), 149-167.

Emekter, R., Tu, Y., Jirasakuldech, B. & Lu, M. (2015). Evaluating credit risk and loan performance in online peer-to-peer (P2P) lending. Applied Economics, 47(1), 54–70.

Fallanca, M., Forgione, A., & Otranto, E. (2020). Forecasting the macro determinants of bank credit quality: a non-linear perspective. The Journal of Risk Finance, doi: 10.1108/JRF-10-2019-0202.

Fernandes-Maciel V., De-Gamboa, U. R., Garcia-Alves, R.E. (2022). Economic Freedom and the Determinants of the Bank Spread in South America. Theoretical Economics Letters, 12, 1884-1902.

Foglia, M. (2022). Non-Performing Loans and Macroeconomics Factors: The Italian Case. Risks, 10(1), 21, doi:10.3390/risks10010021.

Forster, R., & Sun, X. (2022). Taming the Housing Crisis: An LTV Macroprudential Policy. Economic Modelling, 108, 105761.

Fuinhas, J.A., Moutinho, V., & Silva E. (2019). Delinquency and Default in USA Student Debt as a Proportional Response to Unemployment and Average Debt per Borrower. Economies, 7(4), 1-16.

Fuster, A., Plosser, M., Schnabl, P., & Vickery, J. (2019). The role of technology in mortgage lending. The Review of Financial Studies, 32(5), 1854-1899.

Ghosh, A. (2017). Sector-specific analysis of non-performing loans in the US banking system and their macroeconomic impact. Journal of Economics and Business, 93, 29-45.

Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. Journal of Financial Stability, 20, 93–104.

Ghosh, A. (2018). What drives banking industry competition in developing countries? Journal of Economic Development, 43(4), 1–20.

Gohmann, F. S., Hobbs, K. B., & McCrickard, J. M. (2013). Economic freedom, entrepreneurial activity, and the service sector. Journal of Entrepreneurship and Public Policy, 2(2), 144-159.

Goodman, L. S. (2017). Quantifying the Tightness of Mortgage Credit and Assessing Policy Actions. Boston College Journal of Law and Social Justice, 37(2), 235.

Goodman, L., Zhu J., & George, T. (2014). Where Have All the Loans Gone? The Impact of Credit Availability on Mortgage Volume. The Journal of Structured Finance, 20(2), 45-53.

Hardt. J. (2000). European mortgage markets: Structure, funding and future development. In OECD paper. European Mortgage Federation: Brussels, Belgium, 2000.

Havrylchyk, O., Mariotto, C., Rahim, T.-U., & Verdier, M. (2020). The Expansion of the Peer-To-Peer Lending. Review of Network Economics, 19(3), 145-187.

Hodula, M. (2023). Fintech credit, big tech credit and income inequality. Finance Research Letters. 51, 103387.

Holmstrom, B., & Tirole, J. (1997). Financial Intermediation, Loanable Funds and the Real Sector. Quarterly Journal of Economics, 112, 663-691.

Hussain, M. E., & Haque, M. (2016). Impact of economic freedom on the growth rate: A panel data analysis. Economies, 4(2), 5.

Hwang, M., Miller, C. L., & Van Order, R. (2016). Effects of FHA loan limit increases by ESA 2008: Housing demand and adverse selection. George Washington University Working Paper. Available online: https://ssrn.com/abstract=2789620 (accessed on 29 June 2021).

Ichwan, & Kasri, R. (2019). Why are youth intent on investing through peer to peer lending? Evidence from Indonesia. Journal of Islamic Monetary Economics and Finance, 5(4), 741–762.

Igan, D., Kabundi, A., Simone, F.N.D., Pinheiro, M., & Tamirisa, N. (2011). Housing, credit, and real activity cycles: Characteristics and comovement. Journal of Housing Economics, 20(3), 210-231.

Jagtiani, J., & Lemieux. C. (2018). Do fintech lenders penetrate areas that are underserved by traditional banks?. Journal of Economics and Business, 100, 43–54.

Jagtiani, J., & Lemieux C. (2019). The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the Lending Club Consumer Platform. Financial Management, 48(4), 1009-1029.

Jayasuriya, D. D., Ayaz, M., & Williams, M. (2023). The use of digital footprint in the U.S. mortgage market. Accounting and Finance, 63, 353-401.

Jimınez, G., Ongena, S., Peydr, J.-L., & Saurina, J. (2017). Macroprudential policy, countercyclical bank capital buffers and credit supply: Evidence from the Spanish dynamic provisioning experiments. Journal of Political Economy, 125(6), 2126–2177.

Julius, S.M. (2012). Determinants of residential real estate prices in Nairobi. Unpublished MBA Project, University of Nairobi. Available online: http://erepository.uonbi.ac.ke/bitstream/handle/11295/12835/Makena_Determinants%20of%20residential%20real%20estate%20prices%20in%20Nairobi.pdf?sequence=1 ((accessed on 29 June 2021).

Käfer, B. (2018). Peer to Peer Lending – A (Financial Stability) Risk Perspective. Review of Economics, 69(1), 1-25.

Kendo S., & Eboue, C. (2016). Microfinance institutional growth: How driven forces impact their financial integration?, MPRA Paper 70225, University Library of Munich, Germany.

Kim, J., & Stähler, F. (2020). The Impact of Peer-to-Peer Lending on Small Business Loans. CESifo Working Paper Series No8268. Available online: https://www.cesifo.org/en/publications/2020/working-paper/impact-peer-peer-lending-small-business-loans (accessed on 29 June 2021).

Kowalewski, O., Pisany, P., & Slazak, E. (2021). What determines cross-country differences in Fintech and Bigtech credit markets? In IESEG Working Paper Series 2021-ACF-02.

Kuttner, K. N., & Shim, I. (2016). Can non-interest rate policies stabilize housing markets? Evidence from a panel of 57 economies. Journal of Financial Stability, 26, 31 – 44.

Le, T. D. Q., Ho, T. H., Nguyen, D. T., & Ngo, T. (2021). Fintech Credit and Bank Efficiency: International Evidence. International Journal of Financial Studies, 9(3), 44.

Lebovics, M., Hermes, N., & Hudon, M. (2016). Are financial and social efficiency mutually exclusive? A case study of Vietnamese microfinance institutions. Annals of Public and Cooperative Economics, 87(1), 55-77.

Lenz, R. (2017). Peer-to-Peer Lending: Opportunities and Risks. European Journal of Risk and Regulation, 7(4), 688–700.

Liow, K.H., Ibrahim, M.F., & Huang, Q. (2006). Macroeconomic Risk Influences in the Property Stock Market. Journal of Property Investment and Finance, 24(4), 295-323.

Liu, Y., & Feng, C. (2022). How do economic freedom and technological innovation affect green total-factor productivity? Cross-country evidence. Emerging Markets Finance & Trade, 59(5), 1426–43.

Louis, P., Seret, A., & Baesens, B. (2013). Financial efficiency and social impact of microfinance institutions using self-organizing maps. World Development, 46, 197-210.

Louzis, D.P., Vouldis, A.T., and Metaxas, V.L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: a comparative study of mortgage, business and consumer loan portfolios. Journal of Banking and Finance, 36(4), 1012-1027.

Lu, Y. X., Huang, Y. S., & Hsu, C.C. (2023). The Impact of Economic Freedom on Bank Loan Spreads: Evidence from the Financial Crisis. Emerging Markets Finance and Trade.

Mankiw, N.G., & Weil D.N. (1989). The baby boom, the baby bust, and the housing market. Regional science and urban economics, 19(2), 235-258.

Mariotto, C. (2016). Competition for lending in the internet era: The case of peer-to-peer lending marketplaces in the USA. European Commission DG COMP Working Paper. Available online: https://hal.science/hal-01448534 (accessed on 29 June 2021).

Mateus, J. B. L. (2020). The Impact of Unemployment and Income on Delinquency and Default in the USA Universidade da Beira Interior. ProQuest Dissertations Publishing, Portugal, 28762605.

Mogaka, A. J., Mboya, K. J., & Kamau, R.G. (2015). The Influence of Macro Economic Factors on Mortgage Market Growth in Kenya, Journal of Finance and Accounting, 3(4), 77-85.

Möllenkamp, N. (2017). Determinants of Loan Performance in P2P Lending, Thesis, University of Twente.

Morgan, P.J., Regis, P.J., & Salike, N. (2019). LTV policy as a macroprudential tool and its effects on residential mortgage loans. Journal of Financial Intermediation, 37, 89-103.

Nguyen, T., Bermpei, T., & Kalyvas, A. N. (2022). Local Economic Freedom and The Cost of Corporate Borrowing: Evidence From The US States. Available at SSRN: https://ssrn.com/abstract=4187774 or http://dx.doi.org/10.2139/ssrn.4187774

Nigmonov, A., Shams, S. & Alam, K. (2022). Macroeconomic determinants of loan defaults: Evidence from the U.S. peer-to-peer lending market. Research in International Business and Finance, 59, 101516.

Nikolaev, B. N., Boudreaux, C. J., & Palich, L. (2018). Cross-country determinants of early-stage necessity and opportunity-motivated entrepreneurship: accounting for model uncertainty. Journal of Small Business Management, 56, 243-280.

OECD (2020). Framework for SDG Aligned Finance. Available online: https://www.oecd.org/development/financing-sustainable-development/Framework-for-SDG-Aligned-Finance-OECD-UNDP.pdf (accessed on 28 August 2023).

Oh, E. Y., & Rosenkranz, P. (2020). Determinants of peer-to-peer lending expansion: the roles of financial development and financial literacy. Asian Development Bank Economics Working Paper, 613.

Özyilmaz, A. (2022).The role of economic freedom in economic growth. Journal of management and economics research, 20(3), 59-74.

Park, K. A. (2017). Temporary loan limits as a natural experiment in Federal Housing Administration insurance. Housing Policy Debate, 27(3), 449–466.

Pashardes, P., & Savva, C.S. (2009). Factors Affecting House Prices in Cyprus: 1988-2008. Cyprus Economic Policy Review, 3(1), 3-25.

Polena M., & Regner T. (2016). Determinants of borrowers' default in P2P lending under consideration of the loan risk class. Jena Economic Research Papers, 2016-023.

PricewaterhouseCoopers (2015). Peer Pressure: How Peer-to-Peer Lending Platforms are transforming the Consumer Lending Industry. Available online: https://www.pwc.com/us/en/consumer-finance/publications/assets/peer-to-peer-lending.pdf (accessed on 29 June 2021).

Rau, P.R. (2020). Law, trust, and the development of crowdfunding. SSRN Working Paper. Available at SSRN: https://ssrn.com/abstract=2989056

Ricci, P. (2020). How economic freedom reflects on the Bitcoin transaction network. Journal of Industrial & Business Economics, 47, 133-161.

Serrano-Cinca, C., Gutierrez-Nieto, B. & Lopez-Palacios, L. (2015). Determinants of default in P2P lending. PLoS One, 10 (10), e0139427.

Setyaningsih, T., Murti, N. W., & Nugrahaningsih, P. (2019). Fintech Based Peer to Peer Lending: An Opportunity or a Threat? Riset Akuntansi dan Keuangan Indonesia, 4(3), 122-133.

Shaddady, A., & Moore, T. (2019). Investigation of the effects of financial regulation and supervision on bank stability: The application of CAMELS-DEA to quantile regressions. Journal of International Financial Markets, Institutions and Money, 58, 96–116.

Skarica, B. (2014). Determinants of non-performing loans in Central and Eastern European countries. Financial Theory and Practice, 38(1), 37–59.

Sooreea-Bheemul, B., Rasool, U. S., & Sooreea, R. (2020). Does Economic Freedom Matter to Foreign Direct Investment in Sub-Saharan Africa? International Journal of Economics and Financial Issues, 10(3), 195-207.

Subroto, R., Susantiningrum, W., Budi, Jorge T. B., & Somesanook, P. (2023). Financial openness and fintech credit. Finance Research Letters, 56.

Sufian, F., & Habibullah, M.S. (2010). Does economic freedom fosters banks' performance? Panel evidence from Malaysia. Journal of Contemporary Accounting & Economics, 6(2), 77–91.

Sufian, F., & Zulkhibri, M. (2015). The nexus between economic freedom and Islamic bank profitability in the MENA banking sectors. Global Business Review, 16(5), 58S-81S.

Suryono, R. R., Purwandari, B. & Budi, I. (2019). Peer to peer (P2P) lending problems and potential solutions: A systematic literature review. Procedia Computer Science, 161, 204-214.

Tang, H. (2019). Peer-to-Peer Lenders Versus Banks: Substitutes or Complements? The Review of Financial Studies, 32(5), 1900-1938.

Tobback, E.M., Gestel, D.V., & Bart, T&B. (2014). Forecasting Loss Given Default models: Impact of account characteristics and the macroeconomic state. Journal of the Operational Research Society, 65, doi: 10.1057/jors.2013.158.

Tran, D.V. (2019). A study on the impact of economic freedom on economic growth in ASEAN countries. Business and Economic Horizons, 15(3), 423–449.

Tripathi, S. (2019). Macroeconomic Determinants of Housing Prices: A Cross Country Level Analysis. University Library of Munich MPRA Working Paper 98089. Available online: https://mpra.ub.uni-muenchen.de/98089/1/MPRA_paper_98089.pdf (accessed on 29 June 2021).

Wadud, M., Ahmed, A., Joher, H., & Xueli, T. (2020). Factors affecting delinquency of household credit in the U.S.: Does consumer sentiment play a role? The North American Journal of Economics and Finance, 52, 101132.

Wang, B., & Sun, T. (2013). How Effective are Macroprudential Policies in China? IMF Working Paper 13/75. Available online: https://www.imf.org/en/Publications/WP/Issues/2016/12/31/How-Effective-are-Macroprudential-Policies-in-China-40425 (accessed on 29 June 2021).

Wardrop, R., Rosenberg, R., Zhang, B., Ziegler T., Squire, R., Burton, J. E., & Garvey, K., (2016). Breaking New Ground. The Americas Alternative Finance Benchmarking Report. Cambridge Center for Alternative Finance. Available online: https://www.jbs.cam.ac.uk/wp-content/uploads/2020/08/2016-americas-alternative-finance-benchmarking-report.pdf (accessed on 29 June 2021).

Wijesiri, M., Viganò, L., & Meoli, M. (2015). Efficiency of microfinance institutions in Sri Lanka: a two-stage double bootstrap DEA approach. Economic Modelling, 47, 74-83.

Wolfe, B. & Yoo, W. (2018). Crowding Out Banks: Credit Substitution by Peer-To-Peer Lending. SSRN Working paper, 3000593.

Wolfe, B. & Yoo, W. (2018). Crowding Out Banks: Credit Substitution by Peer-To-Peer Lending. SSRN Working paper, 3000593.

Wong, E., Fong, T., Li, K.-f., & Choi, H. (2011). Loan-to-Value Ratio as a Macro-Prudential Tool – Hong Kong's Experience and Cross-Country Evidence. Hong Kong Monetary Authority Working Paper. Available online: https://ssrn.com/abstract=1768546 (accessed on 29 June 2021).

Wu, Y. (2011). Economic freedom, economic growth, and China. The Chinese Economy, 44(5), 104–19.

Xu, T. (2019). Economic freedom and bilateral direct investment. Economic Modelling, 78, 172–79.

Zhang, Z., Hu, W. & Chang, T. (2019). Nonlinear effects of P2P lending on bank loans in a Panel Smooth Transition Regression model. International Review of Economics & Finance, 59C, 468-473.

Zhao, C., Li, M., Wang, J. & Ma, S. (2021). The mechanism of credit risk contagion among internet P2P lending platforms based on a SEIR model with time-lag. Research in International Business and Finance, 57, 101407.

Appendix A (Chapter 1)

Table A.1: Total P2P loan originations over the 2007-2020 period per U.S. state

No.	State name	Loan numbers	percentage of the total	Loan Volumes	percentage of the tota
1	Alabama	39,995	**1.2%**	604,696,480	**1.2%**
2	Alaska	7,647	**0.2%**	135,476,955	**0.3%**
3	Arizona	81,810	**2.4%**	1,230,765,725	**2.3%**
4	Arkansas	25,980	**0.8%**	378,543,055	**0.7%**
5	California	468,146	**13.8%**	7,412,184,995	**14.1%**
6	Colorado	71,002	**2.1%**	1,110,353,915	**2.1%**
7	Connecticut	54,377	**1.6%**	860,245,915	**1.6%**
8	Delaware	9,752	**0.3%**	150,436,360	**0.3%**
9	Florida	248,530	**7.3%**	3,726,453,755	**7.1%**
10	Georgia	112,359	**3.3%**	1,774,233,995	**3.4%**
11	Hawaii	15,537	**0.5%**	254,658,310	**0.5%**
12	Idaho	8,496	**0.3%**	127,267,680	**0.2%**
13	Illinois	135,684	**4.0%**	2,157,826,245	**4.1%**
14	Indiana	56,467	**1.7%**	854,763,945	**1.6%**
15	Iowa	14	**0.0%**	114,075	**0.0%**
16	Kansas	28,354	**0.8%**	434,270,020	**0.8%**
17	Kentucky	32,931	**1.0%**	487,292,890	**0.9%**
18	Louisiana	37,731	**1.1%**	575,593,205	**1.1%**
19	Maine	8,860	**0.3%**	134,198,890	**0.3%**
20	Maryland	80,811	**2.4%**	1,317,530,060	**2.5%**
21	Massachusetts	78,498	**2.3%**	1,260,986,870	**2.4%**
22	Michigan	87,098	**2.6%**	1,280,743,570	**2.4%**
23	Minnesota	58,229	**1.7%**	879,266,785	**1.7%**
24	Mississippi	19,882	**0.6%**	298,839,215	**0.6%**
25	Missouri	54,249	**1.6%**	811,164,140	**1.5%**
26	Montana	9,500	**0.3%**	137,953,770	**0.3%**
27	Nebraska	13,285	**0.4%**	195,084,435	**0.4%**
28	Nevada	49,259	**1.5%**	735,271,935	**1.4%**
29	New Hampshire	16,939	**0.5%**	259,651,785	**0.5%**
30	New Jersey	123,978	**3.7%**	2,013,621,305	**3.8%**
31	New Mexico	17,890	**0.5%**	275,655,995	**0.5%**
32	New York	272,628	**8.0%**	4,005,388,745	**7.6%**
33	North Carolina	93,986	**2.8%**	1,439,722,005	**2.7%**
34	North Dakota	6,008	**0.2%**	96,793,325	**0.2%**
35	Ohio	112,091	**3.3%**	1,655,268,865	**3.2%**
36	Oklahoma	30,814	**0.9%**	481,691,710	**0.9%**
37	Oregon	41,396	**1.2%**	609,927,085	**1.2%**
38	Pennsylvania	112,693	**3.3%**	1,704,349,370	**3.3%**
39	Rhode Island	15,276	**0.5%**	223,534,660	**0.4%**
40	South Carolina	43,132	**1.3%**	666,345,035	**1.3%**
41	South Dakota	6,845	**0.2%**	101,916,905	**0.2%**
42	Tennessee	55,008	**1.6%**	833,862,430	**1.6%**
43	Texas	282,683	**8.3%**	4,561,733,605	**8.7%**
44	Utah	22,788	**0.7%**	355,934,300	**0.7%**
45	Vermont	7,624	**0.2%**	108,064,060	**0.2%**
46	Virginia	93,295	**2.8%**	1,554,603,405	**3.0%**
47	Washington	71,353	**2.1%**	1,134,215,790	**2.2%**
48	West Virginia	15,071	**0.4%**	232,256,165	**0.4%**
49	Wisconsin	44,938	**1.3%**	672,955,965	**1.3%**
50	Wyoming	6,973	**0.2%**	112,574,900	**0.2%**
	Total	3,387,892	**100.0%**	52,426,284,600	**100.0%**

Source: Authors' calculations based on LendingClub database.

Table A.2: Economic Freedom Index by state over the 2007-2020 period

No.	State	Mean	No.	State	Mean
1	Alabama	8.09	**27**	Nebraska	8.09
2	Alaska	7.94	**28**	Nevada	8.11
3	Arizona	8.03	**29**	New Hampshire	8.22
4	Arkansas	7.95	**30**	New Jersey	7.93
5	California	7.93	**31**	New Mexico	7.96
6	Colorado	8.07	**32**	New York	7.82
7	Connecticut	7.99	**33**	North Carolina	8.08
8	Delaware	7.84	**34**	North Dakota	8.08
9	Florida	8.16	**35**	Ohio	7.90
10	Georgia	8.09	**36**	Oklahoma	8.11
11	Hawaii	7.90	**37**	Oregon	7.97
12	Idaho	8.10	**38**	Pennsylvania	8.01
13	Illinois	7.97	**39**	Rhode Island	7.86
14	Indiana	8.09	**40**	South Carolina	8.10
15	Iowa	8.06	**41**	South Dakota	8.15
16	Kansas	8.08	**42**	Tennessee	8.10
17	Kentucky	7.94	**43**	Texas	8.11
18	Louisiana	8.00	**44**	Utah	8.11
19	Maine	8.02	**45**	Vermont	7.98
20	Maryland	8.01	**46**	Virginia	8.09
21	Massachusetts	7.98	**47**	Washington	8.04
22	Michigan	8.02	**48**	West Virginia	7.99
23	Minnesota	7.89	**49**	Wisconsin	8.01
24	Mississippi	7.99	**50**	Wyoming	8.07
25	Missouri	8.02			
26	Montana	8.09		**Total**	8.02

Source: Authors' calculations based on Fraser Institute database.

Table A.3: Variable definition and data sources

Variable name	**Notation**	**Description**	**Data source**
Dependent variable			
P2P volume	P2P	Logarithm of the P2P volume per 10,000 population for the period 2007-2020 at the U.S. state level	LendingClub
Fraser Economic Freedom Index (all-government Index)			
Overall Economic Freedom of North America	EF_overall	The overall all-government Index of Economic freedom measures the degree to which the policies and institutions are supportive of economic freedom. It is measured on a scale from 0 to 10, where a higher value indicates a higher level of economic freedom.	Fraser Institute
Regulation of Credit Markets	EF_area3B	This sub-component identifies the extent to which government regulations put restrictions on credit markets and consequently reduces economic freedom.	Fraser Institute
Business Regulations	EF_area3C	This sub-component measures restrictions imposed by regulations in the field of business activity.	Fraser Institute
Sound Money	EF_area5	This sub-component measures the stability and reliability of a country's monetary system. It assesses the extent to which a country's monetary policies promote price stability, limit inflation, and provide a sound foundation for economic transactions.	Fraser Institute
Freedom to Trade Internationally	EF_area6	This sub-component evaluate the degree of restrictions or barriers imposed by government on residents engaging in voluntary exchange across national boundaries	Fraser Institute
Financial market variables			
Herfindahl-Hirschman Index	HHI	The Herfindahl-Hirschman Index (HHI) is a common measure of market concentration and is used to determine market competitiveness.	Federal Deposit Insurance Corporation (FDIC) Summary of Deposits
Bank branches per 10,000 population	Branches	Logarithm of the number of total commercial bank branches per 10,000 population for the period 2007-2020 at the U.S. state level	Federal Deposit Insurance Corporation (FDIC) Summary of Deposits
Financial Development Index	FDI	FDI is a relative ranking of countries that summarizes how developed financial institutions and financial markets are in terms of their depth, access, and efficiency.	International Monetary Fund (IMF) Data
Economic and demographic variables			
GINI Index	GINI	The GINI coefficient measures the inequality of income shares in a country ranging from 0 (being a perfect equal economy) until 1 (being a perfect unequal one)	U.S. Census Bureau (American Community Survey)

Unemployment rate	UR	The unemployment rate represents the number unemployed as a percent of the labor force in each U.S. state.	U.S. Bureau of Labor Statistics
Personal Income per capita	PIpercapita	Logarithm of annual Personal Income divided by total state population.	U.S. Bureau of Economic Analysis
Young	Young	The proportion of the population in each state aged between 20 and 34 years.	U.S. Census Bureau (American Community Survey)
Bachelor	Bachelor	The percentage of state population with Bachelor's Degree or Higher.	U.S. Census Bureau (American Community Survey)
Black	Black	The percentage of Black or African American in the state population.	U.S. Census Bureau (American Community Survey)
Hispanic	Hispanic	The percentage of Hispanic or Latino in the state population.	U.S. Census Bureau (American Community Survey)

Appendix B (Chapter 2)

Table B.1: Yearly FHA mortgage origination (numbers and volumes) by U.S. state

State Name	Loans	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Alabama	numbers	10,007	24,895	29,109	22,763	19,269	18,771	16,719	11,333	17,255	20,429	18,371
	volumes	2,344,328	3,278,319	4,078,684	3,331,956	2,248,117	2,553,839	2,365,427	1,501,147	2,438,869	2,971,999	2,703,512
Alaska	numbers	1855	3792	5270	4201	3403	3870	2939	2178	3015	2713	2136
	volumes	374,738	799,994	1,116,827	918,931	705,289	838,690	644,072	482,236	735,486	673,518	530,991
Arizona	numbers	10,934	40,791	55,689	43,225	32,808	38,525	34,616	29,110	49,192	48,322	39,194
	volumes	1,946,794	7,341,106	9,201,438	6,787,491	4,557,582	6,219,334	5,769,816	4,861,489	8,874,732	8,912,700	7,470,663
Arkansas	numbers	6292	13,412	16,974	13,544	9967	10,998	9205	6431	9292	10,382	9554
	volumes	669,692	1,651,794	2,197,634	1,724,136	1,263,267	1,404,026	1,148,663	834,634	1,213,734	1,412,320	1,338,445
California	numbers	8,547	88,874	179,181	163,952	129,192	163,841	114,116	79,979	142,264	154,403	112,138
	volumes	2,096,890	23,004,689	46,398,321	45,356,628	33,242,951	44,591,441	31,813,515	22,782,536	44,211,028	45,661,931	36,023,913
Colorado	numbers	14,167	37,062	57,421	41,685	27,686	39,050	31,985	22,376	35,725	36,215	32,334
	volumes	2,494,412	7,074,276	11,445,023	8,588,598	5,284,279	7,690,818	6,393,137	4,818,388	8,227,414	9,623,720	8,420,659
Connecticut	numbers	6,266	13,540	20,920	15,899	11,228	14,137	12,220	7,216	11,542	12,370	11,717
	volumes	1,271,939	2,891,313	4,621,540	3,597,370	2,388,390	2,996,856	2,522,750	1,431,516	2,413,272	2,613,220	2,430,901
Delaware	numbers	1760	5096	7086	5468	3852	4457	3980	2590	4754	5323	4729
	volumes	322,983	1,047,454	1,495,007	1,148,200	747,926	868,474	809,349	474,528	942,084	1,124,475	991,042
Florida	numbers	24,361	62,268	81,760	71,248	56,577	62,939	61,825	52,939	82,484	98,859	93,074
	volumes	3,906,447	10,513,056	12,928,652	10,869,158	8,315,867	9,848,490	10,286,832	8,883,540	14,737,306	18,692,357	18,077,196
Georgia	numbers	27,089	55,633	68,292	49,268	37,230	46,292	42,424	31,383	49,495	56,736	51,810
	volumes	3,870,162	8,590,113	10,783,089	7,459,137	5,251,401	6,791,406	6,277,571	4,741,262	8,047,389	9,613,499	9,065,960
Hawaii	numbers	617	1007	2544	2475	1490	1546	1219	701	1210	1335	1306
	volumes	143,171	343,488	878,766	886,945	510,367	523,002	391,786	260,634	560,372	532,514	547,348
Idaho	numbers	3849	9847	12,837	10,370	7102	7897	6543	5468	9503	9972	8087

	volumes	564,683	1,556,636	1,949,740	1,502,673	943,423	1,111,375	989,050	817,379	1,577,082	1,672,982	1,410,530
Illinois	numbers	18,881	51,948	76,684	49,550	37,370	45,811	40,550	28,421	42,716	46,462	40,172
	volumes	2,984,275	9,159,131	13,910,895	8,769,327	6,033,205	7,768,492	6,670,758	4,476,906	7,493,734	8,247,469	7,299,142
Indiana	numbers	17,377	38,159	50,990	36,401	27,912	34,468	31,100	21,599	31,641	33,972	31,207
	volumes	2,205,972	4,716,339	6,767,092	5,050,934	3,889,165	4,953,455	4,153,620	2,876,453	4,320,388	4,692,474	4,578,013
Iowa	numbers	4402	11,965	20,167	15,512	9954	10,417	7934	5632	8147	8182	6910
	volumes	466,854	1,432,551	2,569,146	2,119,922	1,239,110	1,377,196	1,050,977	697,105	1,107,619	1,090,418	959,193
Kansas	numbers	6063	13,892	20,556	14,985	10,615	11,924	9743	7246	10,284	10,276	9393
	volumes	673,618	1,773,184	2,829,220	2,033,753	1,443,412	1,646,724	1,287,942	918,814	1,486,443	1,443,830	1,348,832
Kentucky	numbers	8086	16,923	22,488	18,606	13,763	15,961	14,223	9717	15,062	16,848	15,226
	volumes	954,884	2,187,345	3,095,901	2,545,093	1,866,404	2,169,212	1,915,011	1,293,266	2,040,861	2,335,935	2,157,339
Louisiana	numbers	5577	14,102	19,880	17,648	13,639	15,482	13,203	10,155	14,893	16,300	14,325
	volumes	723,210	2,054,648	3,015,949	2,726,585	2,123,934	2,356,982	2,062,584	1,654,512	2,578,206	2,693,360	2,369,576
Maine	numbers	1236	3850	5780	4341	3238	3819	2600	1873	3132	3820	3573
	volumes	192,902	637,159	996,224	738,978	520,541	645,411	454,293	290,316	534,005	656,110	626,783
Maryland	numbers	11,563	36,328	51,721	38,156	26,121	32,589	26,649	17,623	33,298	35,511	29,794
	volumes	2,603,829	9,248,148	13,458,107	10,031,837	6,392,617	8,373,731	6,778,483	4,282,974	8,877,566	9,598,855	8,078,286
Massachusetts	numbers	3617	16,865	30,962	25,603	16,707	19,264	14,602	9,885	17,896	18,991	16,457
	volumes	900,780	4,169,051	8,002,952	7,061,338	4,147,324	4,971,662	3,725,716	2,545,512	4,816,685	5,275,117	5,063,311
Michigan	numbers	17,888	41,440	51,370	36,655	31,204	39,579	37,551	28,717	40,067	40,978	35,454
	volumes	2,171,393	5,226,315	6,442,743	4,531,828	3,729,170	5,032,577	4,929,188	3,848,465	5,466,709	5,801,018	5,017,787
Minnesota	numbers	5,880	22,525	38,662	29,674	22,651	29,610	22,883	14,357	23,730	23,068	19,634
	volumes	987,879	3,984,106	6,767,731	5,222,097	3,700,586	5,314,149	4,168,791	2,555,639	4,383,218	4,391,894	4,040,296
Mississippi	numbers	4264	8443	10,683	8899	6833	7519	6680	5118	7551	8853	8994
	volumes	506,032	1,124,047	1,463,573	1,194,164	906,319	1,019,604	941,551	682,164	1,046,971	1,265,512	1,340,750
Missouri	numbers	14,297	36,818	51,990	34,872	24,495	31,287	25,540	16,575	26,541	28,669	25,187
	volumes	1,749,334	4,961,102	7,302,330	4,867,403	3,378,388	4,339,579	3,383,973	2,148,321	3,782,090	4,132,811	3,664,685
Montana	numbers	2040	4330	6433	4609	2974	3222	2736	2024	3137	3152	2901

	volumes	273,170	695,638	1,077,553	754,250	473,648	523,820	454,858	339,860	575,303	616,668	564,877
Nebraska	numbers	2375	7,881	15,496	11,829	7699	8904	7040	4848	7035	6970	5532
	volumes	280,866	1,009,326	2,043,662	1,584,861	1,012,352	1,182,901	965,005	614,329	1,012,762	1,009,005	816,019
Nevada	numbers	10,238	43,264	64,578	51,230	38,769	42,462	34,903	28,168	44,956	51,456	40,065
	volumes	2,206,748	9,070,546	11,358,680	8,440,528	5,993,555	7,041,613	9,136,285	5,108,178	8,573,734	10,066,453	9,019,218
New Hampshire	numbers	783	4049	7459	6138	4430	5421	4389	3042	5362	5770	4926
	volumes	165,996	873,522	1,609,585	1,311,418	947,365	1,097,900	896,906	612,220	1,127,913	1,233,116	1,098,559
New Jersey	numbers	11,879	31,724	54,668	36,258	26,384	32,900	27,317	17,597	32,262	35,270	31,029
	volumes	2,840,221	8,183,286	14,454,586	9,473,011	6,545,745	8,264,974	6,708,618	4,184,173	8,197,643	8,965,115	7,860,588
New Mexico	numbers	3949	9351	13,280	10,619	7371	9250	8155	5589	8112	8891	7736
	volumes	543,366	1,445,930	2,104,651	1,631,528	1,096,929	1,401,303	1,207,420	812,125	1,269,755	1,431,989	1,233,369
New York	numbers	16,152	32,759	51,435	44,357	38,881	39,900	33,357	24,167	34,580	37,398	32,860
	volumes	2,430,715	139,156,284	11,224,820	10,381,914	8,787,457	9,309,548	7,750,718	5,523,950	8,702,391	9,253,347	8,438,396
North Carolina	numbers	17,527	42,683	52,242	38,181	27,006	31,367	29,656	19,508	30,482	33,231	29,838
	volumes	2,342,839	6,241,933	8,024,001	6,057,219	4,125,521	5,014,615	4,533,340	2,922,464	4,684,489	5,499,047	4,976,273
North Dakota	numbers	1403	2717	3960	3861	2870	3019	2333	1854	2669	2458	2059
	volumes	150,747	334,448	528,299	534,891	421,737	469,529	377,435	324,304	493,710	465,823	384,654
Ohio	numbers	24,151	54,044	73,971	53,028	38,050	50,055	48,921	33,241	45,532	49,115	43,971
	volumes	3,011,455	6,907,777	10,104,589	7,291,898	4,919,937	6,736,083	6,337,953	4,011,337	5,973,757	6,670,530	6,264,297
Oklahoma	numbers	8,330	19,837	27,613	21,068	16,420	17,921	14,674	12,222	14,728	15,896	14,566
	volumes	868,183	2,358,885	3,516,646	2,710,686	2,119,029	2,431,765	2,024,925	1,695,249	2,069,946	2,211,946	2,036,065
Oregon	numbers	4,172	15,867	23,378	18,932	12,471	16,889	13,258	8,945	16,359	16,598	14,381
	volumes	801,667	3,331,504	5,022,733	4,063,529	2,702,781	3,489,600	2,720,653	1,829,686	3,651,401	3,811,353	3,411,077
Pennsylvania	numbers	16,626	45,955	71,922	57,142	42,357	47,515	39,555	27,683	42,220	47,010	41,168
	volumes	2,178,041	7,110,253	11,906,541	9,343,193	6,637,483	7,761,038	6,167,154	4,017,724	6,660,292	7,634,675	6,665,558
Rhode Island	numbers	909	3846	6679	5105	3713	4711	4024	2610	4946	5381	5040
	volumes	202,989	824,225	1,392,988	1,077,098	732,214	934,122	774,643	459,674	951,572	1,111,925	1,104,641
South	numbers	6,280	18,830	26,797	19,732	14,088	16,250	15,209	11,576	18,448	21,478	20,299

Carolina	volumes	857,619	2,742,942	4,057,878	2,973,121	2,081,416	2,556,390	2,379,175	1,755,881	2,874,950	3,454,094	3,298,975
South Dakota	numbers	938	2917	4491	3859	2723	3115	2437	1543	2581	2540	2306
	volumes	108,268	393,930	621,209	606,897	382,553	439,184	341,594	217,228	412,928	419,150	369,850
Tennessee	numbers	14,882	34,044	46,813	34,563	25,171	31,279	27,533	18,657	28,438	31,253	29,302
	volumes	1,910,059	4,758,518	6,890,125	5,164,718	3,788,566	4,799,829	4,246,658	2,905,476	4,796,969	5,376,985	5,131,370
Texas	numbers	50,594	93,218	128,474	107,189	87,982	108,223	107,479	78,739	101,604	110,847	95,743
	volumes	6,215,503	12,633,395	18,256,883	15,667,720	12,766,876	15,953,047	16,307,882	12,221,122	17,364,869	20,058,228	18,640,088
Utah	numbers	9598	25,108	38,222	29,816	16,786	27,452	17,970	12,369	23,500	23,254	18,697
	volumes	1,600,967	4,944,125	7,609,881	5,986,409	3,070,730	5,158,900	3,469,221	2,340,611	4,826,728	4,943,182	4,247,342
Vermont	numbers	310	1062	1978	1297	835	880	749	611	976	1131	965
	volumes	50,172	185,789	357,972	240,184	151,395	159,555	133,541	114,802	183,664	204,717	179,721
Virginia	numbers	11,897	42,731	62,249	45,204	32,510	39,633	32,630	20,581	35,604	37,239	31,103
	volumes	2,177,473	9,211,633	14,340,026	11,031,500	7,683,039	9,739,110	7,749,326	4,554,897	8,878,518	9,215,199	7,864,629
Washington	numbers	10,232	33,254	52,144	38,301	25,501	34,478	25,861	17,477	30,551	32,594	27,697
	volumes	2,097,795	7,697,463	12,337,924	9,073,911	5,807,555	7,702,214	5,854,336	3,826,055	7,337,332	8,141,704	7,304,159
West Virginia	numbers	1841	4947	6058	5010	3815	3939	3409	2511	3468	3967	3967
	volumes	231,850	662,400	894,560	665,530	492,623	539,852	484,882	315,222	489,607	556,082	544,627
Wisconsin	numbers	7255	17,836	28,322	20,540	13,221	17,664	14,187	9320	14,535	15,232	12,776
	volumes	989,129	2,686,490	4,337,405	3,267,261	1,997,317	2,754,257	2,153,180	1,364,289	2,152,077	2,364,673	2,030,557
Wyoming	numbers	1328	3477	4459	3171	2463	2682	2206	1838	2576	2474	2218
	volumes	194,231	590,737	772,598	538,761	422,701	459,150	396,217	329,262	511,632	448,442	404,393
total	numbers	470,564	1,265,206	1,862,137	1,446,039	1,078,796	1,309,184	1,111,037	795,342	1,245,350	1,349,594	1,161,921
	volumes	71,857,270	352,816,343	338,562,379	268,936,518	189,989,558	241,326,824	204,506,780	142,559,854	245,687,205	270,293,486	239,444,455

Source: Authors' calculations based on historical Home Mortgage Disclosure Act (HMDA) data provided by the Consumer Financial Protection Bureau.

Table B.2: Yearly P2P loan origination (numbers and volumes) by U.S. state

State Name	Loans	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Alabama	numbers	9	20	56	156	238	696	1602	3035	5347	5329	5142
	volumes	61,700	199,725	492,125	1,527,100	3,065,725	9,731,725	23,100,125	45,167,175	80,590,675	74,902,950	73,776,825
Alaska	numbers	0	5	9	21	49	180	375	599	954	1,006	970
	volumes	0	61,500	112,325	224,000	667,775	2,778,500	6,272,625	10,285,300	16,361,125	17,297,625	16,697,225
Arizona	numbers	14	53	124	258	468	1196	2994	5509	9700	10,462	10,736
	volumes	126,900	462,100	1,238,075	2,713,050	5,461,700	14,889,250	42,835,850	78,694,450	142,326,550	149,029,450	153,743,125
Arkansas	numbers	3	8	24	80	141	424	972	1808	3152	3335	3284
	volumes	7,600	72,150	251,500	791,375	1,525,550	5,343,300	13,234,625	25,833,125	45,878,500	45,923,750	44,037,125
California	numbers	7	456	894	2215	3740	9277	20,885	33,290	58,066	57,888	59,769
	volumes	73,225	4,401,175	9,217,625	23,760,550	44,970,150	123,410,375	302,006,300	488,123,300	891,314,075	880,078,725	917,950,625
Colorado	numbers	19	66	117	272	377	1002	2867	4931	9068	8800	9454
	volumes	146,225	503,800	1,106,600	2,975,400	4,794,375	13,436,675	42,526,475	74,817,350	139,447,350	128,861,575	139,209,475
Connecticut	numbers	12	42	99	260	393	864	1995	3485	6327	6794	7492
	volumes	87,950	413,700	960,575	2,632,600	5,022,675	11,837,625	30,273,300	51,439,700	99,382,550	102,855,450	112,296,900
Delaware	numbers	1	8	23	48	56	120	344	663	1239	1252	1243
	volumes	6,000	74,125	232,800	470,300	601,500	1,656,575	5,081,775	9,981,125	18,608,750	17,587,675	18,663,300
Florida	numbers	85	162	396	857	1566	3987	8666	15,693	29,298	31,727	31,890
	volumes	763,850	1,349,125	3,661,725	8,682,375	17,974,550	50,401,425	119,450,875	220,137,275	423,257,500	444,092,250	456,796,250
Georgia	numbers	37	95	189	459	707	1639	4123	7602	14,110	14,460	14,242
	volumes	364,800	849,650	1,774,800	4,802,850	8,802,100	22,453,175	61,551,325	114,642,800	217,469,100	216,785,925	215,797,475
Hawaii	numbers	0	11	18	44	101	316	774	1198	2083	2019	1997
	volumes	0	66,800	159,325	460,450	1,225,100	4,372,575	11,590,150	18,382,550	32,817,575	31,891,950	31,575,525
Idaho	numbers	0	9	0	0	0	0	2	1	0	1225	1324
	volumes	0	72,350	0	0	0	0	9000	7000	0	17,485,225	18,416,525

Illinois	numbers	3	95	209	509	836	2048	5116	9,630	16,864	17,715	18,292
	volumes	23,750	801,700	2,224,775	5,709,675	9,998,950	28,813,000	76,588,375	147,590,100	264,429,975	268,226,575	280,893,725
Indiana	numbers	19	0	0	0	0	27	2109	4208	7264	7658	7676
	volumes	144,075	0	0	0	0	358,575	32,896,050	61,663,850	106,329,475	108,950,700	109,450,125
Iowa	numbers	0	11	0	1	0	0	1	1	0	0	0
	volumes		90,550	0	9,600	0	0	7200	6725	0	0	0
Kansas	numbers	5	26	48	28	187	503	1243	2105	3736	3567	3677
	volumes	11,600	183,125	458,350	296,400	2,174,600	6,978,450	18,042,500	30,912,975	56,531,625	51,428,800	53,287,650
Kentucky	numbers	1	14	37	102	201	460	1216	2381	4112	4225	4306
	volumes	7000	127,650	327,400	962,900	2,433,025	6,323,875	17,391,500	34,208,550	59,884,500	59,164,475	60,120,725
Louisiana	numbers	8	19	51	131	246	655	1570	2762	5098	4985	4981
	volumes	42,825	107,450	438,825	1,331,075	2,804,075	9,128,150	23,225,450	41,046,825	77,991,300	72,315,575	71,933,675
Maine	numbers	3	0	0	0	0	0	0	1	521	1,410	1,436
	volumes	9,200	0	0	0	0	0	0	29,850	8,092,775	20,426,700	20,191,300
Maryland	numbers	23	62	142	348	538	1183	3008	5566	10,057	10,071	10,831
	volumes	214,525	514,500	1,455,075	3,707,825	6,745,775	16,848,275	46,615,425	87,121,425	160,386,200	158,010,875	169,454,050
Massachusetts	numbers	52	65	192	477	643	1373	2937	5233	9521	9830	10,161
	volumes	339,375	583,075	2,057,875	5,091,975	7,963,500	20,252,100	47,807,300	85,234,050	151,888,350	150,627,725	156,205,850
Michigan	numbers	0	53	123	251	363	1210	3238	6206	11,436	11,604	11,560
	volumes	0	452,775	1,131,475	2,697,500	4,393,100	15,922,075	46,245,500	87,800,700	166,060,275	160,990,375	162,605,725
Minnesota	numbers	0	38	80	195	335	885	2272	4277	7800	7700	7764
	volumes	0	342,725	725,250	2,004,300	3,665,200	11,634,450	32,412,725	60,713,375	116,009,600	109,975,875	111,637,425
Mississippi	numbers	0	12	13	0	1	1	2	1198	2593	2867	2855
	volumes	0	86,575	97,875	0	6,000	4,000	35,975	18,391,075	38,427,250	40,885,550	40,940,175
Missouri	numbers	22	38	73	234	392	845	2050	3789	6698	6951	7058
	volumes	142,250	266,250	660,275	2,444,200	4,378,025	11,123,800	29,600,025	55,070,575	100,114,525	99,016,450	99,619,525
Montana	numbers	3	12	7	25	49	164	395	730	1162	1172	1224
	volumes	52,400	71,400	52,350	189,100	620,075	2,072,350	5,366,050	10,197,975	16,467,725	16,221,625	16,016,725

Nebraska	numbers	8	3	0	0	0	1	2	0	1162	2116	2131
	volumes	50,400	38,550	0	0	0	22,250	17,200	0	17,027,650	28,934,650	29,054,575
Nevada	numbers	2	29	66	124	300	792	1907	3225	5924	6164	6420
	volumes	21,625	249,250	647,725	1,304,175	3,404,775	10,343,175	26,298,675	45,016,500	84,099,025	87,709,500	91,922,875
New Hampshire	numbers	6	11	25	56	89	249	623	1155	2062	2097	2279
	volumes	50,500	105,275	208,850	611,950	1,184,700	3,352,125	8,943,525	17,581,550	31,202,825	30,697,325	33,289,475
New Jersey	numbers	45	95	240	612	970	2100	4980	8863	15,195	15,891	16,164
	volumes	351,800	861,075	2,440,250	6,598,125	12,518,350	29,079,350	76,890,850	139,586,200	244,526,800	247,077,300	253,929,275
New Mexico	numbers	4	15	29	65	90	278	716	1367	2351	2286	2212
	volumes	47,400	153,775	277,575	671,800	948,100	4,007,625	10,911,650	20,619,600	35,603,000	33,214,525	31,749,250
New York	numbers	101	78	511	1246	1984	5102	10,848	19,923	33,844	35,505	37,153
	volumes	965,575	1,655,750	5,161,950	13,506,275	23,516,575	69,237,700	155,520,725	293,232,400	508,856,550	357,662,975	545,586,050
North Carolina	numbers	33	46	0	89	652	1587	3713	6442	12,037	12,279	12,081
	volumes	223,650	384,875	0	958,425	7,653,325	20,604,425	53,347,500	94,354,950	182,433,925	177,079,475	175,260,325
North Dakota	numbers	0	0	0	0	0	0	0	0	480	1051	1011
	volumes	0	0	0	0	0	0	0	0	7,447,300	15,927,050	14,728,100
Ohio	numbers	2	75	186	378	672	1552	4256	8011	14,394	15,000	14,436
	volumes	7,500	692,075	1,699,950	3,705,400	7,958,400	20,812,825	60,551,275	114,606,675	211,130,650	208,673,075	201,676,300
Oklahoma	numbers	0	15	36	85	180	444	1196	2118	3768	4061	3937
	volumes	0	103,225	345,500	932,650	2,158,750	5,697,300	17,715,500	31,491,175	60,860,200	58,976,925	58,309,300
Oregon	numbers	0	26	56	143	233	665	1850	2912	4944	4669	5184
	volumes	0	181,650	508,575	1,444,050	2,727,850	8,183,725	25,149,100	40,318,600	69,877,175	64,481,375	73,306,975
Pennsylvania	numbers	0	83	245	534	772	1747	4475	8426	14,969	14,502	15,026
	volumes	0	584,900	2,314,400	5,412,950	8,836,325	22,906,825	63,729,200	123,262,525	226,444,700	210,137,900	216,211,750
Rhode Island	numbers	0	16	29	59	100	245	536	1043	1843	1881	1964
	volumes	0	135,025	243,950	583,800	970,375	3,082,000	7,646,300	14,890,425	27,194,800	25,689,700	27,588,775
South Carolina	numbers	6	21	64	133	261	631	1448	2971	5056	5492	5444
	volumes	52,150	151,375	640,125	1,395,025	3,058,425	8,467,375	21,542,850	44,817,100	76,763,600	79,521,350	79,821,625

South Dakota	numbers	1	4	6	16	39	120	280	506	835	879	866
	volumes	25,000	10,575	57,100	150,750	401,600	1,431,725	3,747,325	7,122,525	11,814,875	12,552,925	11,938,250
Tennessee	numbers	1	30	0	0	1	0	2046	3907	6902	7272	7112
	volumes	2,825	222,125	0	0	28,000	0	29,895,425	58,688,950	103,132,650	103,680,150	99,931,725
Texas	numbers	5	170	381	887	1436	4265	10,004	18,967	34,698	37,036	37,218
	volumes	25,350	1,606,000	3,661,125	9,566,550	18,404,175	59,458,575	154,894,925	298,467,650	557,706,125	568,130,525	574,759,225
Utah	numbers	9	19	39	77	132	383	1064	1669	2836	2796	2770
	volumes	71,925	180,325	323,300	817,950	1,669,775	5,006,175	15,584,050	24,890,575	42,769,125	41,870,950	41,447,750
Vermont	numbers	1	4	5	14	32	131	169	542	892	942	1041
	volumes	2,500	48,000	37,700	123,550	292,450	1,643,175	2,290,225	7,669,800	12,974,450	12,670,600	13,707,400
Virginia[E]	numbers	20	91	188	478	694	1674	3985	6965	12,032	11,687	12,027
	volumes	153,900	878,250	2,009,175	4,878,850	8,962,450	23,817,750	63,034,900	110,375,675	194,941,075	185,924,000	193,311,525
Washington	numbers	12	49	113	241	456	1229	3200	5118	8917	8301	9031
	volumes	121,725	442,275	1,100,150	2,502,325	5,262,375	16,127,900	47,348,325	76,440,825	138,185,650	125,420,725	137,568,900
West Virginia	numbers	0	2	26	67	89	221	681	1311	1975	770	369
	volumes	0	9,000	221,900	588,225	1,157,025	2,936,475	10,018,675	19,135,575	29,911,400	11,095,800	5,734,450
Wisconsin	numbers	18	24	61	165	241	609	1650	3101	5663	5973	5939
	volumes	150,400	160,925	603,100	1,649,525	3,042,775	8,302,350	23,553,125	44,642,175	82,637,750	80,786,825	83,999,850
Wyoming	numbers	2	0	15	29	40	125	323	583	900	935	822
	volumes	20,000	0	156,425	284,650	482,175	1,726,725	5,211,075	9,148,875	13,874,375	14,339,650	12,769,625
total	numbers	602	2,286	5,245	12,469	21,090	53,205	130,708	235,026	419,885	433,637	442,001
	volumes	4,969,475	21,008,250	51,495,825	131,171,600	253,932,275	716,017,850	1,918,008,900	3,493,859,525	6,401,483,000	6,225,289,125	6,558,920,400

Source: Authors' calculations based on the Lending Club dataset available from https://www.lendingclub.com/info/download-data.action (accessed on 29 June 2021).

Table B.3: Yearly percentage of FHA mortgage origination volume (comparing to the total FHA mortgage volume) for each of the 10 states with the highest concentration of FHA mortgages.

State	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
California	2.9%	6.5%	13.7%	16.9%	17.5%	18.5%	15.6%	16.0%	18.0%	16.9%	15.0%
Texas	2.4%	3.6%	5.4%	5.8%	6.7%	6.6%	8.0%	8.6%	7.1%	7.4%	7.8%
Florida	5.4%	3.0%	3.8%	4.0%	4.4%	4.1%	5.0%	6.2%	6.0%	6.9%	7.5%
Georgia	5.4%	2.4%	3.2%	2.8%	2.8%	2.8%	3.1%	3.3%	3.3%	3.6%	3.8%
New York	5.4%	13.4%	3.3%	3.9%	4.6%	3.9%	3.8%	3.9%	3.5%	3.4%	3.5%
Pennsylvania	1.0%	2.0%	3.4%	3.2%	2.8%	3.2%	3.1%	3.4%	3.3%	3.6%	3.5%
Maryland	3.6%	2.6%	4.0%	3.7%	3.4%	3.5%	3.3%	3.0%	3.6%	3.6%	3.4%
New Jersey	4.0%	2.3%	4.3%	3.5%	3.4%	3.4%	3.3%	2.9%	3.3%	3.3%	3.3%
Virginia	3.0%	3.5%	4.2%	4.1%	4.0%	4.0%	3.8%	3.2%	3.6%	3.4%	3.3%
Illinois	2.0%	2.6%	4.1%	3.3%	3.2%	3.2%	3.3%	3.1%	3.1%	3.1%	3.0%
Total	46.1%	47.1%	49.0%	51.1%	53.1%	53.2%	53.4%	56.7%	57.2%	58.6%	58.3%

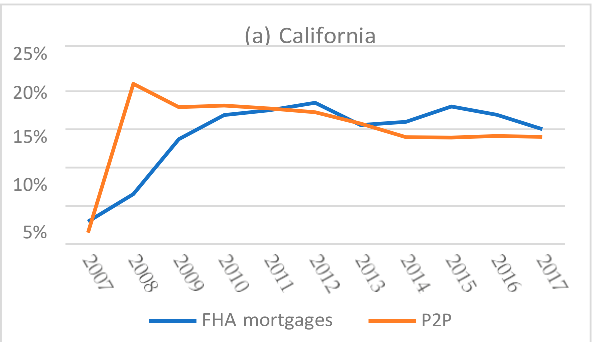
Source: Authors' calculations based on historical Home Mortgage Disclosure Act (HMDA) data provided by the Consumer Financial Protection Bureau.

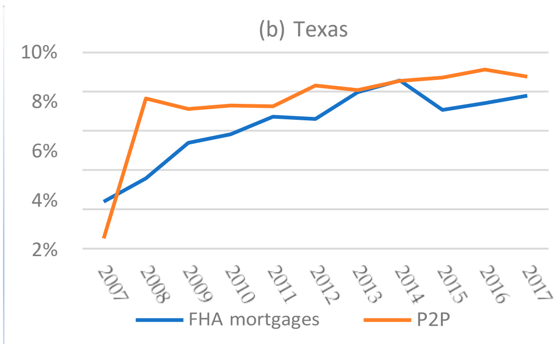
Table B.4: Yearly percentage of P2P loan volume (comparing to the total P2P loans) for each of the ten states with the highest concentration of P2P loans.

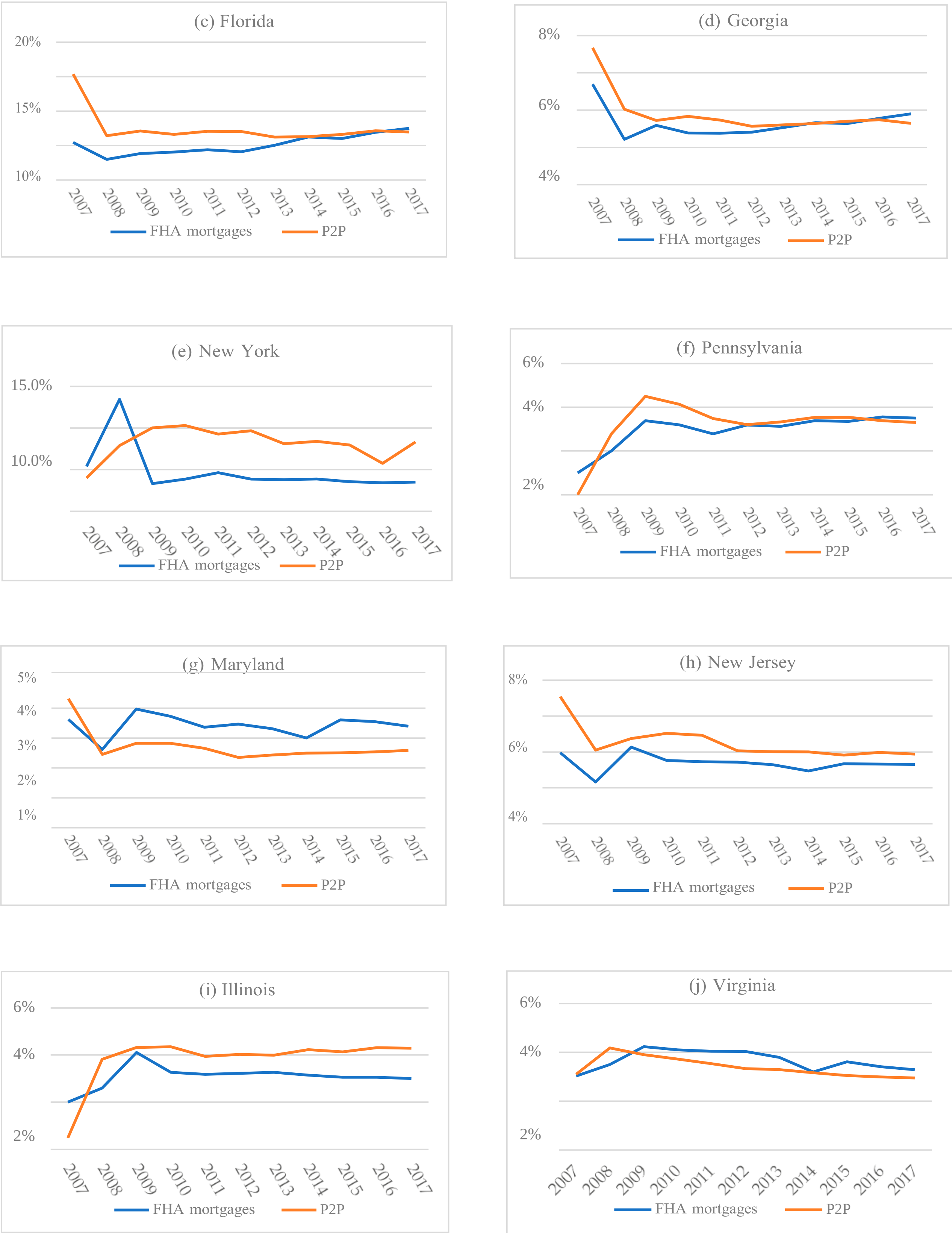
State	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
California	1.5%	20.9%	17.9%	18.1%	17.7%	17.2%	15.7%	14.0%	13.9%	14.1%	14.0%
Texas	0.5%	7.6%	7.1%	7.3%	7.2%	8.3%	8.1%	8.5%	8.7%	9.1%	8.8%
New York	4.0%	7.9%	10.0%	10.3%	9.3%	9.7%	8.1%	8.4%	7.9%	5.7%	8.3%
Florida	15.4%	6.4%	7.1%	6.6%	7.1%	7.0%	6.2%	6.3%	6.6%	7.1%	7.0%
Illinois	0.5%	3.8%	4.3%	4.4%	3.9%	4.0%	4.0%	4.2%	4.1%	4.3%	4.3%
New Jersey	7.1%	4.1%	4.7%	5.0%	4.9%	4.1%	4.0%	4.0%	3.8%	4.0%	3.9%
Pennsylvania	0.0%	2.8%	4.5%	4.1%	3.5%	3.2%	3.3%	3.5%	3.5%	3.4%	3.3%
Georgia	7.3%	4.0%	3.4%	3.7%	3.5%	3.1%	3.2%	3.3%	3.4%	3.5%	3.3%
Virginia	3.1%	4.2%	3.9%	3.7%	3.5%	3.3%	3.3%	3.2%	3.0%	3.0%	2.9%
Maryland	4.3%	2.4%	2.8%	2.8%	2.7%	2.4%	2.4%	2.5%	2.5%	2.5%	2.6%
Total	59.2%	67.6%	69.2%	68.9%	66.4%	65.3%	61.6%	61.2%	60.9%	60.2%	61.4%

Source: Authors' calculations based on the Lending Club dataset available from. https://www.lendingclub.com/ info/download-data.action (accessed on 29 June 2021).

Figures B.1: Yearly evolution of P2P loans and FHA mortgages for each of the ten states







Source: Authors' calculations based on historical Home Mortgage Disclosure Act (HMDA) data provided by the Consumer Financial Protection Bureau and the Lending Club dataset available from https://www.lendingclub.com/info/download-data.action (accessed on 29 June 2021).

Table B.5: Median of the chosen variables by U.S. state

State Name	FHA (in 000s)	P2P (in 000s)	GDP per	UR	HPI	NHU	POPUL
Alabama	2,553,839	9732	38,740	6.80	287.52	−1.35	0.30
Alaska	705,289	2779	74,166	6.95	288.93	1.66	0.91
Arizona	6,787,491	14,889	41,462	6.75	307.15	7.09	1.47
Arkansas	1,338,445	5343	36,488	5.95	251.58	1.71	0.40
California	36,000,000	123,410	56,500	7.45	455.71	4.24	0.83
Colorado	7,690,818	13,437	52,689	4.90	361.25	11.06	1.54
Connecticut	2,522,750	11,838	67,911	7.75	390.20	−9.43	0.17
Delaware	942,084	1657	67,030	6.55	433.92	0.52	0.89
Florida	10,500,000	50,401	40,975	6.25	327.48	5.75	1.28
Georgia	7,459,137	22,453	44,798	7.25	294.12	7.11	1.05
Hawaii	523,002	4373	52,822	4.35	500.81	−7.41	0.96
Idaho	1,410,530	0	36,227	5.60	298.99	8.57	1.24
Illinois	7,493,734	28,813	55,958	7.00	318.08	10.57	0.12
Indiana	4,578,013	359	45,554	5.95	249.49	1.24	0.40
Iowa	1,107,619	0	51,310	4.25	248.65	−1.58	0.53
Kansas	1,443,830	6978	48,787	4.55	238.55	−9.87	0.39
Kentucky	2,157,339	6324	40,198	6.40	291.11	−0.66	0.42
Louisiana	2,356,982	9128	49,683	6.40	246.06	4.87	0.55
Maine	626,783	0	39,817	5.65	467.18	−2.79	0.05
Maryland	8,373,731	16,848	56,830	5.85	433.18	−0.08	0.58
Massachusetts	4,816,685	20,252	66,708	5.75	642.31	−0.70	0.72
Michigan	5,017,787	15,922	42,309	7.90	266.82	11.97	0.05
Minnesota	4,168,791	11,634	55,104	4.95	325.54	2.35	0.69
Mississippi	1,046,971	87	33,386	7.55	248.53	0.60	0.17
Missouri	3,782,090	11,124	44,629	6.10	280.19	−0.98	0.27
Montana	564,877	2072	41,883	5.00	374.56	−0.93	0.84
Nebraska	1,009,326	22	55,363	3.25	252.92	1.95	0.69
Nevada	8,573,734	10,343	47,742	7.85	258.69	8.20	1.50
New Hampshire	1,097,900	3352	51,075	4.25	399.00	−2.13	0.26
New Jersey	8,183,286	29,079	58,742	6.65	483.00	6.37	0.19
New Mexico	1,269,755	4008	41,989	6.70	297.03	−4.17	0.33
New York	8,787,457	69,238	67,614	6.30	579.76	10.17	0.26
North Carolina	4,976,273	20,604	45,083	6.35	321.73	0.26	1.12
North Dakota	421,737	0	67,325	3.10	285.07	1.86	1.47
Ohio	6,337,953	20,813	46,834	6.40	246.87	0.41	0.13
Oklahoma	2,119,029	5697	45,287	4.80	203.62	−7.00	0.81
Oregon	3,411,077	8184	44,736	6.75	406.13	5.17	1.06
Pennsylvania	6,665,558	22,907	50,181	5.85	375.83	−3.09	0.17

Rhode Island	934,122	3082	48,935	7.75	473.31	−2.81	0.01
South Carolina	2,742,942	8,467	37,167	6.55	325.91	10.43	1.28
South Dakota	393,930	1432	52,246	3.40	297.80	−4.91	1.05
Tennessee	4,796,969	222	43,924	6.60	298.44	9.80	0.83
Texas	16,000,000	59,459	54,072	5.15	226.04	4.76	1.77
Utah	4,826,728	5006	45,127	3.80	353.02	8.85	1.91
Vermont	179,721	1643	46,149	4.45	443.02	−1.52	0.09
Virginia	8,878,518	23,818	54,382	5.25	411.49	−0.78	0.97
Washington	7,337,332	16,128	58,086	6.10	435.40	3.90	1.43
West Virginia	539,852	2936	37,340	6.75	213.46	−5.26	0.03
Wisconsin	2,153,180	8302	47,997	5.35	306.65	1.41	0.29
Wyoming	448,442	1727	66,697	4.65	278.39	−1.76	0.83
Total	**2,545,303**	**6298**	**48,791**	**6**	**315.62**	**1.535**	**0.649**

Appendix C (Chapter 3)

Table C.1: Definition of the P2P variables (loan and borrower characteristics) used in the study

Variable name	Description	Value
loan_amnt	The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.	amount (US $)
term	The number of payments on the loan. Values are in months and can be either 36 or 60.	Dummy variable
grade	LC assigned loan grade	Dummy variable
emp_length	Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.	Dummy variable
home_ownership	The home ownership status provided by the borrower during registration or obtained from the credit report. Our values are: RENT, OWN, MORTGAGE, OTHER	Dummy variable
annual_inc	The self-reported annual income provided by the borrower during registration.	amount (US $)
purpose	A category provided by the borrower for the loan request.	Dummy variable
dti	A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower's self-reported monthly income.	Ratio
delinq_2yrs	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years	Number
inq_last_6mths	The number of inquiries in past 6 months (excluding auto and mortgage inquiries)	Number
mths_since_last_delinq	The number of months since the borrower's last delinquency.	Number
mths_since_last_record	The number of months since the last public record.	Number
open_acc	The number of open credit lines in the borrower's credit file.	Number
revol_bal	Total credit revolving balance	Number
revol_util	Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.	Number
chargeoff_within_12_mths	Number of charge-offs within 12 months	Number

Note: The description of the data is from the Data Dictionary file provided by LendingClub.

Table C.2: Macroeconomic variables used in the study

Variable name	Notation	Value	Data source	Expected sign
Real GDP growth rate	GDP	Percentage (annual growth rate)	Bureau of Economic Analysis	−
House Price Index	HPI	Percentage (annual growth rate)	US Federal Housing Finance Agency	−
Unemployment rate	UR	Percentage (annual)	US Bureau of Labor Statistics	+
Standard & Poor's 500 Index	S&P500	Percentage (annual growth rate)	Macrotrends.net	−
Consumer Sentiment Index	CSI	Percentage (annual growth rate)	Survey of Consumers - University of Michigan	−

Note: All the variables, except for unemployment rate, are in growth values at loan origination year and expand between 2007-2020. Real GDP growth rate represents the average annual growth rate of GDP in the U.S. economy. S&P500 annual growth rate shows the change in the annual return from the previous year.

Table C.3: Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)	**Default**	1																
(2)	**loan_amnt**	0.072	1															
(3)	**annual income**	-0.023	0.187	1														
(4)	**dti**	0.065	0.038	-0.081	1													
(5)	**delinq_2yrs**	0.014	-0.005	0.024	-0.010	1												
(6)	**inq_last_6mths**	-0.021	0.100	0.039	-0.040	-0.177	1											
(7)	**mths_since_last_delinq**	-0.121	0.100	0.039	-0.040	-0.177	1	1										
(8)	**mths_since_last_record**	-0.065	-0.021	0.019	-0.010	0.022	-0.087	-0.087	1									
(9)	**open_acc**	-0.008	-0.016	-0.029	0.010	-0.553	0.099	0.099	0.013	1								
(10)	**revol_bal**	0.021	0.182	0.085	0.195	0.051	0.018	0.018	0.137	-0.037	1							
(11)	**revol_util**	0.024	-0.059	-0.003	-0.027	-0.022	-0.190	-0.190	0.061	0.078	-0.015	1						
(12)	**chargeoff_within_12_mths**	0.094	0.008	0.037	0.096	-0.055	-0.097	-0.097	0.275	0.117	0.495	0.092	1					
(13)	**GDP**	0.034	0.044	-0.001	0.029	-0.003	0.003	0.003	-0.047	0.018	0.014	-0.002	0.005	1				
(14)	**HPI**	-0.032	0.059	0.016	0.069	0.038	-0.063	-0.063	-0.100	-0.013	0.070	0.069	0.056	0.265	1			
(15)	**UR**	0.049	-0.036	-0.023	-0.069	-0.016	-0.035	-0.035	0.116	-0.009	-0.049	-0.044	-0.081	-0.312	-0.273	1		
(16)	**S&P500**	-0.031	-0.021	0.003	-0.018	-0.006	0.004	0.004	0.035	-0.005	-0.014	-0.016	-0.035	-0.442	-0.087	0.231	1	
(17)	**CSI**	0.001	0.012	-0.011	0.001	0.011	-0.065	-0.065	0.019	-0.010	0.010	0.006	-0.024	0.538	-0.059	0.168	-0.285	1

Table C.4: Non-parametric test of differences between defaulted and fully paid loans

Variables	Defaulted loans	Fully paid loans	p-value
loan_amnt	Higher	Lower	0.00
annual income	Lower	Higher	0.00
dti	Higher	Lower	0.00
grade	Higher	Lower	0.00
delinq_2yrs	Higher	Lower	0.00
inq_last_6mths	Lower	Higher	0.00
mths_since_last_delinq	Higher	Lower	0.00
mths_since_last_record	Higher	Lower	0.00
open_acc	Lower	Higher	0.00
revol_bal	Higher	Lower	0.00
revol_util	Higher	Lower	0.00
chargeoff_within_12_mths	Higher	Lower	0.00
term	Higher	Lower	0.00
emp_length	Lower	Higher	0.00