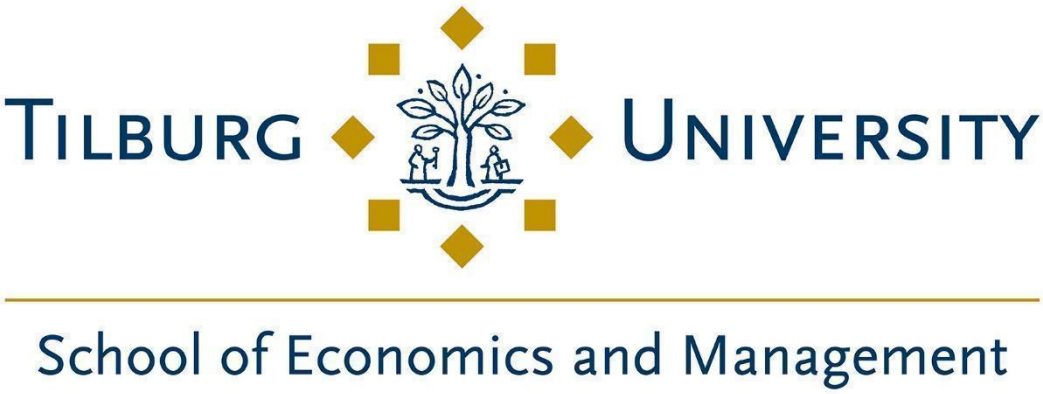


How the Emergence of Peer-to-Peer (P2P) Lending Platforms Impacts the Traditional Banking Sector

Master Thesis Finance

Author Marietta Trampakoula

SNR 2127812

ANR 532893

Supervisor: Piotr Danisewicz

Second reader: Kim Peijnenburg

Date: 26-08-2025

Contents

1. Introduction 3
2. Literature Review 5
3. Data Overview 9
4. Hypotheses Development 13
5. Methodology 15
6. Empirical Findings 20
7. Conclusion 26
8. Appendix 28
9. References 30

1. Introduction

Over the past twenty years, technological breakthroughs have catalyzed substantial transformations in the financial services sector, leading to a new era of innovation, commonly known as Financial Technology. FinTech encompasses the application of contemporary technologies, including artificial intelligence, machine learning, blockchain, and cloud computing, to enhance, automate, or fundamentally transform financial services and infrastructure. Among the many branches of FinTech, one of the most disruptive and rapidly expanding segments is peer-to-peer (P2P) lending. These platforms are becoming increasingly more and more attractive to both borrowers and investors, as they link directly the demand and supply via online platforms, bypassing traditional financial intermediaries such as banks.

The rise of peer-to-peer lending is driven by various factors. The factors encompass escalating frustration with the banking sector following the 2008 global financial crisis, a significant enhancement in technological capabilities, and a heightened demand for alternative credit sources, especially among borrowers inadequately served by conventional institutions. Initially these online lending platforms were not viewed as a threat, as they could solely function in disadvantaged or underserved regions. However, as they have gained popularity, they are no longer seen only as complementary alternatives to bank credit but rather as direct competitors that could reshape the dynamics of the lending market.

The research about fintech has become extensively more popular and dedicated to social lending, and numerous studies have been conducted. The existing literature is mostly about the platform trust and acceptance, the evolution of P2P lending, investors' behaviour on P2P platforms, accessibility to soft information about the borrower, and about the difference between P2P platforms and traditional banking. However, there are still no adequate studies about the impact that marketplace lending has on the traditional banking, and how banks adapt to this situation, as the economic environment is constantly changing. It is important to distinct if banks and crowd lending act as complements, therefore P2P are just filling the unmet demand, or as substitutes, thus the traditional banking system is being threatened.

This thesis enhances the previous research and dims light at the link between the expansion of peer-to-peer lending and fluctuations in the traditional banking sector. It investigates whether P2P expansion reduces the size of traditional bank loan portfolios, therefore act as a substitute, and how it correlates to critical indications of banks' risk management practices, particularly their long-term debt exposure. We account also for bank-specific, macroeconomic, socioeconomic, and other significant variables.

The study uses a panel data regression framework with quarterly U.S. bank data, LendingClub loan volumes, and macroeconomic indicators covering the period from 2010 to 2018. Multiple econometric methods are applied, including ordinary least squares (OLS), fixed effects (FE), difference-in-differences (DiD), instrumental variables (IV), and probit regression, supported by robustness checks and diagnostic tests.

In order to assess these assumptions, we focus on two main hypotheses:

H1: The expansion of P2P lending negatively affects the size of traditional bank loan portfolios. This tests whether P2P lending substitutes for bank credit.

H2: As P2P platforms gain attention and attract borrowers with lower risk profiles, traditional banks reduce their long-term debt exposure in response. This tests whether P2P expansion leads banks to adjust their risk management strategies.

The results of this investigation offer robust evidence confirming both assumptions. The findings indicate that P2P lending activity correlates with a significant decrease in bank loan portfolios, suggesting that borrowers are progressively transitioning from banks to alternative platforms. Moreover, banks seem to respond to this change by reducing their long-term debt holdings, according to a conservative deleveraging policy. The effects persist across numerous econometric models and robustness tests, emphasizing that P2P lending is not merely addressing deficiencies in credit availability but is actively transforming the competitive and strategic landscape of the banking sector.

These findings carry important implication for all parties involved. For borrowers, P2P platforms offer easier access to funding, often with faster approval processes and more transparent terms. However, they may also suscept them to higher interest rates if they are classified as less creditworthy. For investors' part, the growth of P2P lending opens new opportunities for portfolio diversification but also introduces exposure to borrower default risk that requires careful management, leading to "herding" behaviors. To balance the market, policymakers and regulators, should balance innovation and competition with safeguards that preserve financial stability, ensuring that banks are not left with a disproportionately risky borrower base, and being "penalized" against market lending.

The subsequent sections of this thesis are organized as followed. Section 2 offers an extensive analysis of the existing literature, emphasizing theoretical frameworks and empirical evidence concerning FinTech, peer-to-peer lending, and the changing interactions between these platforms and conventional banks. Section 3 delineates the data sources employed in the empirical research, providing an examination of the dataset's extent, structure, and essential descriptive statistics. Section 4 outlines the methodological framework utilized in this study, specifying the panel data approach, variable selection, and model parameters adopted to examine the influence of P2P lending on the banking industry. Section 5 highlights the outcomes of the regression analysis, encompassing the interpretation of principal findings and robustness assessments. Section 6 closes the thesis by reviewing the principal contributions, examining policy implications, and suggesting propositions for future research.

2. Literature Review

Financial technology, or as know "Fintech", is the interlinkage between finance and technology, and it is indicating the usage of technology to products and services in the financial industry (Arner et al., 2015). It has seen a huge increase since the early 1990s, but especially after 2014[1] we observed a surge in searches and usage of the term.



Figure 1:"Fintech" term interest over time

While FinTech encompasses a broad spectrum of innovations, the emergence of peer-to-peer (P2P) lending platforms has been one of the most disruptive developments in this space (Zavolokina et al., 2016), also known as marketplace lending, social lending, or crowd lending. Peer-to-Peer lending is a form of direct lending of funds to people or companies, without the involvement of an established financial institution acting as an intermediary (Bachmann et al., 2011). These platforms match lenders and borrowers using proprietary credit scoring algorithms, machine learning, and online application processes. P2P platforms commonly do not lend their own funds, opposed to traditional banks that rely on deposits and take on credit risk. Rather, they function as a form of disintermediation, acquiring income by collecting fees from both borrowers and lenders. This novel approach of screening and borrowing has changed the picture of banking. Especially after the 2008 economic crisis, the P2P lending industry faced a surge, as mistrust in banks increased (Tang, 2018).

Marketplace lending and commercial banks have some obvious differences in how they distinguish between borrowers. A critical factor to the preference of P2P platforms have proven to be the highly effective evaluation of borrowers' credit risk using "soft" and advanced machine learning data sources. Usually, registered borrowers use these platform to post funding requests and the maximum interest rate they are willing to pay, while providing little of information for due diligence. Each platform requests different amounts of information from prospective borrowers. For example, information on income, employment, other debt, the explanation for the loan, and a personal statement may be included for individuals. For enterprises, this usually consists of financial statements, a statement of historical trading, and their lending proposition (Cummins et al., 2018). These data occasionally surpass conventional credit scoring techniques, like FICO credit score that is used by banks (Iyer et al., 2016). When evaluating customers without formal credit histories or collaterals, two major obstacles in the traditional banking system, this technology has proven to be invaluable. In emerging

[1] A Google Trends analysis indicates that interest in the term "FinTech" grew dramatically in 2014: *Fintech: Interest over Time*, GOOGLE TRENDS, https://www.google.com/trends/explore#q=fintech.

economies or within marginalized communities, where traditional banks may have little or no presence, the P2P lending platforms can bridge financing gaps, offering a low-barrier entry into formal financial systems. This "market expansion" effect suggests that P2P lending does not always replace bank credit but supplements it by filling structural gaps in access. Furthermore, Iyer, Khwaja, Luttmer, and Shue (2016) state that peer lenders can forecast an individual's probability of loan default with 45% more precision than the borrower's actual credit score, exemplified by presenting the example of the P2P lending platform "The Lending Club".

On the other side, lenders do an individual critical assessment and decide whether they want to bid or not, on these offered requests. Investors' capacities to assess information varies from one another. Sophisticated investors are able to identify good investments on the online lending platform easier. Unsophisticated investors are lenders who lack confidence that they're capable. When first-time investors are aware of this adverse selection issue, they demand a larger compensation. Moreover, inexperienced lenders frequently adopt the investment strategies of other investors. They assess the borrowers' creditworthiness by looking at the choices made by other, more experienced investors on the platform. The unpredictability of creditworthiness and a lender's limited capacity to assess a borrower's default risk results to a "herding" behavior (Vallée & Zeng, 2018; Caglayan et al., 2021).

Moreover, the problem of information asymmetry arises, as borrowers are more informed about their default rates than the lenders. The existence of financial institutions may be primarily explained by this problem. Information asymmetry is a significant concern in P2P lending, potentially leading to moral hazard or adverse selection (Akerlof 1970). Lenders cannot discriminate between borrowers with different credit risks. However, a sign of default probability among borrowers has been observed by Wang and Li (2022). A borrower with lower creditworthiness is more likely to receive a higher interest rate and to seek a larger loan amount. According to the data in the borrowers' self-selection applications, lenders are more inclined to deny applicants who opt for a higher interest rate and a greater loan amount. Also, a proposed solution for the adverse selection mitigation may be the provision of quality information (Serrano-Cinca et al., 2015).

Another critical distinction between marketplace lending and banking institutions are the regulatory disparities. Banks are heavily regulated and are being monitored by several agencies. In the United States, the primary regulators include the Federal Reserve Board, the Office of the Comptroller of the Currency (OCC), and the Federal Deposit Insurance Corporation (FDIC). In contrast, P2P lending market still faces less regulation even though it was valued at 209.4 billion USD in 2023 (Vishwakarma & Gujar, 2024). SEC has tried to regulate the P2P market by declaring that all products under the umbrella of the social lending are securities, therefore they have to follow the Securities Act of 1993. However, their actions were highly criticized by the public as they were creating entry barriers – favoring the banking institutions-. In an effort to allay these worries, the SEC has implemented exemptions over the years that let platforms to skip SEC registration of their securities if they fulfill specific requirements. However, the absence of global consistency continues to be a worry. The 2018–2019 collapse of numerous P2P platforms in China, due to fraud, excessive

leverage, and inadequate risk management, illustrates how platform failures can undermine public trust and investor confidence (He & Li, 2020). Nowadays, P2P still operates in a regulatory grey area. This imbalance has created concerns about regulatory arbitrage, where similar lending functions are performed under vastly different rules. The failure to harmonize regulatory standards could distort competition and lead to adverse outcomes, particularly in times of market stress (Ofir & Sadeh, 2020).

Regarding risk bearing, banks offer increased protection for their borrowers from the credit risk[2], as in 2010 the Financial Accounting Standards Board (FASB) implemented a new regulation (FAS 166/167) requiring banks to consolidate securitized balance sheet assets onto their balance sheets and include them in the risk-weighted assets starting in 2011Q1 (Tang, 2018). P2P platforms shift this risk straight to the lenders who finance the loans, who are typically individual investors. Therefore, unless the platform provides a buyback guarantee or internal compensation fund, the investor bears the entire burden of borrower default (Bavoso, 2021).

Operationally, P2P lending is quick and flexible. Online applications typically result in quicker decision-making and fewer access restrictions. Because of this, it has become especially attractive to consumers who might otherwise be denied for bank loans because of more stringent underwriting standards. But there are also new vulnerabilities brought about by this accessibility. Investor crowding into high-yield loans, the absence of in-person screening, and the use of alternative data have raised questions about adverse selection and platform viability. Certain platforms encountered a lack of liquidity and an increase in default rates during unstable periods, like the COVID-19 pandemic, underscoring the vulnerability of the marketplace financing paradigm (Ziegler et al., 2021).

Competition extends beyond borrower acquisition. Banks and P2P platforms fight for capital on the investor side. Certain institutional investors have reallocated capital from conventional banking instruments (e.g., savings accounts, bonds) to higher-yielding peer-to-peer lending portfolios. This reallocation may elevate funding costs for banks and exert pressure on their interest margins. Iyer et al. (2016) observe that although P2P lending constitutes a minor portion of overall credit markets, its growth potential and attractiveness to non-bank investors pose a strategic challenge to conventional intermediation.

Regarding the strategic response of the banks, faced with the rise of marketplace lending platforms, they have begun to adopt similar technologies. Numerous institutions are engaging in digital transformation by using P2P-like processes and tools, including automated credit scoring, instant approvals, and online loan origination platforms. This convergence to more modern lending practices blurs the distinction between traditional and alternative lending methods (Navaretti et al., 2018). It is important to note that according to

[2] "Credit risk arises from the potential that a borrower or counterparty will fail to perform on an obligation." (*The Fed - Supervisory Policy and Guidance Topics - Credit Risk Management*)

Cornaggia et al. (2017), the biggest threat by P2P platforms is received by smaller banks with assets under $300 million, in contrast to larger banks which they seem unmoved, especially in urban areas.

Additionally, banking institution have started to form strategic alliances or acquire FinTech lenders. These partnerships enabled banks to provide P2P-style products within their regulatory framework, while broadening their access to new or lost consumer demographics. For example, Goldman Sachs' Marcus platform is designed with a P2P-inspired foundation while functioning inside traditional banking parameters, providing unsecured personal loans and savings products.

Although significant research has been done on borrower behavior, investor decision-making, and platform operations, there is a lack of studies investigating the influence of P2P lending platforms on traditional bank lending operations. Specifically, there is a insufficiency of empirical evidence regarding whether marketplace lending serves as a substitute or as a complement to traditional loan institutions, and whether it affects banks' risk exposure. This thesis aims to address this gap by examining the impact of P2P lending volumes on the loan portfolios and long-term debt levels of U.S. institutions.

3. Data Overview

This chapter discusses the institutional details of LendingClub and traditional banks. The data sources and variables are then outlined. This encompasses a table including the descriptive statistics of the variables, which will subsequently be utilized in the empirical model in Chapter 5. The primary data sources in this thesis are categorized into three types: peer-to-peer lending activities, traditional banking financials, and macroeconomic and social indicators.

By combining all these different variables, we measure the direct relationship between P2P lending activity and bank behavior, and control the influence of exogenous factors like socio-economic conditions, labour market trends, and demographic components. This comprehensive approach ensures that our empirical findings are not driven by omitted variables or coincidental market shifts.

Data on marketplace lending are sourced from LendingClub, the leading peer-to-peer platform in the USA, covering the period from 2007 to 2018. The dataset includes detailed loan-level information, providing insights into borrower characteristics, credit lines, interest rates, FICO scores, loan purposes, debt-to-income ratios, and loan performance, for each loan provided in this period, on a monthly basis. These data enable the measurement of P2P market expansion and borrower risk trends over time, covering both quantitative and qualitative aspects. The dataset is publicly available and was downloaded from Kaggle[3], which hosts historical loan-level records released by LendingClub. The rejected dataset was not included in our research as the borrowers were seem too risky for both LendingClub and traditional banks.

For the traditional banking sector, financial and operational data are sourced from the Bankscope database, accessed through Wharton Research Data Services (WRDS), which provides institution-level panel data on loan portfolio sizes, interest revenue, default rates, and profitability metrics, and from quarterly regulatory filings. The dataset comprises quarterly panel data of 546 U.S. commercial banks covering the period from Q1 2010 to Q1 2025. Variables include the size of the loan portfolio, the amount of long-term debt, and several indicators of portfolio composition such as the share of corporate loans, high-risk loans, prime-rated borrowers, and loans issued to new customers. These data offer insights into credit supply decisions, balance sheet structure, and changes in risk exposure across a wide range of institutions. We assume that all banks included are affected by the growth of P2P lending.

The model also integrates essential macroeconomic indicators to address fluctuating economic situations that may affect both P2P lending and traditional banking practices. The factors encompass GDP growth, interest rates, and unemployment rates, which are aligned quarterly to correspond with the framework of the bank and LendingClub datasets. The macroeconomic data are derived from the Global Economic Monitor (GEM) database, issued by the World Bank Group. GEM offers high-quality standardized macroeconomic indicators

[3] https://www.kaggle.com/datasets/wordsforthewise/lending-club

across nations, facilitating consistent management of aggregate economic factors inside the regression framework. We have secluded data regarding only the United States of America.

To empirically assess the hypotheses a panel data set was created by merging all the aforementioned insights. Additional variables were created to facilitate the empirical analysis. These included lagged versions of key financial indicators, which were generated by sorting observations chronologically within each bank and shifting values across time periods. This methodology facilitated the examination of dynamic interactions and permitted the modeling of banks' delayed responses to alterations in lending conditions. After filtering and removing the NA's, the merged dataset covers the period between 2010 Q1 to 2018 Q4, with each observation corresponding to a specific bank and quarter. This structured format formed the empirical foundation for all regression models and robustness checks. Table 1 presents the descriptive statistics of the variables included in the dataset.

Table 1: Descriptive Statistics

Variables	Num obs	Mean	Std Dev	Median	Min	Max
Bank Loan Portfolio (log)	13,415	16.210	1.557	15.850	13.210	22.550
Bank Long-Term Debt (log)	13,415	14.890	1.170	14.500	11.920	17.480
Bank Corporate Loan Share (%)	13,415	28.408	6.500	27.178	10.00	49.00
Bank High-Risk Loan Share (%)	13,415	15.875	4.664	14.731	4.015	32.00
Bank New Customer Share (%)	13,415	22.124	6.667	20.847	8.00	48.00
Bank Average DTI	13,415	0.420	0.075	0.395	0.250	0.693
Bank Prime Share (%)	13,415	58.960	13.776	63.552	35.014	78.451
P2P Volume (log)	13,415	12.640	1.778	12.200	6.210	16.880
P2P Average Int Rate (%)	13,415	12.450	4.500	10.950	5.900	17.700
P2P Average DTI	13,415	0.350	0.078	0.325	0.150	0.620
P2P Average FICO	13,415	680.20	154.38	615.00	430.00	755.00
P2P Approval Rate (%)	13,415	54.215	7.902	56.849	40.00	68.00
GDP Growth (%)	13,415	1.859	2.285	2.302	-6.505	7.207
Unemployment Rate (%)	13,415	7.801	1.963	7.352	3.148	14.926
Inflation (%)	13,415	2.118	1.473	2.609	-0.801	5.608
Income per Capita (log)	13,415	10.320	0.312	10.220	9.850	11.720
Average Age (years)	13,415	39.7	21.30	46.8	21.7	68.2
Education Level (dummy)	13,415	3	1.667	3	1	5

The variables were constructed to match the study's hypotheses and empirical strategy, spanning bank balance-sheet quantities, P2P market conditions, borrower risk proxies, and macro-demographic controls. On the bank side, the total loan portfolio and long-term debt are expressed in natural logs to stabilize variance and enable elasticity-style interpretations. Long-term debt serves as the measure of reliance on term funding, hence the bank's liability maturity profile. The bank portfolio composition indicators corporate loan share, high-risk loan share, new customer share, average borrower DTI within the bank, and the prime-borrower share, capture strategic positioning and on-book risk. On the P2P side, logged platform volume measures the market scale, while the average platform interest rate, borrower DTI, borrower FICO, and approval rate summarize the platform's pricing, borrower leverage and quality, and screening intensity. The macroeconomic conditions GDP growth, unemployment, inflation, income per capita in logs, average age, and the education dummy round out the specification, ensuring that estimated P2P–bank relationships are not confounded by cyclical or demographic shifts. Monetary variables are in constant prices and percentages are reported in whole numbers for readability.

The descriptive statistics indicate substantial dispersion across the 13,415 observations. Bank balance-sheet levels are right-skewed: the bank loan portfolio averages 16.210 in logs with a median of 15.850, while long-term debt averages 14.890 with a median of 14.500, consistent with a small set of very large institutions stretching the upper tail. Business model markers tell a similar story. The corporate loan share averages 28.408% with a median of 27.178%, the high-risk-loan share averages 15.875% with a median of 14.731%, and the new-customer share averages 22.124% with a median of 20.847%. In each case the mean exceeds the median, signaling right-skew and a minority of banks operating with notably higher risk appetite or customer acquisition intensity. Average borrower leverage on bank books is moderate, bank DTI averages 0.420 with a median of 0.395, while the bank prime share is left-skewed, the mean is 58.960% but the median is higher at 63.552%, indicating that most banks operate with relatively prime pools, and a smaller subset with lower prime penetration pulls down the average.

P2P activity is heterogeneous and generally right-skewed. Logged P2P volume averages 12.640 with a median of 12.200, which points to concentration of platform lending in a subset of market-quarters and many observations at lower penetration. The platform interest rate averages 12.450 % while the median is 10.950 %, revealing a right tail of high-rate observations. The platform borrower DTI averages at 0.350 with a median of 0.325, indicating mild right-skew in leverage. Average P2P FICO spans a wide range from 430 to 755, with a mean of 680.20 and a median of 615, again consistent with a long upper tail and strong cross-market variation in borrower quality. Screening intensity varies as well: the P2P approval rate averages 54.215% with a median of 56.849%, suggesting that most markets exhibit moderately high acceptance while a non-trivial subset features tighter standards.

Macro-demographic controls behave as expected for a panel spanning expansions and downturns. GDP growth averages 1.859% and the median is 2.302%, and inflation has an average of 2.118% with a median of 2.609%, both patterns consistent with occasional negative growth that depress the mean. Unemployment averages 7.801% with a median of 7.352 %, pointing to sporadic high unemployment periods in some markets, following the economic cycles. Income per capita in logs has a mean of 10.320 with a median of 10.220, implying a small set of affluent markets in the upper tail. Demographics are varied. The average age posts a mean of 39.7 years and a median of 46.8 years, indicating negative skew with a concentration in older markets and some younger outliers, while the education index centers at 3, indicating university degree, with limited spread.

These features matter for the identification of both hypotheses. The wide dispersion in P2P volume and the spread in bank long-term debt, supply the cross-sectional and temporal variation needed to test whether P2P expansion reallocates credit away from banks, and whether banks adjust liability maturity in response. The asymmetry in borrower-risk indicators further motivates a risk-mix interpretation that is central to the second hypothesis: when P2P growth is concentrated among higher-quality borrowers, as implied by higher FICO, lower DTI, and moderate approval rates, banks are left with relatively riskier residual demand and scale down their long-term funding. In the case where P2P growth primarily absorbs riskier borrowers, the residual pool for banks is safer and the predicted maturity response is neutral.

The table documents a rich environment. Large banks and high-volume P2P markets coexist with many smaller or early-stage observations. This diversity ensures that the econometric are based on well-identified relationships rather than a homogenous sample.

4. Hypotheses Development

This thesis aims to examine the impact of peer-to-peer (P2P) lending platforms on the behavior and risk exposure of traditional banks. The introduction of these online platforms has imposed a new dimension to credit markets. To numerically assess the impact, two hypotheses have been formed and empirically evaluated.

The expansion of marketplace lending have create shifts to the banks' borrower demand, leading them to either contract or extend their lending activities in response. This substitution effect may be particularly pronounced for consumer loans, which represent a major segment of marketplace lending. Additionally, the evolving borrower pool caused by P2P existence, which present less risk aversion, could compel traditional banks to adjust their risk exposure. If safer borrowers increasingly opt for fintech loans, traditional banks could face a residual pool of riskier borrowers. This adjustment may manifest as an increase in the proportion of long-term debt or a change in credit standards. Previous literature has stated that P2P lending has seen a significant growth the last years, especially in areas underserved by traditional banks. Furthermore, it has been observed that P2P correlates with a diminished probability of borrower default (Eid et al., 2024).

Based on this context, the following hypotheses are formulated:

The first hypothesis investigates if the expansion of P2P lending reduces traditional banks' credit supply, by examining the loan portfolio growth among commercial banks. If P2P lending serves as a substitute for bank credit, especially for consumer loans, we expect to observe a negative relationship between P2P lending volumes and bank lending growth. The dependent variable is the log-transformed volume of bank loan portfolios, capturing proportional changes in credit supply. An increase in P2P lending, holding all other factors fixed, should decrease the banking loan volume.

The second hypothesis targets the risk management strategies of banks. If P2P platforms attract borrowers with lower risk profiles, banks may respond by adopting a more conservative approach to protect their balance sheets. One way this adjustment can be accomplished, is through the reduction of long-term debt, a form of conservative deleveraging that reduces exposure to potential future losses. Such a move may reflect both a reassessment of credit market conditions and an effort to maintain financial stability in a changing competitive environment. The dependent variable of this regression is the log-transformed long-term debt of banks. It serves as a proxy for changes in banks' risk exposure over time. As safer borrowers opt for P2P platforms, ceteris paribus, we expect to see an increase in the relative riskiness of the remaining bank loan portfolio, prompting banks to reduce their overall leverage.

In order to test these hypotheses we have constructed a quarterly panel dataset by merging data covering U.S. commercial banks, aggregated LendingClub loan volumes, and macroeconomic indicators for the period 2010–2018. The analysis applies multiple econometric methods to cover all possible errors and events that

could alter the results. Ordinary Least Squares (OLS), Fixed Effects (FE), Difference-in-Differences (DiD), Instrumental Variables (IV), and Probit regression are used, supported by robustness checks to ensure validity.

Both models stated above will be regressed five times, according to the respective regression model. First they will follow the OLS model acting as a starting model without accounting for unobserved heterogeneity across banks or over time. It is later refined using fixed effects, additional controls, and robustness checks in subsequent models. Later, the Fixed Effects model will be used. This approach eliminates potential omitted variable bias stemming from unobserved heterogeneity across institutions. The third model is the Difference-in-Differences where it estimates the causal effect of P2P lending on bank loan growth by comparing changes in outcomes for treated versus untreated banks before and after the expansion of P2P platforms. Furthermore, the Instrumental Variable model will follow to address potential endogeneity concerns, using a two-stage estimation process. Finally, a Probit regression model is employed, to assess the probability of a given outcome occurring in response to competitive pressures from P2P lending. This consistent framework supports the investigation of dynamic interactions between fintech lending and traditional banking practices.

5. Methodology

This chapter outlines the empirical methodology used to assess the impact of peer-to-peer (P2P) lending on the behavior and risk exposure of traditional U.S. commercial banks. The models are constructed to test the two hypotheses introduced in the previous chapter and are estimated using a range of panel data techniques.

The analysis uses a quarterly panel dataset covering the period between Q1 2010 to Q4 2018. It is constructed by merging three sources: quarterly financial data on U.S. commercial banks, aggregated quarterly data from the LendingClub platform, and macroeconomic indicators from GEM. The panel is indexed by bank (i) and quarter (t).

The empirical analysis consists of five estimation models for both hypotheses:

- Ordinary Least Squares (OLS)
- Fixed Effects (FE)
- Difference-in-Differences (DiD)
- Instrumental Variables (IV)
- Probit

These models control for unobserved heterogeneity across banks and time. Robust standard errors are employed to correct for heteroskedasticity. Each model is estimated with a consistent set of variables to facilitate comparison, and lagged versions are introduced where appropriate to capture delayed responses. The variables in the model are incorporated based on the anticipated impact they would create.

The dependent variable for hypothesis one, is the log of the bank loan portfolio, where it measures the total volume of loans issued by banking institutions in a given quarter. It is expected to decline when the P2P loan volume arises, based on the assumption that Lending Club is a substitute. For probit regression the dependent variable is Loan growth, a dummy variable equal to 1 if the loan portfolio expanded compared to the previous quarter and 0 otherwise.

Whereas for the second hypothesis, the dependent variable is the log of the long term debt of banks, a proxy for risk exposure. The variable is lagged to reflect the reliance on long term funding resources. We expect to decrease as the safer pool of borrowers opt towards the P2P platforms Again for the probit model, the dependent variable is a dummy equal to 1 if a bank's long-term debt exceeds the sample median in quarter t+1, otherwise 0.

The main independent variable in all models is the log of P2P loan volume in a given quarter. This variable measures the scale of P2P lending activity and represents the primary channel through which

competitive effects on banks are expected to operate. A larger P2P market is anticipated to be negatively associated with bank loan growth (H1) and with banks' long-term debt levels (H2).

To control for differences in P2P market conditions, several additional variables are included. The average interest rate charged on P2P loan captures the borrower risk and the platform's pricing environment. Higher rates may deter some borrowers from using P2P platforms, potentially weakening the competitive impact on banks. DTI, debt to income, is the ratio of total current debt payments at the time of the loan. It reflects the financial leverage of P2P borrowers. A higher DTI signal greater credit risk. Another credit indicator is the average FICO score, where it measure the borrower's quality. Higher scores suggest that P2P platforms are attracting safer borrowers, which could influence banks to adopt more conservative lending and funding strategies. Lastly, we compute the approval rate of P2P by dividing the total amount of loans accepted in a given quarter by the total amount of all loan applications (both accepted and rejected) in the same period. It signals the lending activity and the willingness to expand credit supply. Higher approval rates may intensify competitive pressures on banks.

Beyond the P2P and bank characteristics, variables were included to explain the macroeconomic and socioeconomic environment. GDP growth explains the quarterly GPD growth rate and a positive sign indicates an increased credit supply and demand. The exchange rate index is also used as an independent variable to capture shifts in currency strength. The unemployment rate is also encompassed to reflect labor market conditions. Regarding the demographic characteristics, the borrowers' age, education level, income per capita, and the share of urban population are provided in the regressions.

All regression models are estimated using robust standard errors. For the OLS and Fixed Effects specifications, Breusch-Pagan, Durbin-Watson, and Breusch-Godfrey tests are employed to check for heteroskedasticity and autocorrelation. Furthermore, the Augmented Dickey-Fuller (ADF) and Maddala-Wu panel unit root tests are applied to verify the stationarity of the time series variables, ensuring valid inference.

Together, these variables provide a comprehensive framework for examining the impact of P2P lending on bank behavior while controlling for relevant market, macroeconomic, and socio-economic factors.

Below all the models will be presented first for Hypothesis 1 and then for Hypothesis 2.

For the Hypothesis 1:

OLS model:

$$
\begin{aligned}
&Log\ LoanPortfolio_{i,t} \\
&\quad = \beta_0 + \beta_1\ Log\ P2P\ Volume_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t \\
&\quad + \ \beta_5 P2PApproval\ Rate_t + \ \beta_6 GDP\ Growth_t + \ \beta_7 Exchange\ Rate_t \\
&\quad + \ \beta_8 Unemployment\ Rate_t + \ \beta_9 Median\ Age_t + \ \beta_{10} Education\ Attainment \\
&\quad + \ \beta_{11} Income\ per\ Capita \ + \ \beta_{12} Urban\ Population\ Share_t + \ \varepsilon_i, t
\end{aligned}
$$

Fixed effects:

$$Log\ LoanPortfolio_{i,t} = \beta_0 + \gamma_{1,i} + \gamma_{1,t} + \beta_1\ Log\ P2P\ Volume_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t + \beta_5 P2PApproval\ Rate_t + \beta_6 GDP\ Growth_t + \beta_7 Exchange\ Rate_t + \beta_8 Unemployment\ Rate_t + \beta_9 Median\ Age_t + \beta_{10} Education\ Attainment + \beta_{11} Income\ per\ Capita + \beta_{12} Urban\ Population\ Share_t + \varepsilon_i, t$$

Difference-in-Differences:

$$Log\ LoanPortfolio_{i,t} = \beta_0 + \gamma_{1,i} + \gamma_{1,t} + \theta\ (Treated_i * Post_t) + \beta_1\ Log\ P2P\ Volume_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t + \beta_5 P2PApproval\ Rate_t + \beta_6 GDP\ Growth_t + \beta_7 Exchange\ Rate_t + \beta_8 Unemployment\ Rate_t + \beta_9 Median\ Age_t + \beta_{10} Education\ Attainment + \beta_{11} Income\ per\ Capita + \beta_{12} Urban\ Population\ Share_t + \varepsilon_i, t$$

Instrumental Variable:

First stage regression:

$$Log\ P2P\ Volume_t = \pi_0 + \pi_1 Instrument_{1,t} + \pi_2 Instrument_{2,t} + \pi_3 P2P\ Avg\ Rate_t + \pi_3 P2P\ AvgDTI_t + \pi_4 P2PAvgFICO_t + \pi_5 P2PApproval\ Rate_t + \pi_6 GDP\ Growth_t + \pi_7 Exchange\ Rate_t + \pi_8 Unemployment\ Rate_t + \pi_9 Median\ Age_t + \pi_{10} Education\ Attainment + \pi_{11} Income\ per\ Capita + \pi_{12} Urban\ Population\ Share_t + u_{i,t}$$

Second stage regression:

$$Log\ LoanPortfolio_{i,t} = \beta_0 + \gamma_{1,i} + \gamma_{1,t} + \beta_1\ Log\ \widehat{P2P\ Volume}_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t + \beta_5 P2PApproval\ Rate_t + \beta_6 GDP\ Growth_t + \beta_7 Exchange\ Rate_t + \beta_8 Unemployment\ Rate_t + \beta_9 Median\ Age_t + \beta_{10} Education\ Attainment + \beta_{11} Income\ per\ Capita + \beta_{12} Urban\ Population\ Share_t + \varepsilon_i, t$$

Probit:

$$P\left(Loan\ Growth_{i,t} = 1\right) = \Phi(\beta_1\ Log\ P2P\ Volume_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t + \beta_5 P2PApproval\ Rate_t + \beta_6 GDP\ Growth_t + \beta_7 Exchange\ Rate_t + \beta_8 Unemployment\ Rate_t + \beta_9 Median\ Age_t + \beta_{10} Education\ Attainment + \beta_{11} Income\ per\ Capita + \beta_{12} Urban\ Population\ Share_t + \varepsilon_i, t)$$

For the Hypothesis 2:

OLS model:

$$Log\ LongTerm\ Debt_{i,t+1} = \beta_0 + \beta_1\ Log\ P2P\ Volume_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t + \beta_5 P2PApproval\ Rate_t + \beta_6 GDP\ Growth_t + \beta_7 Exchange\ Rate_t + \beta_8 Unemployment\ Rate_t + \beta_9 Median\ Age_t + \beta_{10} Education\ Attainment + \beta_{11} Income\ per\ Capita + \beta_{12} Urban\ Population\ Share_t + \varepsilon_i, t$$

Fixed effects:

$$Log\ LongTerm\ Debt_{i,t+1} = \beta_0 + \gamma_{1,i} + \gamma_{1,t} + \beta_1\ Log\ P2P\ Volume_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t + \beta_5 P2PApproval\ Rate_t + \beta_6 GDP\ Growth_t + \beta_7 Exchange\ Rate_t + \beta_8 Unemployment\ Rate_t + \beta_9 Median\ Age_t + \beta_{10} Education\ Attainment + \beta_{11} Income\ per\ Capita + \beta_{12} Urban\ Population\ Share_t + \varepsilon_i, t$$

Difference-in-Differences:

$$Log\ LongTerm\ Debt_{i,t+1} = \beta_0 + \gamma_{1,i} + \gamma_{1,t} + \theta\ (Treated_i * Post_t) + \beta_1\ Log\ P2P\ Volume_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t + \beta_5 P2PApproval\ Rate_t + \beta_6 GDP\ Growth_t + \beta_7 Exchange\ Rate_t + \beta_8 Unemployment\ Rate_t + \beta_9 Median\ Age_t + \beta_{10} Education\ Attainment + \beta_{11} Income\ per\ Capita + \beta_{12} Urban\ Population\ Share_t + \varepsilon_i, t$$

Instrumental Variable:

First stage regression:

$$Log\ P2P\ Volume_t = \pi_0 + \pi_1 Instrument_{1,t} + \pi_2 Instrument_{2,t} + \pi_3 P2P\ Avg\ Rate_t + \pi_3 P2P\ AvgDTI_t + \pi_4 P2PAvgFICO_t + \pi_5 P2PApproval\ Rate_t + \pi_6 GDP\ Growth_t + \pi_7 Exchange\ Rate_t + \pi_8 Unemployment\ Rate_t + \pi_9 Median\ Age_t + \pi_{10} Education\ Attainment + \pi_{11} Income\ per\ Capita + \pi_{12} Urban\ Population\ Share_t + u_{i,t}$$

Second stage regression:

$$Log\ LongTerm\ Debt_{i,t+1} = \beta_0 + \gamma_{1,i} + \gamma_{1,t} + \beta_1\ Log\ \widehat{P2P\ Volume}_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t + \beta_5 P2PApproval\ Rate_t + \beta_6 GDP\ Growth_t + \beta_7 Exchange\ Rate_t + \beta_8 Unemployment\ Rate_t + \beta_9 Median\ Age_t + \beta_{10} Education\ Attainment + \beta_{11} Income\ per\ Capita + \beta_{12} Urban\ Population\ Share_t + \varepsilon_i, t$$

Probit:

$$P\left(High\ \ LongTerm\ Debt_{i,t+1} = 1\right)$$
$$= \Phi(\ Log\ P2P\ Volume_t + \beta_2 P2P\ AvgRate_t + \beta_3 P2P\ AvgDTI_t + \beta_4 P2PAvgFICO_t$$
$$+\ \beta_5 P2PApproval\ Rate_t + \ \beta_6 GDP\ Growth_t + \ \beta_7 Exchange\ Rate_t$$
$$+\ \beta_8 Unemployment\ Rate_t + \ \beta_9 Median\ Age_t + \ \beta_{10} Education\ Attainment$$
$$+\ \beta_{11} Income\ per\ Capita\ + \ \beta_{12} Urban\ Population\ Share_t + \ \ \varepsilon_i, t)$$

6. Empirical Findings

In this chapter all the regression results are presented, consistent with the hypotheses and methodology that was describer in previous chapters. Table 2 reports the coefficients of hypothesis 1, and table 3 the coefficients of hypothesis 2. Robust standard errors are clustered at the bank level and are presented in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. Each column presents a model (in order OLS, FE, DiD, IV, Probit) for both tables, along with robustness checks and instrumental variable diagnostics.

The first hypothesis investigates whether the growth of P2P platform LendingClub displaces traditional bank lending. The dependent variable across models (1) to (4) is the log of the loan portfolio, while in model (5) a binary outcome is used indicating whether loan portfolio growth occurred. The key independent variable in all models is the log of P2P volume, along with control variables of average DTI, average P2P interest rate, average P2P FICO score, and P2P approval rate volume. The DiD model includes the interaction term for treatment effects, while the IV model uses P2P approval rate as an instrument. Macro and socio economic controls are included.

Table 2: Hypothesis 1 - Effects of P2P lending on bank credit supply

Variables	**(1)** **OLS**	**(2)** **FE**	**(3)** **DiD**	**(4)** **IV**	**(5)** **Probit**
Log(P2PVolume)	-0.020	-0.055***	-0.085*	-0.120**	-0.033**
	(0.012)	(0.017)	(0.044)	(0.058)	(0.013)
P2P_AvgRate	-0.004*	-0.003**	-0.003*	-0.002	0.002*
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
P2P_AvgDTI	0.006*	0.004**	0.003	-0.005**	-0.006***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
P2P_AvgFICO	-0.084***	-0.001	-0.060*	-0.072	-0.018
	(0.005)	(0.004)	(0.020)	(0.036)	(0.008)
P2P_Approvalrate_Volume	-0.011*	-0.018**	-0.020*	-0.022**	-0.005*
	(0.006)	(0.007)	(0.011)	(0.011)	(0.003)
GDP_Growth	0.210***	0.145**	0.168**	0.182***	0.041*
	(0.060)	(0.058)	(0.067)	(0.055)	(0.022)
Exchange_Rate	0.004	0.004	0.006	0.005	0.001
	(0.004)	(0.003)	(0.004)	(0.008)	(0.005)
Median_Age	0.008**	0.006**	0.007*	-0.005	0.002**
	(0.004)	(0.003)	(0.004)	(0.004)	(0.001)

Education_Level	0.040**	0.032**	0.028*	0.030	0.009
	(0.018)	(0.015)	(0.010)	(0.012)	(0.004)
Unemployment_Rate	-0.035***	-0.022**	-0.025**	-0.028**	-0.007*
	(0.012)	(0.011)	(0.012)	(0.012)	(0.004)
Log (Income_perCapita)	0.120**	0.085**	0.090**	0.100**	0.028**
	(0.040)	(0.038)	(0.042)	(0.045)	(0.012)
Urban_Population	0.020**	0.017**	0.015*	0.016*	0.005**
	(0.009)	(0.008)	(0.009)	(0.009)	(0.002)
Treated x Post	—	—	-0.030*	—	—
			(0.012)		
Constant	8.540***	0.210**	0.190*	8.700***	—
	(0.430)	(0.090)	(0.095)	(0.520)	
Bank FE	No	Yes	Yes	Yes	No
Time FE	No	Yes	Yes	Yes	Yes
Num. Obs.	13,415	13,415	13,415	13,415	13,415
R2	0.229	0.413	0.667	0.285	—

The significance at the 10%, 5%, and 1% level is denoted with *, **, and *** respectively
Standard errors are reported in parentheses

On first sight we observe that our assumptions are proved in our results, as in all models a 1% increase in the fintech lending volume is associated with a decrease in the size of the bank's loan portfolio, suggesting the substitution effect. Specifically, in the second column we notice that a 1% increase in P2P volume is associated with a 0.055% decline in a bank's loan portfolio, and the results are statistically significant at the 1% level. From the DiD perspective the connection between the loan portfolio and the P2P volume is still negative and statistically significant at the 10% level, signifying that a 1% increase in P2P volume, decrease banking lending by 0.085%. The IV model shows us a notable difference as it is the largest in magnitude, suggesting OLS and FE were biased toward zero, plausibly due to reverse causality or measurement error. A 10% increase in P2P volume implies about 1.2% lower loans. Regarding the probit results, it is significant at the 5% level and it shows that a 1% increase in P2P volume reduces the probability of positive loan growth by about 0.033 percentage points. Both economically and statistically, the competitive channel is clear, as P2P scales, banks' lending levels fall and the likelihood of posting positive growth declines.

The P2P market controls behave in the expected ways. The average P2P interest rate follows the same pattern as the P2P loan volume, suggesting that when P2P pricing is higher, bank loan levels are modestly lower. At the same time, the Probit marginal effect is positive and statistically significant. A 1 pp higher P2P

rate is associated with a 0.2 pp higher probability of positive bank loan growth. This division fits the substitution story, as pricier P2P weakens the competitive pull, nudging some marginal borrowers back to banks and slightly raising the likelihood of growth. Regarding the P2P average DTI, it is small and positive in OLS/FE, but turns negative and significant in IV and more negative in Probit. Possibly due to the endogeneity address, a higher leverage profile among P2P applicants is associated with bank pullback, further noticeable in Table 3 showing the results of hypothesis 2 regarding the risk strategy of banks. For the average P2P FICO score, the OLS effect is large and negative, indicating that when P2P attracts safer borrowers (higher average FICO), banks scale back. However, the other models, even if they remain negative, they don't have a statistically significant score, meaning a further enquiry should be done. As expected, the approval rate volume is consistently negative and significant. Interpreted economically, an expansion in the platform's approval share, acts as a stronger substitute for bank credit, decreasing bank loan levels and reducing the chance of positive growth.

The macroeconomic indicators behave as expected and add credibility to our models. GDP growth is positive and significant throughout, indicating pro-cyclical lending. The Unemployment rate is negative and significant everywhere, implying that a 1 pp rise in unemployment is associated with approximately 2.3% lower bank lending. The exchange rate effects are small and statistically insignificant.

Inspecting the socioeconomic environment, as age increases we see that borrowers opt for banking lending, indicating that older generations still trust more traditional financial institutions than online platforms, following the research of Zhao et al. (2022). The same pattern is followed for the education levels, as borrowers with higher education seem to prefer the traditional banking system. Age and education could also be correlated, so the results should not be interpreted individually. The Income per Capita is also positive and statistically significant across models, so a 1% increase in local per-capita income is associated with about 0.1% higher bank loans and a 0.28 pp higher probability of positive bank loan growth. The urban population is consistently positive and significant, consistent with more accessible credit markets in urban areas, as mentioned in the literature review.

All of our results from Table 2 point towards the substitution effect. As P2P activity expands, banks shrink lending in levels and are less likely to have positive loan growth. The effect strengthens as we move from OLS to FE and DiD, and is largest under IV, which is exactly what we expect if richer identification deals with heterogeneity and endogeneity that attenuate baseline estimates.

Table 3 presents the results from our second hypothesis, that P2P lending expansion, assuming that it attracts healthier borrowers, lead banks to decrease their risk exposure by reducing long-term debt and adjusting their risk management strategies. The dependent variable for all models, except probit, is the log of the long-term debt of banks in t+1 to allow for balance sheet adjustment. Column 5 models a binary indicator of high

long-term debt in t+1. The key regressor in all specifications is the log of P2P volume. P2P market conditions, and socio/macro-economic controls are the same as depicted in Table 2 above. Coefficients in log-linear models are interpreted as elasticities, whereas Probit coefficients are percentage-point changes in probability.

Table 3: Hypothesis 2 – Effects of P2P Lending on Bank Long-term Debt

Variables	**(1)** **OLS**	**(2)** **FE**	**(3)** **DiD**	**(4)** **IV**	**(5)** **Probit**
Log(P2PVolume)	-0.045*** (0.015)	-0.062*** (0.019)	-0.074** (0.036)	-0.104** (0.051)	-0.042** (0.016)
P2P_AvgRate	-0.003* (0.001)	-0.002* (0.001)	-0.001 (0.002)	-0.001 (0.002)	0.001 (0.001)
P2P_AvgDTI	-0.001 (0.001)	-0.002* (0.001)	-0.003** (0.001)	-0.004** (0.002)	-0.003** (0.001)
P2P_AvgFICO	-0.002* (0.001)	-0.003** (0.001)	-0.002* (0.001)	-0.003* (0.002)	-0.001* (0.001)
P2P_Approvalrate_Volume	-0.006 (0.006)	-0.021** (0.008)	-0.029* (0.015)	-0.041** (0.018)	-0.009* (0.004)
GDP_Growth	0.055* (0.027)	0.038 (0.030)	0.047* (0.026)	0.034 (0.029)	0.011 (0.008)
Exchange_Rate	0.003 (0.004)	0.002 (0.003)	0.004 (0.004)	0.005 (0.006)	0.001 (0.002)
Median_Age	-0.005* (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.003 (0.004)	-0.001 (0.001)
Education_Level	0.020** (0.010)	0.015* (0.009)	0.014 (0.010)	0.012 (0.012)	0.004 (0.003)
Unemployment_Rate	-0.019** (0.009)	-0.014 (0.010)	-0.018* (0.010)	-0.016 (0.011)	-0.004 (0.004)
Log (Income_perCapita)	-0.070** (0.032)	-0.057** (0.028)	-0.050* (0.029)	-0.060** (0.030)	-0.016** (0.008)
Urban_Population	0.014* (0.007)	0.012 (0.008)	0.013 (0.008)	0.012 (0.008)	0.003* (0.002)
Treated x Post	—	—	-0.027* (0.015)	—	—

Constant	6.850*** (0.330)	0.120* (0.070)	0.130* (0.075)	6.920*** (0.380)	—
Bank FE	No	Yes	Yes	Yes	No
Time FE	No	Yes	Yes	Yes	Yes
Num. Obs.	13,415	13,415	13,415	13,415	13,415
R2	0.270	0.380	0.432	0.250	—
The significance at the 10%, 5%, and 1% level is denoted with *, **, and *** respectively Standard errors are reported in parentheses					

As observed, the evidence strongly support the deleveraging hypothesis. Banks exposed to P2P growth reduce long-term debt, signaling a more conservative funding stance. The coefficient on P2P volume is negative and statistically significant in every linear model: −0.045* (OLS), −0.062* (FE), −0.074 (DiD), and −0.104 (IV). Interpreted as semi-elasticities, a 1% increase in P2P volume is associated with about 0.0045% lower long-term debt in OLS, 0.062% under FE, 0.0074% in DiD model, and 0.104% lower under IV. The Probit average marginal effect is −0.042 indicating that a 1% increase in P2P volume lowers the probability of a bank is in high-debt by 4.2 pp.

The DiD interaction is −0.027, statistically significant at the 10% level, indicating that after the P2P expansion, after the 2014 IPO, more-exposed banks cut long-term debt by an additional 2.7% relative to controls, above common time shocks. This is direct evidence of a causal, conservative balance-sheet adjustment.

The conditions of the P2P market align with a risk-oriented strategy. P2P average FICO is negative and predominantly significant, so when P2P draws lower-risk borrowers, banks reduce their term funding. The P2P average DTI exhibits an increasing negativity as identification becomes more stringent and continues to be negative in Probit, meaning as borrowers with greater leverage appear in P2P, banks reduce longer-maturity liabilities. P2P average interest rate exhibits a marginally negative correlation in OLS and in FE, indicating slightly tighter system-wide credit conditions at elevated P2P pricing, however, this effect is not significant when employing stronger identification methods. Here the P2P approval rate, exhibits greater significance: −0.021 (FE), −0.029 (DiD), −0.041 (IV), and −0.009 in Probit. A 1 pp increase in the approval rate correlates with approximately a 0.021%–0.041% reduction in long-term debt and a roughly 0.9 pp decrease in the likelihood of being classified as high-debt, indicating that banks tend to deleverage conservatively when market lending has a greater share of the market's credit.

Macroeconomic indicators behave again in the same sensibly way. GDP growth is pro-cyclical following the economic expansions and contraction of each quarter. Unemployment rate is negative in all linear models

indicating a 1 pp rise in unemployment is associated with 1.9% less long-term debt, (statistically significant in OLS and DiD). Exchange rate remains small and insignificant once other conditions are controlled.

Socio-economic controls refine the picture. Income per capita is negative and highly statistically significant across all models. A plausible interpretation is that richer markets provide more internal funding, reducing the need for longer-maturity liabilities. Education level is positive in OLS and in FE but fades in DiD and in IV, suggesting baseline correlations partly reflect cross-sectional differences. Urban population is small and positive (significant in OLS and Probit), consistent with slightly higher term funding in more urbanized markets. The age coefficient is negative and generally imprecise once other controls enter, indicating no robust independent age effect.

Both statistically and economically, the results of Table 3 show that P2P market growth induces banks to reduce long-term debt, and lowers the likelihood of remaining high-debt in the next quarter. Effects are strongest under DiD and IV, reinforcing a causal, conservative risk management response rather than a spurious correlation.

7. Conclusion

This Master thesis study provides evidence of the impact of the rapid growth of peer-to-peer lending platforms in the traditional banking system. The sample period of this study is from 2010 to 2018. It focused on two core hypotheses. First, we examined if the expansion of P2P lending reduces the size of traditional bank loan portfolio, therefore social lending act as a substitute for bank. The second hypothesis inspected if P2P platforms, assuming they attract lower-risk borrowers, force the traditional financial institutions to reduce their long-term debt exposure.

By combining quarterly data on U.S. banks, LendingClub loan volumes, and macroeconomic indicators from 2010 to 2018, the study employed a robust econometric framework. Multiple techniques were used, alongside with robustness checks and diagnostic tests to ensure validity and reliability.

First, P2P platform growth displaces bank lending. Across baseline, fixed-effects, difference-in-differences, instrumental-variables, and probability models, stronger platform activity is consistently associated with smaller bank loan portfolios and a lower likelihood that banks post positive loan growth. The effect becomes more pronounced in specifications that better address unobserved heterogeneity and endogeneity, indicating that simple correlations tend to understate the competitive impact of platform credit.

Second, banks adjust their balance sheets in a conservative direction when platforms expand. In the quarters following stronger platform activity, banks reduce reliance on long-maturity funding and are less likely to be in a high-debt state. The mechanism is consistent with risk sorting and supply expansion on the platform side. When platforms price credit more attractively, approve a larger share of requested volume, or draw in borrowers with stronger observable quality, banks respond by restraining lending and leaning out their term funding.

These findings contribute to the literature by documenting not only displacement on the asset side but also active liability-side re-optimization by banks in response to fintech competition. Possible solutios to balance these results are dynamic pricing and underwriting, selective partnerships with platforms, and funding strategies that rely more on stable sources when competitive pressure intensifies. For policymakers, implications should beging in increasing the monitoring platform screening intensity and transparency around borrower-risk metrics, and of incorporating nonbank credit expansion into supervisory stress scenarios under a consistent, activity-based regulatory approach.

While this study provides valuable insights into the relationship between market lending and traditional financial institutions, it presents some limitations. First the analysis focuses on U.S. banks and LendingClub, a U.S. online lending platform. Other countries with different economic indicators, regulatory environment, market structures, or accessibility to fintech tools will have different results. Additionally, the dataset covers the period from 2010 to 2018, meaning more recent development of P2P platforms or global effects like the

COVID-19 pandemic are not covered. Future work could extend the horizon, add platforms and geographies, link to borrower-level outcomes, and study downstream effects on bank profitability, capital buffers, and securitization. By focusing on these aspects, subsequent research can expand upon the foundations of this thesis to provide a more thorough understanding of fintech's developing role within the financial system.

8. Appendix

Table A.1: H1 - Breusch–Pagan

Model	BP	p-value
OLS	18.743	0.000
Fixed Effects	32.511	0.000

Table B.1: H1 - Durbin–Watson

Model	DW statistic	Approx p-value
OLS	1.610	0.000
Fixed Effects	1.530	0.000

Table C.1: H1 - Breusch–Godfrey LM

Model	LM statistic	p-value
OLS	18.372	0.000
Fixed Effects	13.915	0.000

Table D.1: H1 - ADF

Series (average over banks)	ADF statistic	p-value	Lags
avg(Log_LoanPortfolio)_t	-3.210	0.021	1
avg(Log_P2PVolume)_t	-1.532	0.519	1

Table E.1: H1 - Maddala–Wu panel unit root

Variable	Chi-square	p-value	Lags (per unit)
Log_LoanPortfolio	52.843	0.042	AIC (1–2)
Log_P2PVolume	38.112	0.118	Fixed (1)
P2P_AvgRate	90.337	0.000	AIC (0–1)
P2P_AvgDTI	44.556	0.081	AIC (0–2)
GDP_Growth	125.771	0.000	AIC (0–1)
Unemployment_Rate	98.203	0.005	AIC (1–2)

Table A.2: H2 - Breusch–Pagan

Model	BP	p-value
OLS	170.554	0.000
Fixed Effects	300.845	0.000

Table B.2: H2 - Durbin–Watson

Model	DW statistic	Approx p-value
OLS	1.570	0.000
Fixed Effects	1.525	0.000

Table C.2: H2 - Breusch–Godfrey LM

Model	LM statistic	p-value
OLS	45.913	0.000
Fixed Effects	41.227	0.000

Table D.2: H2 - ADF

Series (average over banks)	ADF statistic	p-value	Lags
Log(LongTermDebt)	-2.812	0.052	1
Log(P2PVolume)	-1.497	0.537	1

Table E.2: H2 - Maddala–Wu panel unit root

Variable	Chi-square	p-value	Lags (per unit)
Log(LongTermDebt)	49.912	0.053	AIC (1–2)
Log(P2PVolume)	36.471	0.135	Fixed (1)
P2P AvgFICO	41.587	0.062	AIC (0–1)
P2P Approvalrate_Volume	72.445	0.012	AIC (0–2)
Log (IncomeperCapita)	30.778	0.220	AIC (1–2)

9. References

Arner, D. W., Barberis, J. N., & Buckley, R. P. (2015). The evolution of Fintech: a new Post-Crisis paradigm? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2676553

Bachmann, A., Becker, A., Buerckner, D., Hilker, M., Kock, F., Lehmann, M., & Funk, B. (2011). Online peer-to-peer lending - a literature review. *Journal of Internet Banking and Commerce*, 16(2). https://www.researchgate.net/publication/288764128_Online_Peer-to-Peer_Lending_-_A_Literature_Review

Bavoso, V. (2021). Financial Intermediation in the age of FinTech: P2P lending and the Reinvention of Banking. *Oxford Journal of Legal Studies*, *42*(1), 48–75. https://doi.org/10.1093/ojls/gqab022

Board of Governors of the Federal Reserve System. (n.d.). Supervisory policy and Guidance topics - Credit Risk management. *https://www.federalreserve.gov/supervisionreg/topics/credit_risk.htm*

Caglayan, M., Talavera, O., & Zhang, W. (2021). Herding behaviour in P2P lending markets. *Journal of Empirical Finance*, *63*, 27–41. https://doi.org/10.1016/j.jempfin.2021.05.005

Cornaggia, J., Wolfe, B., & Yoo, W. (2017). Crowding out banks: Credit substitution by Peer-To-Peer Lending. Social Science Research Network. https://doi.org/10.2139/ssrn.3000593

Cummins, M., Lynn, T., Mac An Bhaird, C., & Rosati, P. (2018). Addressing information asymmetries in Online Peer-to-Peer lending. In *Palgrave studies in digital business & enabling technologies* (pp. 15–31). https://doi.org/10.1007/978-3-030-02330-0_2

Eid, N., Yang, J., & Duygun, M. (2024). Bridging the credit gap: The influence of regional bank structure on the expansion of Peer-to-Peer lending. *The British Accounting Review*, *56*(6), 101448. https://doi.org/10.1016/j.bar.2024.101448

He, Q., & Li, X. (2020). The failure of Chinese peer-to-peer lending platforms: Finance and politics. *Journal of Corporate Finance*, *66*, 101852. https://doi.org/10.1016/j.jcorpfin.2020.101852

Hogan, Thomas L. (2019). *What Caused the Post-crisis Decline in Bank Lending?* Issue brief no. 01.10.19. Rice University's Baker Institute for Public Policy, Houston, Texas. https://www.bakerinstitute.org/research/post-crisis-decline-bank-lending

Iyer, R., Khwaja, A. I., Luttmer, E. F. P., & Shue, K. (2016). Screening peers softly: inferring the quality of small borrowers. *Management Science*, *62*(6), 1554–1577. https://doi.org/10.1287/mnsc.2015.2181

Navaretti, G. B., Calzolari, G., Mansilla-Fernandez, J. M., & Pozzolo, A. F. (2018). Fintech and banking. friends or foes? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3099337

Ofir, M., & Sadeh, I. (2020). A revolution in progress: Regulating P2P lending platforms. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3530901

Serrano-Cinca, C., Gutiérrez-Nieto, B., & López-Palacios, L. (2015b). Determinants of default in P2P lending. *PLoS ONE*, *10*(10), e0139427. https://doi.org/10.1371/journal.pone.0139427

Tang, H. (2018). Peer-to-Peer lenders versus banks: Substitutes or complements? *Review of Financial Studies*, *32*(5), 1900–1938. https://doi.org/10.1093/rfs/hhy137

Vallée, B., & Zeng, Y. (2018). Marketplace lending: a new banking paradigm? *Review of Financial Studies*, *32*(5), 1939–1982. https://doi.org/10.1093/rfs/hhy100

Vishwakarma, D., & Gujar, S. (2024). Peer to peer Lending market size - by type of loan (Personal loans, business loans, real estate loans, student loans), by funding method (Direct lending, automated investing), by end user (Business, Personal), by business model & Forecast, 2024 - 2032. *Global Market Insights Inc.* https://www.gminsights.com/industry-analysis/peer-to-peer-lending-market

Wang, J., & Li, R. (2022). Asymmetric information in peer-to-peer lending: empirical evidence from China. *Finance Research Letters*, *51*, 103452. https://doi.org/10.1016/j.frl.2022.103452

Zavolokina, L., Dolata, M., & Schwabe, G. (2016). FinTech – What's in a Name? *Thirty Seventh International Conference on Information Systems*. https://doi.org/10.5167/uzh-126806

Zhao, H., Peng, H., & Li, W. (2022). Analysis of factors affecting individuals' online consumer credit behavior: Evidence from China. *Frontiers in Psychology*, 13. https://doi.org/10.3389/fpsyg.2022.922571

Ziegler, T., Shneor, R., Wenzlaff, K., Suresh, K., De Camargo Paes, F. F., Mammadova, L., Wanga, C., Kekre, N., Mutinda, S., Wang, B., Closs, C. L., Zhang, B. Z., Forbes, H., Soki, E., Alam, N., & Knaup, C. (2021). *The 2nd Global Alternative Finance Market Benchmarking Report*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3878065

Artificial intelligence tools were used in this thesis to support, the research process. Specifically, AI was employed for grammar and language refinement, plagiarism checking to ensure originality, and coding assistance.