FinTech Lending and Divergent Monetary Policy: Evidence From the COVID-19 and Russo-Ukrainian War

Stephen Fan
University of Sydney Business School
NSW, 2006
Australia
Stephen.fan@sydney.edu.au

Suk-Joong Kim
University of Sydney Business School
NSW, 2006
Australia
Sukjoong.kim@sydney.edu.au

Abstract:

This research examines the impact of divergent monetary policy during the COVID-19 pandemic and the Russo-Ukrainian War on FinTech lending. Leveraging data from the Prosper Marketplace, we explore how FinTech platforms adjusted lending terms for first-time and repeat borrowers under expansionary and contractionary regimes. During COVID-19, characterized by monetary easing, FinTech platforms complemented traditional banks by offering favorable terms to attract first-time borrowers, while also providing larger loans to repeat borrowers. In contrast, during the Russo-Ukrainian War, tighter monetary policies and heightened risks saw FinTech platforms increasingly substituting for traditional banks, extending credit to riskier, lower-quality borrowers, particularly in highly concentrated banking markets. These findings highlight the adaptability of FinTech lending to varying macroeconomic conditions, revealing the dual role as a complement and substitute in response to crisis-driven shifts in monetary policy.

Keywords: FinTech lending, Prosper, Refinance, COVID-19, Russo-Ukrainian War

JEL: G21, G23

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1. Introduction

FinTech lending has transformed access to credit for consumers and small businesses, offering convenience and rapid service, which enhances financial inclusion and consumer welfare by providing affordable, accessible capital (Buchak et al., 2018; Fuster et al., 2019; Gopal & Schnabl, 2022). Existing literature suggests FinTech loans often serve to refinance bank debt, enabling borrowers to consolidate and reduce borrowing costs through lower rates (Agarwal et al., 2013; Dunn & McConnell, 1981; Kalotay et al., 2008; Yang & Maris, 1993). Refinance loans generally face less scrutiny than first-time loans due to established borrower creditworthiness. However, the literature has yet to show whether FinTech lenders provide preferential loan terms to refinance borrowers.

Previous studies document the critical role of refinancing, particularly during financial hardship, as a stabilizing tool for households and businesses (Campello et al., 2010; Dynan et al., 2012). Traditional banks typically refinance loans to offer more favorable terms, such as lower interest rates or extended maturities (Bennett et al., 2001; Buchak et al., 2018), However, banks operate under stringent regulatory frameworks, and the strict regulatory frameworks often slow the refinancing process, limiting its flexibility in response to economic distress (Fuster et al., 2019).

Refinancing borrowers generally exhibit lower uncertainty due to their established financial histories and stability (Acharya & Steffen, 2020). Coupled with the operational flexibility of FinTech platforms, this study investigates whether FinTech platforms offer preferential terms to refinancing borrowers (Bartlett et al., 2022). We explore whether this differential treatment is shaped by prevailing economic conditions, focusing specifically on how refinancing affects key FinTech loan characteristics. Our analysis centers on variations in loan amounts, interest rates, and maturities between first-time and repeat borrowers.

The importance of FinTech lending becomes even more pronounced during periods of economic hardship. FinTech platforms have demonstrated their effectiveness in offering timely loans during liquidity shocks and natural disasters, helping borrowers navigate short-term financial difficulties through their rapid and flexible response capabilities (Allen et al., 2023; Beaumont et al., 2022; Gopal & Schnabl, 2022). However, studies also highlight a decline in loan applications on marketplace platforms during crises, driven by a reduced credit supply from FinTech lenders and rising delinquency rates (Bao & Huang, 2021; Ben-David et al., 2021).

The COVID-19 pandemic caused an abrupt economic shock, unlike the gradual build-up of the 2008 Global Financial Crisis (Ramelli & Wagner, 2020). Heightened household anxiety led to reduced spending and increased savings (Levine et al., 2021), while the stock market faced adverse effects (Angosto-Fernández & Ferrández-Serrano, 2022; Ashraf, 2021; Baker et al., 2020; Neupane et al., 2024). In response, the U.S. Federal Reserve implemented expansionary policies, including rate cuts and quantitative easing, supported by fiscal stimulus packages to aid small businesses and individuals (Acharya & Steffen, 2020; Chodorow-Reich et al., 2022).

Conversely, the Russo-Ukrainian War (RU-War) introduced severe supply chain disruptions and driven significant commodity price shocks, notably in oil and gas, adding to the demand-pull inflationary pressures in the U.S. (Gaio et al., 2022; Hossain et al., 2024; Wu et al., 2023; Yousaf et al., 2022). Unlike the COVID-19 crisis, which saw aggressive fiscal and monetary easing to counteract a demand-driven economic shock, the RU-War introduced supply-driven inflation that complicated the Federal Reserve's efforts to manage price stability. In contrast to the pandemic's expansive policies, the RU-War triggered a reversal of the monetary policy stance to a tighter monetary policy to address the additional cost-push pressures from the geopolitical tensions to the existing inflationary pressures. This created a markedly different economic environment, further straining borrowers and influencing the strategic adaptations of financial institutions. Thus, the COVID-19 and RU-War crises serve as critical case studies to explore how FinTech platforms adapt, revealing their roles as either complements or substitutes to traditional banking under contrasting economic conditions[1].

We employ data from Prosper Marketplace (Prosper), a representative leading U.S. FinTech lending platform. Prosper specializes in providing loans up to $50,000 for various purposes, including debt refinancing, home improvements, and small business financing. The database provides a large amount of data at the loan application level to the public, covering more than 500 variables per application. These variables include detailed borrower demographics and the loan's origination status. We limit our sample period from May 1, 2017, to December 31, 2022, to account for significant structural breaks in the data[2].

Our analysis reveals that refinance borrowers consistently secured better loan terms, including higher amounts, lower interest rates, and longer maturities, compared to non-refinance borrowers across all sample periods. Notably, significant differences emerged between first-time and repeat refinance borrowers during both pre-crisis and crisis periods. During COVID-19, characterized by aggressive expansionary monetary policies, FinTech platforms offered larger loans and lower interest rates to repeat borrowers, while strategically attracting first-time borrowers with even lower rates. This competitive strategy succeeded in drawing new customers, despite offering slightly shorter maturities and smaller loan amounts. In contrast, the RU-War, marked by geopolitical uncertainty and rising interest rates, led to a more cautious lending stance,

[1] Although inflation started to rise in the US due to the prior COVID-19 related expansionary fiscal and monetary policies before the onset of the Russo-Ukrainian War, it was not until March 17, 2022, that the US Federal Reserve began tightening monetary policy.
[2] In April 2017, Prosper transitioned its credit evaluation process from Experian to TransUnion, altering the underlying credit assessment framework.

reducing loan amounts for first-time borrowers. However, repeat borrowers continued to receive larger loans and longer maturities, reflecting the increased trust FinTech lenders placed in borrowers with established credit histories (Balyuk, 2023).

To further explore the contrasting lending behaviors of FinTech platforms, we explore the role of FinTech platforms as either a complement or substitute for traditional bank loans across varying monetary policy regimes and risk environments. Previous studies indicate that FinTech lending can both complement and substitute traditional banking across different segments (De Roure et al., 2016; Erel & Liebersohn, 2022; Tang, 2019; Yeo & Jun, 2020). According to Tang (2019), the impact of FinTech lending platforms on borrower quality depends on their relationship with traditional banks. When FinTech platforms substitute for bank loans, borrower quality tends to decline as lower-quality borrowers shift to FinTech. In contrast, when FinTech platforms complement bank loans, borrower quality improves as higher-quality borrowers seek better terms or availability through FinTech.

Following the methodology proposed by Tang (2019), we examine the role of FinTech platforms in the migration of borrower quality across different monetary policy regimes and in normal versus heightened-risk environments during two crises. Using FICO scores as a proxy for borrower quality, our analysis reveals that during COVID-19, aggressive monetary policies and near-zero interest rates attracted higher-quality borrowers to FinTech platforms for refinancing and new loans, thereby improving the overall borrower profile. In contrast, during RU-War, rising borrowing costs and traditional banks' increased risk aversion pushed lower-quality borrowers toward FinTech platforms. Notably, repeat borrowers demonstrated greater resilience, maintaining higher credit scores, which enabled FinTech platforms to offer them more favorable loan terms even in challenging economic conditions.

Recognizing that regions with varying bank market concentrations may rely differently on FinTech platforms, we conduct additional analyses of FinTech loan origination numbers and average loan size relative to the bank branch concentration index (HHI-Branch). Our findings suggest that during COVID-19, FinTech platforms acted as a complement to traditional banks, as evidenced by the negative relationship between FinTech lending activity and bank market concentration. However, during the RU-War, FinTech platforms increasingly substituted for traditional banks, particularly for first-time borrowers in states with higher market concentration. In these areas, FinTech platforms offered alternatives for borrowers facing tighter lending constraints from traditional institutions.

We perform a battery of additional tests to ensure the robustness of our results. First, we perform regression tests on loan terms, incorporating alternative fixed effects to account for potential unobserved heterogeneity and time-varying factors. To assess changes in borrower quality across periods, we reclassify borrower FICO scores into five quintiles, representing equal segments of the borrower population. This allows for a more comprehensive analysis of shifts in the distribution of borrower quality. Additionally, we use the Prosper Score as an alternative measure of borrower quality, which includes factors such as credit history, debt-to-income ratio, and employment status. To explore the relationship between FinTech and traditional bank lending, we employ HHI-Deposit to determine whether FinTech serves as a complement or substitute. HHI-Deposit captures market deposit concentration, providing a complementary perspective to HHI-Branch, which measures physical bank presence. Finally, we use bank loan data from FDIC Call Reports to examine the relationship between bank lending and total FinTech loan amounts. The results remain consistent.

Our study adds to the growing literature on FinTech (Allen et al., 2023; Balyuk, 2023; Balyuk et al., 2022; Balyuk & Davydenko, 2019; Bartlett et al., 2022; Buchak et al., 2018; Tang, 2019) by exploring how FinTech Platforms adapt their lending practices during economic crises. We highlight the strategic adjustments FinTech Platforms make to support both first-time and repeat borrowers during periods of instability. Repeat borrowers benefit more from refinancing during crises, securing larger loans and lower interest rates due to their established credit history. This study emphasizes the critical role of FinTech lending in maintaining financial stability and accessibility during economic hardship.

The study also highlights the varying impacts of different economic crises on FinTech lending practices (Angosto-Fernández & Ferrández-Serrano, 2022; Bao & Huang, 2021; Batten et al., 2023; Fahlenbrach et al., 2021; Fu & Mishra, 2022; Levine et al., 2021; Çolak & Öztekin, 2021) Our findings suggest that FinTech platforms can either complement or substitute traditional lending, depending on the prevailing monetary policies. These findings enhance the understanding of the dynamic interplay between FinTech lending and economic crises, revealing the adaptive strategies of FinTech platforms in response to varying economic conditions.

Our findings carry significant policy implications for enhancing financial system resilience. FinTech platforms are critical in providing liquidity and facilitating credit access during economic crises, effectively complementing traditional banks and promoting financial inclusion. Policymakers should consider fostering a supportive regulatory environment that encourages FinTech innovation while ensuring robust risk management practices are in place. Targeted interventions, such as supporting refinancing options for higher-quality borrowers during periods of economic distress, can help maintain credit flow and mitigate financial hardship. This study offers valuable insights for developing policies that leverage the strengths of FinTech to bolster economic stability and resilience.

The paper proceeds as follows. Section 2 proposes the research questions for our analysis. Section 3 describes the data. Section 4 shows the empirical models. Section 5 discusses the empirical results. Section 6 presents the robustness tests. Section 7 concludes.

2. Research Questions

2.1. Refinancing and FinTech: Exploring Preferential Terms for Borrowers

Refinancing has long been a critical mechanism in traditional banking, allowing borrowers to replace existing loans with new ones that offer more favorable terms, such as lower interest rates or extended maturities (Bennett et al., 2001; Buchak et al., 2018). This financial strategy plays a vital role in reducing debt burdens for households and businesses, and it acts as a stabilizing force during periods of economic distress. Dynan et al. (2012) emphasize its role in post-recession recovery, noting that refinancing alleviates debt obligations, which can revive consumer spending. Campello et al. (2010) show that businesses facing financial constraints often miss valuable investment opportunities due to limited refinancing options, worsening economic downturns. However, the regulatory environment of traditional banking often makes refinancing slow and inflexible, particularly in times of financial uncertainty (Fuster et al., 2019).

FinTech platforms have transformed the refinancing landscape by leveraging technological innovations that streamline processes and enhance borrower accessibility. Unlike traditional banks, FinTech platforms operate under different regulatory frameworks, which enable a more efficient and accessible refinancing process. Studies such as Bartlett et al. (2022) and Fuster et al. (2019)

highlight how these platforms have significantly lowered refinancing costs, making them more appealing to borrowers. Eichenbaum et al. (2022) further note that FinTech platforms have played a key role in expanding access to credit during periods of economic volatility by offering a faster, more flexible option.

Given the importance of refinancing in mitigating financial distress and the operational advantages of FinTech platforms, it is important to examine how FinTech platforms treat refinancing borrowers. Since refinancing borrowers generally exhibit lower uncertainty due to their established credit histories and stability, it is plausible that FinTech platforms, with their operational flexibility, offer more favorable terms to these borrowers. This leads to our first research question:

- Research Question 1: Do FinTech platforms offer preferential terms to refinancing borrowers?

Building on this, we seek to investigate whether these preferential terms vary according to the economic environment. The existing literature emphasizes the significant role of FinTech platforms, particularly during periods of economic hardship. Beaumont et al. (2022) and Allen et al. (2023) show that FinTech platforms are especially effective in delivering timely loans during liquidity shocks and natural disasters, helping firms navigate short-term financial challenges more efficiently. FinTech lenders, responding with greater speed and flexibility than traditional banks, significantly increase loan volumes and demonstrate a higher degree of credit supply elasticity (Gopal & Schnabl, 2022). The ease of access to FinTech loans, combined with the lack of stringent collateral requirements, makes these platforms especially appealing to highly leveraged households, providing critical support in times of financial distress.

However, research also reveals a decline in loan volumes on these platforms during crises, driven by reduced credit supply from FinTech lenders and rising delinquency rates (Bao & Huang, 2021; Ben-David et al., 2021). As delinquency rates increase, FinTech platforms often tighten their lending standards, resulting in fewer approved loans and a contraction of available credit. This supply-side tightening, coupled with increased borrower risk aversion, further diminishes loan application volumes during economic downturns.

Given the contrasting monetary policies and economic environments of the two crisis periods, we aim to explore whether FinTech platforms' responsiveness to economic shocks extends to their treatment of refinancing borrowers. The distinction between expansionary and contractionary regimes provides an opportunity to examine how adaptable FinTech platforms are to broader macroeconomic conditions. This leads to our second research question:

- Research Question 2: Do FinTech platforms' preferential terms depend on economic environments and whether borrowers are repeat or first-time borrowers?

We utilize the two distinct crisis periods and the Pre-COVID period, to highlight the potential differences in lending decisions by FinTech platforms.

2.2. FinTech's Relationship with Banking: Substitutes or Complements under Divergent Monetary Policy Regimes.

The role of FinTech platforms as substitutes or complements to traditional banks has garnered considerable attention in the academic literature, particularly in the context of financial crises and credit supply shocks. Tang (2019) provides evidence that FinTech platforms, especially peer-to-peer (P2P) lending, often emerge as substitutes for traditional banks when credit supply is constrained. The findings demonstrate that following a regulatory-induced shock to the banking sector, P2P lending increased significantly, with a notable shift in borrower quality towards lower-credit borrowers who had previously relied on banks. This pattern suggests that P2P platforms fill the void left by traditional banks, offering credit to borrowers excluded from conventional lending channels due to tightened credit criteria.

De Roure et al. (2016) support this view, showing that FinTech platforms predominantly serve higher-risk borrowers who are marginalized by traditional banks. This supports the notion that FinTech acts as a substitute, particularly by providing credit access to individuals and businesses that fail to meet the strict criteria of conventional lenders during times of financial stress. On the other hand, Yeo and Jun (2020) argue that FinTech lending can function as both a substitute and complement to traditional banking. Their study highlights the dual role of P2P platforms, enhancing credit access for underserved segments while also serving as an alternative financing source when traditional banks retreat from the market. Fuster et al. (2019) further suggest that FinTech platforms, with their technological sophistication and streamlined processes, can complement traditional banking by offering faster and more flexible lending solutions. This complementary role becomes particularly important when traditional banks face operational constraints or adopt conservative lending practices in response to economic uncertainty.

Building on this body of literature and incorporating the distinct monetary policy responses to the COVID and RU-War, a significant gap in the literature exists regarding how FinTech platforms adapt to such divergent economic conditions. The unprecedented global monetary easing during COVID contrasts sharply with the restrictive monetary stance during RU-War, providing unique contexts to examine the strategic behavior of FinTech platforms. While existing studies, such as those by Tang (2019) and De Roure et al. (2016), have documented the role of FinTech platforms as substitutes when traditional credit supply is constrained, these investigations primarily focus on earlier financial stress periods or regulatory shifts. There is limited research on how FinTech platforms adjust their strategies during crises characterized by varying monetary policies. Given the transformative role of FinTech in modern financial systems, it is crucial to understand whether these platforms mitigate credit access disruptions by serving as substitutes or complements to traditional lenders. This brings us to our third research question:

- Research Question 3: Do FinTech platforms function as substitutes or complements to traditional lending across varying monetary policy regimes and risk environments?

We investigate whether the role of FinTech platforms in relation to banks changes across different economic environments.

3. Data and Summary Statistics.

Our research draws upon a comprehensive dataset from Prosper, one of the largest peer-to-peer (P2P) lending platforms in the United States. Launched in February 2006, Prosper specializes in providing loans of up to $50,000 for various purposes, such as debt refinancing, home improvements, and small business funding. These loans are structured with monthly amortization and maturities of 24, 36, or 60 months, with interest rates ranging from 5-6% for the lowest-risk borrowers to 35-36% for the highest-risk borrowers. Prosper publicly provides an extensive dataset at the loan application level, comprising over 500 variables per application[3]. These include detailed borrower demographics and loan origination status. As of March 2024, Prosper has facilitated over $27 billion in loans to more than 1.7 million borrowers.

[3] We accessed the data by performing unauthenticated requests to Prosper's public API. The data can be downloaded from Prosper's investor marketplace at: https://www.prosper.com/investor/marketplace#/download.

The lending process begins with an online application where borrowers specify the desired loan amount, consent to a credit check, and provide additional financial information such as employment status and monthly income. Eligibility criteria include having a bank account, verifiable income, and a minimum FICO score of 640. Borrowers must specify the intended loan purpose, although Prosper does not verify or monitor the actual use of loan proceeds post-disbursement. To enhance transparency, Prosper provides credit scores, income verification, and other financial metrics. It retrieves credit bureau reports and employs a proprietary algorithm to determine the appropriate interest rate for each loan, which is then listed on the platform for investor funding. The investor base is diverse, comprising both retail and institutional participants.

Prosper determines fixed loan interest rates, which borrowers must agree to before investors can submit the loan applications, thereby preventing any negotiation between borrowers and lenders. All funding for these loans is sourced directly from investors. Prosper randomly allocates priced loan applications to different investment channels (Balyuk & Davydenko, 2019)[4]. For instance, among these channels, the Note Channel mandates that retail investors collectively commit to funding at least 70% of the requested loan amount for the loan to be issued[5] (Balyuk, 2023).

Our sample period runs from May 1, 2017, to December 31, 2022, accounting for significant structural breaks in the data. In April 2017, Prosper transitioned from using the

[4] Prosper, one of the earliest and largest peer-to-peer lending platforms in the U.S. holds a significant position in consumer lending FinTech. Its practices likely reflect broader industry trends due to its market influence and longevity. Given that many other platforms, such as Upstart, share similar business models focused on personal loans, debt consolidation, and refinancing, Prosper can reasonably serve as a proxy for the broader FinTech lending sector.

[5] Prosper allows borrowers to list their loan requests on the platform, where they remain until fully funded by investors. However, if a loan request does not reach the required funding level, the borrower has the option to withdraw their listing without any penalties. In our sample period (2017-2022), the average percentage funded is 99.03%.

Experian Credit Bureau to the TransUnion Credit Bureau, which fundamentally altered its credit assessment framework. To ensure consistency, we exclude the pre-April 2017 period from our analysis.

<Insert Table 1 here>

Table 1 presents summary statistics for FinTech loan terms and borrower characteristics. Panel 1 shows the mean values of aggregate descriptive statistics. Column (1) displays the characteristics of all borrowers, while Columns (2) and (3) compare first-time borrowers to repeat borrowers. Following Balyuk (2023), we define repeat borrowers as those who have engaged with the platform more than once and first-time borrowers as those who have only done so once.

Our dataset includes 703,200 borrowers, with 614,497 first-time borrowers and 88,703 repeat borrowers. The average number of daily loans issued is approximately 437. The average loan amount is $13,090, with repeat borrowers taking out larger loans on average ($13,360) compared to first-time borrowers ($12,930). The average borrower interest rate across all borrowers is 18.38%, with repeat borrowers receiving a lower average rate of 17.69%, while first-time borrowers face a higher average rate of 18.80%. The average loan maturity is 44.49 months, with little variation between first-time and repeat borrowers.

Panel 1B presents the summary statistics for borrower characteristics and the U.S. federal funds rate. Debt refinancing is the most common loan purpose, accounting for 68% of all loans. The average FICO score across all borrowers is 710. First-time borrowers have a slightly lower average FICO score (706) than repeat borrowers (715), indicating a more robust credit profile for repeat borrowers. The average debt-to-income ratio is 0.30 for all borrowers, rising to 0.32 for repeat borrowers. The average employment tenure is 8.82 years, and homeownership is low at 5%.

Borrowers have an average credit history of 23 years. The U.S. federal funds rate during the study period averages 1.58%.

We analyze these statistics across three timeframes: Pre-COVID (January 1, 2017 – March 12, 2020), representing a period of normalcy before the global pandemic; COVID (March 13, 2020 – February 23, 2022), which begins with the U.S. national emergency declaration; and RU-War (February 24, 2022 – December 31, 2022), marking the period after Russia's invasion of Ukraine.

<Insert Figure 1 here>

Figure 1 presents the average daily total loan origination numbers, along with the average loan amounts, borrower interest rates, and maturities for both first-time and repeat borrowers, spanning the period from January 2017 to December 2022. First-time borrowers exhibit greater volatility in loan numbers, amounts, and interest rates than repeat borrowers. Notably, first-time borrowers display higher daily loan origination numbers during Pre-COVID and RU-War but receive smaller loan amounts than repeat borrowers during both crisis periods. Additionally, first-time borrowers face higher interest rates, especially during RU-War, while both groups experience a rise in loan maturities. Repeat borrowers demonstrate greater stability, consistently securing lower interest rates, steadier loan amounts, and longer maturities compared to first-time borrowers.

Panel 2 of Table 1 provides the descriptive statistics of daily average FinTech loan terms across the specified periods. During Pre-COVID, the daily average number of loans is approximately 437. Borrowers took out loans averaging $13,470 with an interest rate of 18.70% and an average maturity of 43 months, with 70% of loans used for refinancing. First-time borrowers faced slightly higher interest rates compared to repeat borrowers. During COVID, the average daily loan origination numbers declined sharply to around 245, with a reduced average loan amount of $12,800, a lower interest rate of 16.62%, and longer loan terms of 45.53 months. Refinancing activity also slightly decreased to 65%. However, during RU-War, there was a significant resurgence in daily loans, particularly for first-time borrowers, reaching approximately 437. First-time borrowers, however, continued to receive smaller loan amounts than repeat borrowers ($11,590 vs. $14,150, respectively). Throughout this period, repeat borrowers consistently benefited from lower interest rates than first-time borrowers (17.06% vs. 19.82%)[6].

4. Empirical Models

4.1. FinTech Loan Terms for Refinancing Borrowers

To empirically investigate whether FinTech platforms offer preferential terms to refinancing borrowers during periods of economic uncertainty, we utilize an Ordinary Least Squares (OLS) regression framework. Our analysis employs data at the borrower-loan level, where each loan is denoted by i, providing a granular perspective on lending behaviors and borrower outcomes

$$Y_i = a + \beta_1 \cdot Refinance + \delta \cdot Controls_i + FEs + \varepsilon_i \tag{1}$$

In Equation (1), Y_i represents the dependent variables, which include FinTech Loan Amount (in thousands), Borrower Interest Rate (as a percentage), and Loan Maturity (in months). The subscript i represents borrower-loan datapoint. The FinTech Loan Amount captures the value of loans issued through the FinTech platform, the Borrower Interest Rate reflects the annual percentage rate set by the platform, and Loan Maturity indicates the loan duration.

[6] Please see Appendix Table 1 for variable definitions.

The primary variable of interest is the dummy variable *Refinance*, coded as one if the borrower uses the FinTech loan for debt refinancing, and zero otherwise. This variable allows us to distinguish between loans used for refinancing and other purposes. Control variables, based on the methodology outlined in Balyuk (2023), include FICO Credit Score (a proxy for borrower quality), Debt-to-Income Ratio (reflecting borrower leverage), Log of Borrower Income (ln[Income]), Log of Credit History (ln[Years in Market]), and Log of Employment Duration (ln[Employment]). Home Ownership is also included as a binary variable, and the Federal Interest Rate captures macroeconomic conditions influencing borrowing costs. State-level and time-level fixed effects are incorporated to account for unobserved heterogeneity, and standard errors are clustered at the borrower level to address potential correlations in borrowing behavior over time.

The coefficient of interest, β_1 measures the differential impact of refinancing on the dependent variables (Loan Amount, Borrower Interest Rate, and Maturity). We expect that β_1 will be positive for loan amounts and maturity, and negative for interest rates, reflecting better loan terms for refinancing borrowers that are generally more experienced (Bartlett et al., 2022), who typically seek to consolidate debt (Agarwal et al., 2013; Dunn & McConnell, 1981; Kalotay et al., 2008; Yang & Maris, 1993).

4.2. Economic Cycles and FinTech Loan Terms

Next, we interact Refinance with different period dummies to identify if there are significant changes in the impact of refinancing on FinTech loan characteristics during different crisis periods, particularly during COVID and RU-War. The regression model is specified as follows:

$$Y_i = a + \beta_1 \cdot Refinance + \beta_2 \cdot TimePeriod + \beta_3 \cdot Refinance \times TimePeriod$$

$$+ \delta \cdot Controls_i + FEs + \varepsilon_i \tag{2}$$

We examine three distinct periods: Pre-COVID, COVID, and RU-War. *TimePeriod* represents a set of dummy variables for these periods, allowing us to capture different economic environments and policy responses. The interaction term β_3 reveals how the effect of refinancing on loan characteristics—loan amount, borrower interest rate, and maturity—changes across these periods.

As discussed previously, during COVID, the Federal Reserve cut interest rates to near zero, prompting FinTech platforms to likely increase loan amounts and offer lower interest rates, especially to borrowers vetted by traditional banks. In contrast, the RU-War brought geopolitical uncertainty and rising interest rates, leading to more conservative lending, likely resulting in smaller loans, shorter maturities, and higher interest rates for refinancing borrowers. As a result, we hypothesize that during COVID, β_3 will be positive for loan amounts and maturities, and negative for interest rates. This reflects the expectation that the FinTech platform offered more favorable terms to refinancing borrowers during this period of low interest rates, as these borrowers were likely seen as lower risk. Conversely, during RU-War, we expect β_3 to be negative for loan amounts and maturities, and positive for interest rates, indicating less favorable terms for refinancing borrowers due to increased risk and higher interest rates.

Furthermore, we posit that repeat borrowers—those who have previously secured loans—may be better off during these periods, particularly during COVID. These borrowers likely had established credit histories and relationships with FinTech platforms, which could lead to more favorable refinancing terms. On the other hand, first-time borrowers may face higher scrutiny and potentially less favorable terms, especially during RU-War when lenders were more risk-averse due to the heightened geopolitical uncertainty.

4.3. Borrower Quality Changes and FinTech's Substitution/Complementarity Role

We then investigate whether FinTech platforms function as a substitute or complement to traditional lending across varying monetary policy regimes and risk environments. Following Tang (2019), we assess borrower quality changes, using FICO scores to categorize borrowers into five ranges: FICO < 680, 680-699, 700-719, 720-739, and FICO >= 740.

Depending on whether FinTech lending can be substitutes or complements to bank loans, borrowers migrating from the banking sector during crisis periods can deteriorate or improve the overall borrower quality of FinTech lenders (Tang, 2019). We employ a logistic regression model to examine whether significant borrower quality changes have occurred across different periods. The dependent variable is a binary indicator of whether a borrower's FICO score falls within a specific range.

The logistic regression model is structured to analyze each borrower (i) on a daily frequency (t) and is specified as follows:

$$Logit[P(FICO\_Range_i = 1)] = a + \beta_1 \cdot TimePeriod + \delta \cdot Controls_i + FEs + \varepsilon_i \quad (3)$$

$FICO\_Range_i$ is a binary indicator variable for each borrower *i* that signifies whether the borrower's FICO score falls within one of the five defined ranges. These ranges are used to represent the borrower's credit quality. *TimePeriod* is a dummy variable indicating the period of Pre-COVID, COVID, or RU-War. The settings for different FICO ranges allow for examining how the probability of a borrower's FICO score falling within each specific range (and thus their credit quality) changes over different periods. In our analysis, we utilize the same control variables and fixed effects as mentioned above to minimize potential bias and control for unobserved heterogeneity at the state and time levels. Standard errors are clustered at the borrower level.

The regression results yield coefficients for each period, allowing us to assess shifts in borrower quality, as measured by FICO scores, across the different time frames. The coefficients for Pre-COVID serve as the baseline for comparison, while those for COVID and RU-War provide insights into how the likelihood of borrowers falling into each FICO range has evolved.

During COVID, aggressive US monetary policies, such as near-zero interest rates and liquidity injections, eased financial conditions. One might expect FinTech platforms to attract higher-quality borrowers by offering competitive rates, complementing traditional banks, and enhancing borrower quality. In contrast, during RU-War, rapid monetary tightening and geopolitical uncertainty led to more cautious bank lending. Borrowers unable to secure loans from banks may have turned to FinTech platforms, potentially lowering borrower quality and indicating a substitutive role for the platform during this time.

4.4. FinTech Lending and Bank Market Concentration

While borrower quality and the role of FinTech platforms as substitutes or complements to banks are crucial factors, focusing solely on these may overlook the impact of banking infrastructure and market dynamics. For example, bank market concentration can influence the reliance on FinTech platforms, independent of borrower quality, potentially skewing the interpretation of whether FinTech platforms substitute or complement traditional banks. To account for these influences, we extend our analysis to include FinTech loan origination and bank branch concentration (Fuster et al., 2019; Tang, 2019), providing a more comprehensive view of how these factors shaped outcomes during the two crises.

We construct a panel dataset by merging state-level quarterly data on bank branch numbers and market share from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits with our FinTech loan origination numbers and average loan amounts. Each observation represents a unique combination of state and quarter, allowing us to track traditional bank and FinTech lending activities over time. Our regression analysis is performed on a state-quarter basis, as specified below:

$$Y_{s,t} = \alpha + \beta_1 \cdot HHI_{s,t} + \beta_2 \cdot TimePeriod + \beta_3 \cdot HHI_{s,t} \times TimePeriod$$

$$+\delta \cdot Controls_{s,t} + FEs + \varepsilon_{s,t} \tag{4}$$

The dependent variable $Y_{s,t}$ represents the average daily total loan origination numbers and the average loan size. The average daily total loan origination numbers are calculated as the average number of loans originated per day in state *s* during quarter *t*. The average loan size is the ratio of the quarterly average loan amount to the number of loans originated in that period. Focusing on loan origination numbers allows us to capture new loans processed, providing a clear measure of customer engagement with FinTech platforms. Additionally, the ratio of the average loan amount to the number of loans reflects the typical loan size issued by FinTech lenders.

These approaches allow us to better capture the interaction between FinTech lending and bank concentration, reducing distortions from focusing solely on loan values. We conduct robustness tests by examining the ratio of the daily average loan amounts to loan origination numbers, which helps account for how loan size impacts customer behavior and market dynamics.

Our key variable of interest is the interaction term "$X_{s,t} \times TimePeriod$", where $X_{s,t}$ proxies for bank concentration, measured using the Herfindahl-Hirschman Index (HHI).

The HHI captures the market share distribution among banks in a state (Tang, 2019; Fluster et al., 2019; Levine et al., 2021). It is calculated by first determining the market share of each bank, defined as the proportion of branches it operates relative to the total number of branches within a state. Each bank's market share is then squared to account for the disproportionate influence of larger shares on overall market concentration. The final HHI value is obtained by summing these squared market shares across all banks operating within the state. Higher HHI values indicate greater bank concentration (less competition), while lower HHI values indicate a more competitive banking environment. We utilize the same control variables as discussed in Section 4.1. To minimize potential bias and account for unobserved heterogeneity at both the state and time levels, we incorporate Borrower State Fixed Effects and Year-Quarter Fixed Effects into our analysis.

If FinTech platforms complement traditional banking, we expect higher FinTech lending activity in states with lower bank concentration (lower HHI). In these competitive markets, FinTech platforms are likely to thrive by offering innovative products that enhance consumer choice and work alongside banks (Fuster et al., 2019). Conversely, if FinTech platforms act as substitutes for traditional banking, we anticipate higher FinTech lending in regions with greater bank concentration (higher HHI). In areas with high bank market concentration and limited competition, FinTech platforms may replace traditional lending by offering alternative solutions to underserved borrowers or those dissatisfied with dominant banks' offerings.

5. Empirical Results

5.1. FinTech Loan Terms for Refinancing Borrowers

Table 2 presents the results from the baseline OLS regressions (Equation 1), where the dependent variables represent proxies for FinTech loan terms across the entire sample period. Using loan-level data allows us to provide a detailed and granular analysis of FinTech loan dynamics. The results for FinTech Loan Amount are shown in columns 1 to 3, Borrower Interest Rate in columns 4 to 6, and Loan Maturity in columns 7 to 9. The analysis is further segmented by borrower categories, as discussed in Section 3. Following Balyuk (2023), repeat borrowers are defined as individuals who have used the FinTech platform more than once, while first-time borrowers are those new to the platform. Specifically, columns 1, 4, and 7 report the results for the overall sample, columns 2, 5, and 8 for first-time borrowers, and columns 3, 6, and 9 for repeat borrowers.

<Insert Table 2 here>

The results show that refinancing borrowers receive significantly different loan terms compared to the general borrower population. For the loan amount (Column 1), the coefficient for *Refinance* is 1.8141, statistically significant at the 1% level, suggesting that refinancing borrowers secure loans that are $1,841 higher on average. Similar trends are observed for first-time borrowers (Column 2, coefficient 1.7657) and repeat borrowers (Column 3, coefficient 2.0232). Notably, repeat refinancing borrowers secure the largest loan amounts, potentially reflecting a pattern of debt consolidation or the acquisition of additional funds through multiple refinancing events.

For borrower interest rates, refinancing borrowers are associated with lower rates. At the aggregate level, refinancing is linked to a 29.8 basis point reduction in interest rates (Column 4).

This reduction suggests that FinTech platforms perceive refinancing borrowers as lower risk, offering them lower interest rates. Interestingly, first-time refinancing borrowers (Column 5, coefficient -0.3964) receive even larger interest rate reductions compared to repeat borrowers (Column 6), likely due to the platforms' strategy of offering more favorable terms to attract new customers.

Regarding loan maturity, refinancing borrowers benefit from longer repayment periods, facilitating improved cash flow management. On average, refinancing borrowers receive loans that are 0.29 months longer (Column 7). First-time borrowers (Column 8) experience a slightly smaller increase in loan maturity (coefficient 0.26), while repeat borrowers (Column 9, coefficient 0.4340) secure the longest repayment terms. This suggests that repeat borrowers benefit the most from refinancing, as they receive the longest maturities, which may be advantageous for managing more substantial or complex debt loads.

In addition to refinancing, the control variables provide further insights into FinTech loan characteristics. Higher FICO scores, income levels, and homeownership status are associated with larger loan amounts, longer terms, and lower interest rates, indicating that more creditworthy borrowers receive more favorable loan conditions. The debt-to-income ratio is positively correlated with both loan amount and term, suggesting that borrowers with higher debt are offered larger loans and extended repayment periods, likely to ease repayment pressures. However, these borrowers also face higher interest rates, reflecting their increased risk. Moreover, higher U.S. federal interest rates correspond to smaller loan amounts and shorter maturities, indicating that rising borrowing costs lead to more conservative lending practices.

Overall, our results align with expectations and existing literature (Agarwal et al., 2013; Dunn & McConnell, 1981; Kalotay et al., 2008; Yang & Maris, 1993). Refinancing borrowers consistently secure more favorable financial terms, including larger loan amounts, lower interest rates, and longer maturities. Repeat borrowers benefit the most from refinancing, as evidenced by their ability to secure higher loan amounts and extended maturities, leveraging the advantages of FinTech lending. On the other hand, FinTech platforms attract new customers by offering lower interest rates, albeit with shorter maturities and smaller loan amounts, highlighting the dual role in optimizing financial terms for existing customers while expanding their customer base.

5.2. Economic Cycles and FinTech Loan Terms

The underlying economic environment can have a significantly different impact on how FinTech platforms operate relative to traditional lenders. We examine the impact of refinancing on FinTech loan characteristics across different systemic periods by analyzing the interaction between refinancing and specific time periods. Tables 3, 4, and 5 present the effects of refinancing on FinTech loan amounts, borrower interest rates, and loan maturities, respectively. In each table, columns 1 to 3 show results for Pre-COVID, columns 4 to 6 for COVID, and columns 7 to 9 for RU-War.

5.2.1. Refinancing on FinTech Loan Amount

Table 3 shows the regression results with loan amounts as the dependent variable, focusing on the interaction between Refinance and Period Dummies (Pre-COVID, COVID, RU-War). During COVID, refinancing had divergent effects on loan amounts for first-time and repeat borrowers. First-time borrowers received slightly higher loan amounts, while repeat borrowers received lower amounts than the general borrower population. The interaction term *Refinance* × *COVID* is significantly positive for both borrower types, indicating that refinancing during COVID was associated with higher loan amounts. For first-time borrowers, the interaction coefficient is

0.3223, meaning they received an average of $322 more when refinancing during COVID. For repeat borrowers, the coefficient is 0.6427, signifying they received $643 more than non-refinancing borrowers.

Conversely, during RU-War, the interaction term is significantly negative for the overall sample (-0.0961) and for first-time borrowers (-0.4158), suggesting lower loan amounts for these groups when refinancing. However, for repeat borrowers, the interaction term remains significantly positive (0.6673), indicating they secured higher loan amounts despite the crisis.

<Insert Table 3 here>

These differences can be attributed to the unique economic conditions and government policies in each period. During COVID, aggressive U.S. monetary policies, including near-zero interest rates, stimulated refinancing demand (Fahlenbrach et al., 2021) as borrowers capitalized on lower interest rates offered by FinTech platforms. This led to larger loan amounts, particularly for borrowers with strong credit profiles. In contrast, RU-War brought heightened geopolitical uncertainty and rising interest rates, prompting a more cautious lending approach (Batten et al., 2023). As a result, overall loan amounts decreased, particularly for first-time borrowers. However, repeat borrowers, with their established credit histories, were still able to secure larger loans, as they were viewed as lower risk.

5.2.2. Refinancing on FinTech Loan Interest Rate

Table 4 presents the results on the impact of refinancing on borrower interest rates through FinTech platforms. During Pre-COVID, there is no evidence that refinancing affected borrower interest rates across all borrower types, as indicated by the insignificant coefficients for the interaction terms. However, significant differences emerge when comparing COVID and RU-War.

During COVID, the interaction term is significantly negative across all borrower types, indicating the substantial impact of refinancing during this time. First-time borrowers, in particular, benefited from even lower interest rates when refinancing. On average, first-time borrowers who refinanced their loans paid $35.18 less per year in interest compared to repeat borrowers ($61.29 - $26.11)[7]. This finding underscores how FinTech platforms aggressively lowered interest rates to attract new customers during a period of near-zero interest rates. By offering more favorable terms to first-time borrowers, FinTech platforms successfully drew in new business, demonstrating its competitive strategies in a challenging economic environment.

<Insert Table 4 here>

In contrast, RU-War presents a different scenario. The interaction term is significantly positive across all borrower types, indicating that refinancing during this period led to higher interest rates. On average, borrowers who refinanced their loans during RU-War paid $34.25 more per year in interest. Specifically, first-time borrowers paid $18.00 more per year in interest than repeat borrowers ($46.06 - $28.06)[8]. This outcome reflects the strategy of FinTech lenders during RU-War, where it increased interest rates to manage risk, resulting in higher costs for first-time borrowers compared to repeat borrowers. These results can be attributed to heightened geopolitical uncertainty (Batten et al., 2023), increased volatility in financial markets (Gaio et al., 2022;

[7] First-time borrowers who refinanced during COVID paid $4.788 less per $1,000 of loan amount per year in interest. For the average $12,800 loan, this translates to $61.29 less per year. Repeat borrowers who refinanced during COVID paid $2.04 less per $1,000 of loan amount per year in interest. For the average $12,800 loan, this translates to $26.11 less per year.

[8] First-time borrowers who refinanced during RU-War paid $3.753 more per $1,000 of loan amount per year in interest. For the average $12,270 loan, this translates to $46.06 more per year. Repeat borrowers who refinanced during RU-War paid $2.288 more per $1,000 of loan amount per year in interest. For the average $12,270 loan, this translates to $28.06 more per year.

Hossain et al., 2024; Wu et al., 2023; Yousaf et al., 2022), and rising interest rates enforced by the U.S. government during this period.

5.2.3. Refinancing on FinTech Loan Maturity

Table 5 shows the impact of refinancing on FinTech loan maturities. During Pre-COVID, refinancing loans were associated with shorter loan maturities across all borrower types, with reductions ranging from 0.6 to 0.9 months. This suggests that FinTech lenders adopted a more conservative lending strategy in a stable economic environment by offering shorter repayment periods for refinancing borrowers.

During COVID, we observe a negative relationship between refinancing and loan maturity, primarily driven by first-time borrowers, who experienced maturities shortened by 0.39 months. However, repeat borrowers' loan maturities remained stable, suggesting that FinTech platforms maintained consistent terms for these borrowers despite the pandemic-induced uncertainties.

<Insert Table 5 here>

In contrast, refinancing during RU-War resulted in longer loan maturities for all borrower types. For the overall sample, the interaction term is 1.1571, indicating maturities were extended by 1.15 months. For first-time borrowers, the interaction term is 1.0481, and for repeat borrowers, it is slightly higher at 1.5077, both significantly positive. The extension of loan maturities during RU-War likely reflects FinTech platforms' strategy of mitigating the impact of rising interest rates by allowing borrowers to manage their monthly payments over a longer period, ensuring affordability amid economic disruptions (Allen et al., 2023; Beaumont et al., 2022).

5.2.4. Summary

Our findings indicate that FinTech platforms offer preferential terms to refinancing borrowers, with repeat borrowers generally securing higher loan amounts compared to first-time borrowers, aligning with Balyuk (2023). Repeat borrowers benefited more from refinancing during crises, receiving larger loan amounts, lower interest rates, and longer maturities. This outcome reflects FinTech platforms’ greater trust in borrowers with an established credit history during periods of heightened uncertainty. This first round of results answers the first research question posed. That is, refinance customers indeed are treated favorably by FinTech platforms due to their perceived higher credit quality.

During COVID, U.S. monetary policies significantly influenced lending behavior. FinTech platforms capitalized on these policies by attracting first-time borrowers with competitive rates and favorable terms. Both first-time and repeat borrowers experienced increases in loan amounts, with the increase more pronounced for repeat borrowers, indicative of FinTech lenders’ preference for less risky, established borrowers. In contrast, RU-War prompted a more conservative approach, with loan amounts decreasing for first-time borrowers while repeat borrowers continued to receive higher amounts. This behavior highlights FinTech lenders' risk aversion and their preference for borrowers with proven credit histories in a volatile economic environment.

The findings on loan maturities further reveal strategic adjustments by FinTech platforms. During COVID, first-time borrowers received loans with shorter maturities, reflecting lenders' cautious stance toward new borrowers. Conversely, during RU-War, loan maturities were extended for all borrower types, facilitating more manageable repayment schedules amid rising interest rates and economic disruption (Allen et al., 2023; Beaumont et al., 2022). The differential impact of the two crisis periods we document addresses the second research question regarding the time-dependent responses by FinTech platforms in determining the loan conditions for different types of borrowers.

5.3. FinTech vs. Banks: Substitute or Complement?

FinTech platforms can serve as either complements or substitutes to traditional banks, depending on borrower access to both lending sources and the prevailing economic environment. When borrowers have access to both, FinTech platforms may complement bank loans by offering alternative financing options and expanding the range of available services. However, during periods of heightened risk or when borrowers have riskier profiles, FinTech platforms may substitute banks by offering credit where traditional lenders are less willing due to higher risk assessments.

The COVID and RU-War present an opportunity to test whether the relationship between FinTech and bank lenders is dependent on the different cycles of monetary policy and risk environments. To test this research question (posed as the third research question in section 2), we investigate two additional sets of investigations. First, to determine if there were significant shifts in the risk profiles of FinTech borrowers during each crisis period, and second, to consider whether bank concentration impacts their access to credit.

5.3.1. Borrower Quality Changes and FinTech's Substitution/Complementarity Role

Given the discussion above, during COVID, FinTech platforms offered lower interest rates to attract first-time borrowers, while repeat borrowers experienced a more pronounced increase in loan amounts. Conversely, during RU-War, the focus on repeat borrowers could have led to an overall increase in borrower quality. Repeat borrowers, typically with more established credit histories and perceived as lower risk, may have elevated the average quality of borrowers receiving loans. This dynamic suggests a potential shift in overall borrower quality, influenced by the mix of first-time and repeat borrowers and their respective risk profiles, which may indicate either a complementarity or substitution effect.

Therefore, we extend our analysis to examine variations in borrower quality across these distinct periods. Following Tang (2019), we use FICO scores as a proxy for borrower quality. Our dataset allows us to categorize FICO scores into five groups: FICO < 680, 680-699, 700-719, 720-739, and FICO >= 740.

Table 6 illustrates the distribution of borrower quality across these periods. Panel A shows that, before the pandemic, 26.46% of borrowers had FICO scores below 680, while 23.21% had scores above 740. During COVID, the proportion of low-quality borrowers (FICO < 680) dropped to 20.19%, while high-quality borrowers (FICO ≥ 740) rose to 30.99%. This trend reversed during RU-War, with low-quality borrowers increasing to 34.79% and high-quality borrowers dropping to 20.15%.

<Insert Table 6 here>

Panel B focuses on first-time borrowers. Pre-COVID, 27.76% of first-time borrowers had FICO scores below 680, and 22.51% had scores above 740. During COVID, lower-quality borrowers declined to 24.28%, while higher-quality borrowers increased to 28.51%. However, RU-War saw a sharp shift, with 40.21% of first-time borrowers falling below 680, and only 16.19% above 740. Panel C examines repeat borrowers. Before COVID, 24.89% had FICO scores below 680, and 23.83% had scores above 740. During COVID, low-quality borrowers decreased to 15.71%, while high-quality borrowers rose to 33.70%. During RU-War, the proportion of low-quality borrowers increased to 19.76%, while the share of high-quality borrowers slightly decreased to 31.12%. These shifts suggest an improvement in borrower quality during COVID, followed by a deterioration during RU-War, especially among first-time borrowers. However, repeat borrowers maintained relatively high credit quality throughout both crisis periods.

While Table 6 highlights distinct patterns for first-time and repeat borrowers, it does not clarify how much of the observed differences in borrower quality are attributable to borrower type versus period effects. Notably, repeat borrowers do not exhibit any significant shift in credit quality during RU-War. To further quantify these changes, we conduct a logistic regression analysis as specified in Section 4.2.

Table 7 reports the logistic regression results. Pre-COVID, the coefficient for borrowers with FICO scores below 680 is 0.4620, indicating a higher prevalence of lower-quality borrowers. The coefficients for the mid-range FICO categories (680-699 and 700-719) are 0.0073 and -0.224, respectively, showing a slight increase in mid-range borrowers and a decrease in higher mid-range borrowers. For borrowers with higher credit scores (720-739 and above 740), the coefficients are -0.1296 and -0.2303, respectively, indicating a lower prevalence of high-quality borrowers.

<Insert Table 7 here>

During COVID, borrower quality improved significantly. The coefficient for FICO scores below 680 is -0.3082, reflecting a substantial reduction in lower-quality borrowers. Borrowers in the higher FICO ranges (720-739 and above 740) increased, as shown by positive coefficients, suggesting that FinTech platforms attracted higher-quality borrowers under favorable monetary policy. In this context, FinTech platforms complemented the banking sector by providing credit to more creditworthy individuals.

However, RU-War reveals a decline in borrower quality. The coefficients for FICO scores below 680 and between 680-699 are 0.2122 and 0.0703, respectively, indicating an increase in lower-quality borrowers. Conversely, the coefficients for higher credit score ranges are negative, particularly for borrowers within the 720-739 range and above 740, with values of -0.1408 and -0.1846. These findings reflect a decrease in higher-quality borrowers during RU-War, highlighting the impact of economic challenges and geopolitical tensions on lending behavior. The heightened economic uncertainty and increased risk perceptions led traditional banks to adopt a more cautious approach, tightening their lending criteria (Batten et al., 2023). Consequently, lower-quality borrowers were compelled to seek alternative lending sources, such as FinTech platforms. This shift supports the substitution effect, where lower-quality borrowers, unable to secure loans from traditional banks, turned to FinTech platforms as banks became more risk-averse (Tang, 2019).

Table 8 compares first-time and repeat borrowers. Panel A focuses on first-time borrowers, showing a significant prevalence of lower-quality borrowers Pre-COVID. During COVID, borrower quality improved, with a decline in low-quality borrowers and an increase in high-quality borrowers. However, during RU-War, borrower quality worsened, with a sharp increase in low-quality borrowers. Panel B presents the results for repeat borrowers, where we observe a similar pattern. Borrower quality improved during COVID, as evidenced by a reduction in low-quality borrowers and an increase in high-quality borrowers. However, unlike first-time borrowers, repeat borrowers did not exhibit a significant decline in credit quality during RU-War, maintaining relatively stable creditworthiness. This is an important and noteworthy finding, as it indicates that the overall deterioration in borrower quality during RU-War is primarily attributable to first-time borrowers. Meanwhile, repeat borrowers maintained relatively stable credit quality, indicating their established creditworthiness and FinTech lenders' confidence in offering them consistent terms, even during periods of heightened economic uncertainty.

<Insert Table 8 here>

To sum up, COVID shows an overall improvement in borrower quality for both first-time and repeat borrowers, suggesting that FinTech platforms complement traditional banks by attracting higher-quality borrowers during a time of constrained bank credit supply. The improvement in borrower quality during this period can be attributed to several factors. Traditional banks tightened their lending standards due to the economic uncertainty caused by the pandemic (Acharya & Steffen, 2020; Chodorow-Reich et al., 2022; Li, Li, et al., 2020; Li, Strahan, et al., 2020). Additionally, the decrease in U.S. interest rates during the pandemic made borrowing more attractive, further incentivizing higher-quality borrowers to seek credit. As a result, these higher-quality borrowers, facing limited options from traditional banks, turned to FinTech platforms for better terms and availability.

In contrast, the decline in borrower quality during RU-War can be attributed to the significant economic uncertainty caused by the geopolitical conflict (Gaio et al., 2022; Hossain et al., 2024; Wu et al., 2023; Yousaf et al., 2022). This uncertainty led traditional banks to adopt a more risk-averse stance (Batten et al., 2023), causing lower-quality borrowers, particularly first-time borrowers, to turn to FinTech platforms when they could not secure financing from traditional banks. The heightened risk perceptions during the conflict made traditional banks more selective, pushing these lower-quality, first-time borrowers toward alternative financing sources like FinTech platforms. Additionally, the increased risk and economic challenges constrained the overall supply of credit, leading these borrowers to seek loans from the more accessible FinTech platforms, which may have maintained more lenient lending criteria compared to traditional banks during this period.

This shift emphasizes the substitution effect of FinTech platforms on traditional lending during RU-War.

5.3.2. FinTech Lending and Bank Market Concentration

To further assess the role of FinTech platforms as either complements or substitutes to traditional banks, we extend our analysis to include FinTech loan origination and the market concentration of bank branches (Fuster et al., 2019; Tang, 2019). This broader approach seeks to uncover how banking infrastructure and market dynamics, particularly bank market concentration, influence the role of FinTech platforms, providing a more comprehensive understanding beyond borrower quality alone.

<Insert Table 9 here>

In Table 9, we observe a significant negative correlation between FinTech loan origination numbers and bank market concentration during COVID, as measured by the Herfindahl-Hirschman Index (HHI) of bank branches. Specifically, FinTech loan origination was higher in states with lower HHI-Branch values, indicating lower bank market concentration, more intense competition, and a more even distribution of market share across multiple institutions. This suggests that FinTech platforms played a complementary role in these environments (Fuster et al., 2019). FinTech platforms may offer alternative lending products and faster processing times. As a result, FinTech platforms attracted customers who might have otherwise sought loans from traditional banks. The Federal Reserve's expansionary monetary policies during COVID, including significant interest rate cuts, supported this complementary role by ensuring ample liquidity, enabling FinTech platforms to offer competitive credit options in regions where traditional banks were less dominant.

In contrast, during RU-War, our analysis reveals a significant shift: FinTech loan origination numbers became significantly and positively correlated with bank market concentration (HHI-Branch), particularly among first-time borrowers. This shift suggests that FinTech platforms transitioned from a complementary role to a distinctly substitutive one. As the Federal Reserve implemented tighter monetary policies to combat rising inflation during RU-War, including increased interest rates and reduced liquidity, traditional banks tightened their lending criteria. In states with higher HHI-Branch, where bank market concentration was greater and competition was lower, these stricter lending criteria made it more difficult for many borrowers to secure loans from banks, leading them to turn to FinTech platforms as an alternative source of credit.

Interestingly, the coefficient for repeat borrowers during RU-War remains negative, indicating that these borrowers were more likely to secure loans from traditional banks. This suggests that FinTech platforms continued to play a complementary role for repeat borrowers even during RU-War, aligning with our earlier findings that repeat borrowers maintained stable credit quality, reflecting their established creditworthiness.

In Table 10, we explore the relationship between the average FinTech loan size—calculated as the ratio of the quarterly average loan amount to the quarterly average loan origination numbers—and bank market concentration. This analysis shifts focus to loan size to provide a deeper understanding of lending dynamics, capturing not just loan volume but also the value extended to borrowers.

<Insert Table 10 here>

During COVID, we find a significant negative correlation between FinTech loan size and bank market concentration, suggesting that FinTech platforms offered larger loans on average in regions with lower bank concentration, further reflecting a complementary effect. Conversely, during RU-War, we observe a positive correlation between FinTech loan size and bank concentration, particularly among first-time borrowers. This shift indicates that FinTech platforms began offering larger loans in areas with higher bank concentration and less competition, positioning themselves as an alternative to traditional banks, thus demonstrating a substitute effect.

6. Robustness Tests

6.1. Refinancing and FinTech Loan Terms

To confirm the robustness of our results, we conducted additional tests by implementing alternative regression models to validate the impact of refinancing on FinTech loan terms across three distinct periods: Pre-COVID, COVID, and RU-War. Instead of using interaction terms for refinancing and time period dummies, we divided the sample based on these classifications. Our analysis incorporates borrower state, year-month, and state-year-month fixed effects to control for potential unobserved heterogeneity and time-varying factors that influence loan characteristics. By including these fixed effects, we aimed to more accurately isolate the impact of refinancing on FinTech loan attributes, ensuring that our results are robust to variations across states and over time.

The findings, detailed in Tables B1, B2, and B3 in the appendix, remain consistent and indicate that repeat borrowers benefited more from refinancing during crisis periods than first-time borrowers. Specifically, as shown in Table B1, repeat borrowers received significantly larger loan amounts, particularly during COVID and RU-War, reflecting lenders' increased confidence in their established creditworthiness. Table B2 reveals that refinancing was associated with lower APRs for both one-time and repeat borrowers before and during COVID, although this effect diminishes for repeat borrowers during RU-War, possibly due to heightened economic uncertainty influencing lenders' risk assessments. Table B3 shows that refinancing generally resulted in longer loan maturities for repeat borrowers across all periods, with the most significant increases observed during RU-War, further emphasizing the perceived stability and lower risk of repeat customers during uncertain economic conditions.

These supplementary analyses provide robust support for our main findings, demonstrating that repeat borrowers consistently benefited from refinancing in terms of larger loan amounts, favorable APRs, and longer maturities, especially during periods of economic crisis.

6.2. FinTech vs. Banks: Substitute or Complement?

To assess changes in borrower quality across periods, we employ an alternative classification of borrower FICO scores and rerun Equation 3. Specifically, we categorize all borrowers into five quintiles, ranging from low to high FICO scores, with each quintile representing an equal number of borrowers. This approach allows for a comprehensive analysis of shifts in borrower quality distribution during these critical periods. Additionally, we conduct further OLS regression analyses as robustness tests, using the Prosper Score as a supplementary proxy for borrower quality. The Prosper Score, a numerical rating assigned by Prosper Marketplace, considers factors such as credit history, debt-to-income ratio, employment status, and other financial behaviors. This score aids lenders in making informed decisions regarding lending and interest rate setting, based on the perceived risk of the borrower.

The results, presented in Tables B4 and B5, indicate that overall borrower quality improved significantly during COVID, followed by a notable decline during RU-War. Notably, repeat borrowers demonstrated greater resilience, showing modest improvements in borrower quality during COVID and further enhancements during RU-War, underscoring their reliability even amid economic disruptions.

To further validate our findings, we employed the Herfindahl-Hirschman Index based on deposits (HHI-Deposit) to examine the interplay between FinTech lending and traditional bank lending, specifically to determine whether FinTech acts as a complement or substitute. Using HHI-Deposit allows us to assess whether FinTech lending serves as a complement or substitute to traditional bank lending by analyzing market power and competition indirectly through deposit concentration.

The results are consistent with our previous findings. As shown in Tables B6 and B7, we document a negative relationship between FinTech loan origination numbers and HHI during COVID, but a positive association during RU-War, particularly among first-time borrowers. These findings suggest that FinTech lending activities were more pronounced in states with higher market competition during the pandemic and in states with lower market competition during RU-War. This pattern indicates that FinTech platforms played a complementary role in COVID, which then shifted to a substitutive role during RU-War.

6.3. Additional Test: FinTech lending and Bank Loans

In this section, we extend our analysis by incorporating data on bank loans sourced from the FDIC Call Reports. Specifically, we examine the relationship between bank lending and FinTech loan amounts under varying monetary policy conditions. The analysis is conducted using a panel dataset at the state (s) and quarter (t) levels, allowing us to account for both cross-sectional and temporal variations. This panel structure facilitates the incorporation of the same set of control variables and fixed effects, as outlined in Section 4.4.

$$Y_{s,t} = \alpha + \beta_1 \cdot BankLoan_{s,t} + \beta_2 \cdot TimePeriod + \beta_3 \cdot BankLoan_{s,t} \times TimePeriod$$
$$+\delta \cdot Controls_{s,t} + FEs + \varepsilon_{s,t} \quad (5)$$

The dependent variable is the total FinTech loan amount in state s and quarter t, $BankLoan_{s,t}$ represents the total amount of bank loans. The interaction term captures how this relationship shifts across different monetary policy periods, specifically during COVID and RU-War.

If FinTech platforms act as complements, one would expect a positive interaction term during periods of favorable monetary policies. In these times, both FinTech platforms and traditional banks are likely to expand their lending activities in response to increased demand for credit. Conversely, if FinTech platforms serve as substitutes, one would anticipate a negative interaction term. In this scenario, traditional banks may reduce their lending due to heightened uncertainty or tighter financial conditions, while FinTech platforms increase their lending to fill the resulting credit gap.

The results, presented in Table B8, show that the interaction terms are negatively correlated with FinTech loan amounts in Pre-COVID. However, during COVID, we observe a positive relationship, which turns negative again during RU-War. These findings suggest that FinTech platforms complemented traditional bank lending during COVID by expanding credit availability alongside banks, effectively meeting the increased demand for financing. In contrast, during RU-War, as bank lending contracted, FinTech platforms stepped in as a substitute source of credit, illustrating their substitutive role in response to reduced bank lending.

Furthermore, the magnitudes of interaction terms for first-time borrowers are consistently larger than those for repeat borrowers across all periods. These differences highlight FinTech platforms' ability to address distinct credit needs. During COVID, lending to first-time borrowers was notably higher, reflecting a more aggressive strategy aimed at attracting new customers. In contrast, during RU-War, FinTech platforms became a critical alternative to traditional banks, especially for first-time borrowers. This underscores the pivotal role of FinTech in maintaining credit access during crises, particularly for underserved or unbanked borrowers, aligning with our main findings.

6.4. Post-COVID period analyses

To ensure the robustness of our findings, we include the Post-COVID period in our analysis. This period begins on August 3, when the U.S. reached the 70% initial vaccination milestone, signaling a move towards recovery and market stabilization, and extends until the onset of the RU-War. By incorporating this timeframe, we capture the economic dynamics that emerged after the initial pandemic shock and analyze the persistence of inflationary trends as the economy transitioned from crisis to recovery. Our findings during this period remain consistent with those observed during the COVID phase (see Appendix B, Tables B9 and B10).

Both the COVID and Post-COVID periods were marked by aggressive expansionary monetary policies, including near-zero interest rates and large-scale quantitative easing. These measures, along with substantial fiscal stimulus, were essential in mitigating the economic impact of the pandemic and fostering recovery. Despite a rise in inflation driven by these policies, the Federal Reserve did not begin tightening monetary policy until March 17, 2022. This delay suggests that domestic demand-pull inflationary pressures alone were insufficient to prompt an immediate policy response.

In contrast, the RU-War introduced significant economic complexities. The geopolitical risks and market disruptions stemming from the war led to severe supply chain constraints and sharp increases in commodity prices, especially in the energy sector. These supply-side shocks intensified cost-push inflation, exacerbating the inflationary environment and compelling the Federal Reserve to adopt a tighter monetary policy. By including the Post-COVID period as a robustness check, we provide evidence that our results remain consistent under conditions of sustained monetary easing while also highlighting the distinct impact of the RU-War on economic conditions and policy responses affecting FinTech platforms.

7. Conclusion

We examine the adaptive strategies employed by a representative FinTech lending platform during economic crises, specifically focusing on the COVID pandemic and RU-War. Through a detailed analysis of loan characteristics and borrower quality across these periods, we find that refinancing borrowers consistently received more favorable financial terms. Repeat borrowers, in particular, benefited from improved loan conditions, reflecting their established credit histories and lower perceived risk. In contrast, the terms for first-time borrowers varied significantly, shaped by the distinct economic environments of each crisis.

During COVID, FinTech platforms complemented traditional banks by attracting higher-quality borrowers and actively participated in states with lower bank market concentration. This dynamic was driven by expansionary monetary policies allowing FinTech platforms to offer competitive terms in regions where traditional banks faced heightened competition. Conversely, during RU-War, FinTech platforms increasingly substituted for traditional banks, particularly in states with higher bank market concentration. As rising borrowing costs and increased risk aversion made it more challenging for lower-quality borrowers to secure loans from traditional banks, these borrowers increasingly turned to FinTech platforms for credit access. Additionally, our findings indicate that repeat borrowers exhibited greater resilience in maintaining borrower quality compared to first-time borrowers during RU-War, underscoring the platforms' confidence in established borrowers even under adverse conditions.

The role of FinTech lenders during these crises highlights the need for a well-calibrated regulatory framework. Policymakers should consider frameworks that promote innovation and mitigate potential risks associated with FinTech lending, particularly as these platforms increasingly substitute traditional banking during periods of monetary tightening. Regulatory measures could include monitoring credit risk management practices and ensuring that FinTech lenders maintain robust risk buffers to prevent systemic vulnerabilities. Furthermore, fostering greater collaboration between FinTech platforms and traditional banks may enhance credit distribution, especially during crisis periods when liquidity is most constrained.

Future research could explore how FinTech platforms operate across different countries or regions during crises to provide a broader understanding of their global role in financial stability. Additionally, studying borrower outcomes, such as default rates or financial health, over time on FinTech platforms during these crises could offer deeper insights into the risks and resilience of FinTech borrowers. Finally, further work could investigate regulatory frameworks that balance innovation with systemic risk management, particularly given the growing reliance on FinTech platforms during periods of economic distress.

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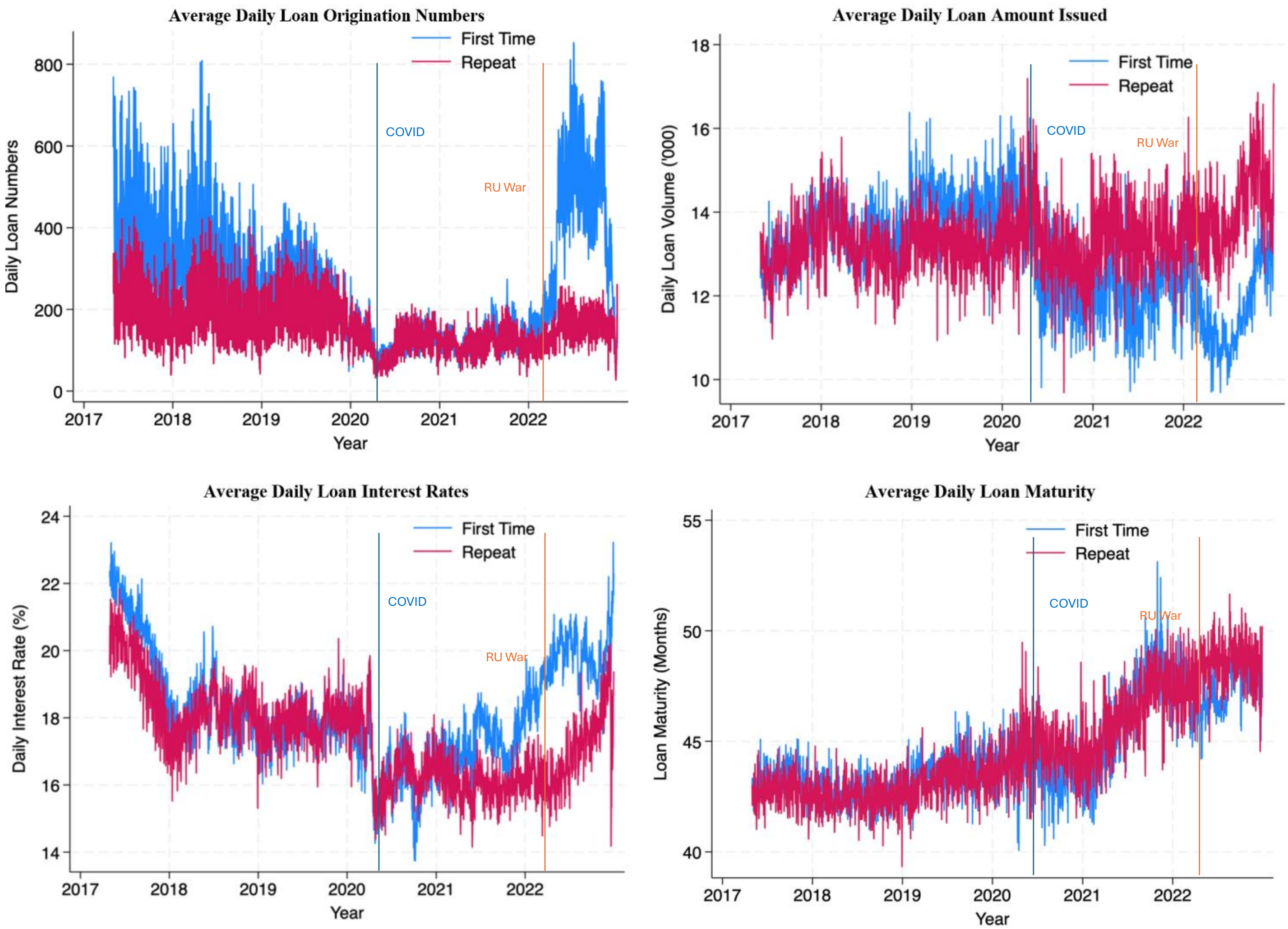
Figure 1: Average Daily Loan Origination Numbers and Loan Terms



Notes. Figure 1 shows the average daily loan origination numbers, volume, interest rates, and maturities for first-time and repeat loans from January 2017 to December 2022. The data is segmented into three key periods: Pre-COVID, COVID, and the Russo-Ukrainian War (RU-War).

Table 1: Summary Statistics

Panel 1: All Sample

	All borrowers N = 703,200	First-time borrowers N = 614,497	Repeat borrowers N = 88,703
	(1)	(2)	(3)
Panel 1A: Daily Average FinTech Loan Terms			
Daily Loan Origination Numbers	436.54	270.14	166.55
Loan Amount ($'000)	13.09	12.93	13.36
Borrower interest rate (%)	18.38%	18.80%	17.69%
Loan maturity (months)	44.49	44.59	44.35
Panel 1B: Borrower Characteristics and US Interest Rates			
Refinancing purpose (1/0)	0.68	0.66	0.70
FICO score (midpoint)	709.85	706.49	715.29
Debt-to-income	0.30	0.29	0.32
Employments (year)	8.82	8.22	9.77
Homeowner (1/0)	0.05	0.04	0.05
Credit History (years in market)	23.16	22.10	24.88
U.S Interest Rate	1.58	1.63	1.50

Panel 2: Pre-COVID, COVID, and RU-War

	Pre-COVID			COVID			RU-War		
	All	First	Repeat	All	First	Repeat	All	First	Repeat
N=	417,260	370,066	47,194	123,761	101,445	22,316	152,390	134,956	17,434
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel 2A: Daily Average FinTech Loan Terms									
Daily Loan Numbers	519.43	316.98	202.83	245.28	128.12	117.15	595.04	437.38	157.66
Loan Amount ($'000)	13.47	13.63	13.21	12.80	12.36	13.28	12.27	11.59	14.15
Borrower APR (%)	18.70%	18.88%	18.41%	16.62%	17.00%	16.22%	19.09%	19.82%	17.06%
Loan maturity (months)	43.09	43.22	42.89	45.53	45.47	45.59	47.64	47.32	48.54
Panel 2B: Borrower Characteristics and US Interest Rates									
Refinancing purpose (1/0)	0.70	0.69	0.72	0.65	0.63	0.67	0.64	0.63	0.65
FICO score (midpoint)	709.98	709.09	711.36	718.53	714.27	723.18	701.25	694.90	718.87
Debt-to-income	0.31	0.31	0.32	0.29	0.26	0.31	0.27	0.25	0.32
Employment (year)	9.18	8.91	9.61	9.07	8.01	10.17	7.49	6.65	9.83
Homeowner (1/0)	0.04	0.04	0.04	0.06	0.04	0.07	0.05	0.04	0.08
Credit History (years in market)	23.42	22.89	24.23	23.67	21.81	25.70	21.92	20.35	26.28
U.S Interest Rate	1.81	1.78	1.85	0.25	0.25	0.25	2.16	2.17	2.14

Notes. Table 1 presents summary statistics regarding the terms associated with daily average FinTech loans and the successful borrowers' characteristics. Panel 1 shows the aggregate descriptive statistics. Panel 2 presents the descriptive statistics of FinTech loan terms across the Pre-COVID, COVID, and RU-Wars, respectively. Both tables reports the mean values.

Table 2: Impact of Refinancing on FinTech Loan Terms

	FinTech Loan Amount			Borrower Interest Rate			Loan Maturity		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Refinance	1.8141***	1.7657***	2.0232***	-0.2979***	-0.3964***	-0.1516***	0.2918***	0.2570***	0.4340***
	(0.071)	(0.071)	(0.076)	(0.018)	(0.023)	(0.025)	(0.050)	(0.059)	(0.053)
FICO Score	0.0326***	0.0361***	0.0278***	-0.0969***	-0.0992***	-0.0925***	0.0280***	0.0328***	0.0209***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Debt-to-income	3.6639***	3.8060***	3.6224***	4.1691***	4.0348***	4.4619***	1.4021***	1.5490***	1.2332***
	(0.104)	(0.109)	(0.114)	(0.355)	(0.334)	(0.393)	(0.194)	(0.162)	(0.271)
Log(Income)	7.1187***	7.4311***	6.7736***	-1.2333***	-1.3283***	-1.0261***	1.5824***	1.7427***	1.4011***
	(0.038)	(0.039)	(0.047)	(0.021)	(0.024)	(0.025)	(0.056)	(0.058)	(0.064)
Log(Years in Market)	0.1525***	0.2661***	-0.0061	-0.3598***	-0.3382***	-0.3787***	0.7026***	0.8530***	0.4493***
	(0.035)	(0.028)	(0.049)	(0.020)	(0.018)	(0.027)	(0.065)	(0.061)	(0.079)
Log(Employments)	-0.1348***	-0.0920***	-0.1856***	-0.0039	-0.0142**	0.0124	0.0214**	0.0416***	-0.0001
	(0.008)	(0.008)	(0.014)	(0.007)	(0.008)	(0.008)	(0.016)	(0.019)	(0.020)
Homeowner	0.1188***	0.2789***	-0.0352	-0.3635***	-0.3928***	-0.3366***	0.3120***	0.5047***	0.1226
	(0.045)	(0.067)	(0.067)	(0.025)	(0.025)	(0.041)	(0.074)	(0.086)	(0.113)
Interest Rate	-0.1746***	-0.1668***	-0.2096***	0.3808***	0.3895***	0.3110***	-0.2343***	-0.1964***	-0.2969***
	(0.033)	(0.043)	(0.063)	(0.029)	(0.038)	(0.043)	(0.054)	(0.068)	(0.077)
Constant	-25.0345***	-28.1024***	-21.0488***	88.8009***	90.7219***	85.1262***	19.3862***	15.4900***	25.1040***
	(0.526)	(0.519)	(0.563)	(1.471)	(1.617)	(1.241)	(0.401)	(0.474)	(0.421)
Number of Observations	887,091	545,995	341,096	887,091	545,995	341,096	887,091	545,995	341,096
R-Squared	0.2818	0.3127	0.2441	0.4119	0.4209	0.3910	0.0534	0.0586	0.0495
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes. Table 2 presents the results of the baseline OLS regression from Equation (1), where the dependent variables are proxies for FinTech loan terms across the aggregate sample period.

$$Y_i = a + \beta_1 \cdot Refinance + \delta \cdot Controls_i + FEs + \varepsilon_i \quad (1)$$

The FinTech loan amount is analyzed in columns 1 to 3, Borrower APR in columns 4 to 6, and loan maturity in columns 7 to 9. Columns 1, 4, and 7 report results for the overall sample; columns 2, 5, and 8 focus on first-time borrowers; and columns 3, 6, and 9 report results for repeat borrowers. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table 3: Impact of Refinancing on FinTech Loan Amount Across Periods

	Dependent Variable: FinTech Loan Amount								
	Pre-COVID			**COVID**			**RU-War**		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Refinance	1.9689***	1.6853***	2.5360***	1.7151***	1.7127***	1.8604***	1.8344***	1.8708***	1.9208***
	(0.075)	(0.069)	(0.092)	(0.068)	(0.070)	(0.071)	(0.075)	(0.079)	(0.077)
Pre-COVID	0.4796***	0.7370***	0.3714**						
	(0.096)	(0.118)	(0.166)						
COVID				-0.1876***	-0.1216	-0.2158*			
				(0.060)	(0.084)	(0.106)			
RU-War							-0.3224***	-0.3968***	-0.6030***
							(0.097)	(0.104)	(0.172)
Refinance x Pre-COVID	-0.2638***	0.1381***	-0.8634***						
	(0.045)	(0.052)	(0.059)						
Refinance x COVID				0.5035***	0.3223***	0.6427***			
				(0.042)	(0.052)	(0.073)			
Refinance x RU-War							-0.0961*	-0.4158***	0.6673***
							(0.056)	(0.055)	(0.096)
Number of Observations	887,091	545,995	341,096	887,091	545,995	341,096	887,091	545,995	341,096
R-Squared	0.2818	0.3127	0.2447	0.2819	0.3127	0.2444	0.2818	0.3128	0.2443
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes. Table 3 presents the results of Equation (2), analyzing the effect of refinancing on FinTech loan amounts across different time periods.

$$Y_i = a + \beta_1 \cdot Refinance + \beta_2 \cdot TimePeriod + \beta_3 \cdot Refinance \times TimePeriod + \delta \cdot Controls_i + FEs + \varepsilon_i \quad (2)$$

Columns 1 to 3 report the results for the Pre-COVID period, columns 4 to 6 display findings for the COVID, and columns 7 to 9 illustrate outcomes for RU-War. Control variables, specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table 4: Impact of Refinancing on FinTech Loan Interest Rate Across Periods

	Dependent Variable: FinTech Interest Rate								
	Pre-COVID			**COVID**			**RU-War**		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Refinance	-0.3081***	-0.3835***	-0.1739***	-0.2349***	-0.3192***	-0.1006***	-0.3585***	-0.4920***	-0.1872***
	(0.023)	(0.029)	(0.029)	(0.020)	(0.025)	(0.030)	(0.019)	(0.024)	(0.028)
Pre-COVID	-0.8064***	-0.8285***	-0.7663***						
	(0.064)	(0.066)	(0.145)						
COVID				0.6409***	0.7546***	0.6077***			
				(0.040)	(0.054)	(0.063)			
RU-War							-0.3510***	-0.4110***	-0.4204***
							(0.047)	(0.065)	(0.081)
Refinance x Pre-COVID	0.0173	-0.0223	0.0375						
	(0.028)	(0.031)	(0.048)						
Refinance x COVID				-0.3233***	-0.4788***	-0.2040***			
				(0.025)	(0.037)	(0.038)			
Refinance x RU-War							0.2792***	0.3753***	0.2288***
							(0.036)	(0.044)	(0.052)
Number of Observations	887,091	545,995	341,096	887,091	545,995	341,096	887,091	545,995	341,096
R-Squared	0.4119	0.4209	0.3910	0.4120	0.4210	0.3909	0.4119	0.4210	0.3910
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes. Table 4 presents the results of Equation (2), focusing on the effect of refinancing on FinTech loan interest rates across various time periods.

$$Y_i = a + \beta_1 \cdot Refinance + \beta_2 \cdot TimePeriod + \beta_3 \cdot Refinance \times TimePeriod + \delta \cdot Controls_i + FEs + \varepsilon_i \quad (2)$$

Columns 1 to 3 report the results for the Pre-COVID period, columns 4 to 6 display findings for the COVID, and columns 7 to 9 illustrate outcomes for RU-War. Control variables, specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table 5: Impact of Refinancing on FinTech Loan Maturity Across Periods

	Dependent Variable: FinTech Loan Maturity								
	Pre-COVID			**COVID**			**RU-War**		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Refinance	0.7107***	0.6093***	0.9629***	0.3215***	0.3201***	0.4071***	0.0400	-0.0124	0.2037***
	(0.074)	(0.076)	(0.097)	(0.049)	(0.059)	(0.050)	(0.042)	(0.054)	(0.049)
Pre-COVID	0.5091***	0.7968***	0.1606						
	(0.173)	(0.199)	(0.262)						
COVID				0.1542	0.4660***	-0.2570			
				(0.110)	(0.141)	(0.182)			
RU-War							-0.7976***	-1.2085***	-0.4358**
							(0.142)	(0.183)	(0.242)
Refinance x Pre-COVID	-0.7142***	-0.6051***	-0.8906***						
	(0.063)	(0.056)	(0.097)						
Refinance x COVID				-0.1520**	-0.3953***	0.1065			
				(0.068)	(0.068)	(0.105)			
Refinance x RU-War							1.1571***	1.0481***	1.5077***
							(0.071)	(0.072)	(0.139)
Number of Observations	887,091	545,995	341,096	887,091	545,995	341,096	887,091	545,995	341,096
R-Squared	0.0536	0.0588	0.0498	0.0534	0.0587	0.0495	0.0538	0.0590	0.0500
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes. Table 5 reports the results of Equation (2), examining the impact of refinancing on FinTech loan maturity over different time periods.

$$Y_i = a + \beta_1 \cdot Refinance + \beta_2 \cdot TimePeriod + \beta_3 \cdot Refinance \times TimePeriod + \delta \cdot Controls_i + FEs + \varepsilon_i \quad (2)$$

Columns 1 to 3 report the results for the Pre-COVID period, columns 4 to 6 display findings for the COVID, and columns 7 to 9 illustrate outcomes for RU-War. Control variables, specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table 6: Borrower Quality Distribution Across Periods

Number Distribution, FICO Score Range

Panel A: All Borrowers

Periods	FICO Score Range				
	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]
Pre-COVID	26.46%	18.20%	17.71%	14.40%	23.21%
COVID	20.19%	16.53%	17.66%	14.63%	30.99%
RU-War	34.79%	17.36%	16.08%	11.62%	20.15%

Panel B: First-Time Borrowers

Periods	FICO Score Range				
	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]
Pre-COVID	27.76%	18.22%	17.31%	14.20%	22.51%
COVID	24.28%	17.06%	16.76%	13.40%	28.51%
RU-War	40.21%	17.65%	15.52%	10.42%	16.19%

Panel C: Repeat Borrowers

Periods	FICO Score Range				
	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]
Pre-COVID	24.89%	18.31%	18.29%	14.68%	23.83%
COVID	15.71%	15.96%	18.64%	15.99%	33.70%
RU-War	19.76%	16.55%	17.61%	14.95%	31.12%

Notes: Table 6 illustrates the distribution of borrower quality across these periods. Panel A presents the distribution of borrower quality for all borrowers. Panel B focuses on first-time borrowers. Panel C reports repeat borrowers. Borrower quality is proxied by FICO scores (Tang, 2019), which are segmented into five categories: FICO < 680, 680-699, 700- 719, 720-739, and FICO > 740.

Table 7: Overall Borrower Quality Change Across Periods

	Dependent Variable: FICO Range														
	Pre-COVID					COVID					RU-War				
FICO Range	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Pre-COVID	0.4620***	0.0073***	-0.1224***	-0.1296***	-0.2303***										
	(0.036)	(0.039)	(0.037)	(0.041)	(0.033)										
COVID						-0.3082***	-0.0503	0.0969***	0.1443***	0.2160***					
						(0.021)	(0.024)	(0.024)	(0.027)	(0.021)					
RU-War											0.2122***	0.0703**	-0.0718**	-0.1408***	-0.1846***
											(0.025)	(0.029)	(0.030)	(0.034)	(0.027)
Observations	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091
Pseudo R-Squared	0.0489	0.0044	0.0027	0.0085	0.0322	0.0490	0.0044	0.0027	0.0086	0.0323	0.0488	0.0044	0.0027	0.0085	0.0322
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State	State	State	State	State	State	State

Table 7 presents the results of the logit regression model from Equation (3), which captures overall changes in borrower quality across different periods.

$$Logit[P(FICO\_Range_i = 1)] = a + \beta_1 \cdot TimePeriod + \delta \cdot Controls_i + FEs + \varepsilon_i \tag{3}$$

Columns 1 to 5 report borrower quality during the Pre-COVID period, columns 6 to 10 display results for the COVID, and columns 11 to 15 show outcomes for RU-War. Control variables, as specified in Section 5.1, include the debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table 8: First-Time and Repeat Borrower Quality Change Across Periods

Panel A: First Time Borrowers

	Dependent Variable: FICO Range														
	Pre-COVID					COVID					RU-War				
FICO Range	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Pre-COVID	0.5509***	-0.0430	-0.1949***	-0.1442***	-0.2519***										
	(0.046)	(0.051)	(0.049)	(0.055)	(0.043)										
COVID						-0.3509***	-0.0211	0.1637***	0.1708***	0.2658***					
						(0.026)	(0.031)	(0.032)	(0.037)	(0.030)					
RU-War											0.2377***	0.0550***	-0.1298***	-0.1773***	-0.2529***
											(0.031)	(0.038)	(0.040)	(0.048)	(0.041)
Observations	545,995	545,995	545,995	545,995	545,995	545,995	545,995	545,995	545,995	545,995	545,995	545,995	545,995	545,995	545,995
Pseudo R-Squared	0.0529	0.0045	0.0031	0.0118	0.0397	0.0529	0.0045	0.0032	0.0118	0.0398	0.0527	0.0045	0.0031	0.0118	0.0397

Panel B: Repeat Borrowers

	Dependent Variable: FICO Range														
	Pre-COVID					COVID					RU-War				
FICO Range	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]	[<680]	[680, 699]	[700, 719]	[720, 739]	[>740]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Pre-COVID	0.3811***	0.0736**	-0.0468	-0.1246*	-0.2129***										
	(0.060)	(0.063)	(0.060)	(0.064)	(0.051)										
COVID						-0.0827**	-0.0707*	-0.0006	0.0653	0.0660**					
						(0.037)	(0.038)	(0.037)	(0.040)	(0.031)					
RU-War											0.0953	0.0619	0.0276	-0.0253	0.0207
											(0.045)	(0.046)	(0.045)	(0.048)	(0.037)
Observations	341,032	341,032	341,032	341,032	341,032	341,032	341,032	341,032	341,032	341,032	341,032	341,032	341,032	341,032	341,032
Pseudo R-Squared	0.0415	0.0056	0.0023	0.0049	0.0275	0.0414	0.0056	0.0023	0.0049	0.0275	0.0414	0.0056	0.0023	0.0049	0.0275

Notes: Table 8 presents the findings on first-time and repeat borrower quality changes across periods. Panel A shows the quality migration for first-time borrowers, while Panel B shows the changes for repeat borrowers. Columns 1 to 5 report borrower quality during the Pre-COVID period, columns 6 to 10 cover the COVID, and columns 11 to 15 display the results for RU-War. Control variables, as specified in Section 5.1, include the debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table 9: FinTech Loan Entries and Bank Market Concentration

	Dependent Variable: FinTech Loan Origination Numbers								
	Pre-COVID			COVID			RU-War		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HHI Branches	-0.3047***	-0.4716***	-0.1403***	0.1758***	0.1807***	0.1898***	0.0217	0.0175	0.0156
	(0.050)	(0.079)	(0.023)	(0.047)	(0.068)	(0.025)	(0.054)	(0.083)	(0.032)
Pre-COVID	-2.2974***	-3.1114**	-2.0288***						
	(0.741)	(1.239)	(0.337)						
COVID				2.6947***	4.0980***	1.7307***			
				(0.503)	(0.753)	(0.262)			
RU-War							-1.4573*	-3.6565***	0.1534
							(0.794)	(1.263)	(0.464)
HHI Branches x Pre-COVID	0.2510***	0.3070***	0.2022***						
	(0.014)	(0.022)	(0.007)						
HHI Branches x COVID				-0.3379***	-0.4926***	-0.1889***			
				(0.014)	(0.021)	(0.008)			
HHI Branches x RU-War							0.1182***	0.3091***	-0.0782***
							(0.023)	(0.036)	(0.014)
Number of Observations	2,240	1,121	1,119	2,240	1,121	1,119	2,240	1,121	1,119
R-Squared	0.7939	0.8394	0.9527	0.8120	0.8769	0.9433	0.7673	0.8229	0.9122
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes. Table 9 presents the results of Equation (4), examining the relationship between FinTech loan entries and bank branch market concentration.

$$Y_{s,t} = \alpha + \beta_1 \cdot HHI_{s,t} + \beta_2 \cdot TimePeriod + \beta_3 \cdot HHI_{s,t} \times TimePeriod + \delta \cdot Controls_{s,t} + FEs + \varepsilon_{s,t} \tag{4}$$

Columns 1 to 3 report results for the Pre-COVID period, columns 4 to 6 display findings for the COVID, and columns 7 to 9 illustrate outcomes for the RU-War period. Control variables, as specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table 10: Average loan size and Bank Market Concentration

	Dependent Variable: FinTech Loan Amount / Numbers								
	Pre-COVID			**COVID**			**RU-War**		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HHI Branches	-0.0412**	-0.0679***	-0.0183	-0.0164	-0.0361*	0.0002	-0.0209	-0.0305	-0.0142
	(0.017)	(0.019)	(0.025)	(0.017)	(0.019)	(0.024)	(0.017)	(0.019)	(0.025)
Pre-COVID	-0.2910	-0.5507*	0.0979						
	(0.254)	(0.303)	(0.362)						
COVID				0.2130	0.5354**	-0.0608			
				(0.180)	(0.208)	(0.257)			
RU-War							-0.0646	-0.5203*	0.1312
							(0.256)	(0.292)	(0.367)
HHI Branches x Pre-COVID	0.0119**	0.0103*	0.0128*						
	(0.005)	(0.005)	(0.007)						
HHI Branches x COVID				-0.0193***	-0.0303***	-0.0072			
				(0.005)	(0.006)	(0.007)			
HHI Branches x RU-War							0.0128*	0.0404***	-0.0152
							(0.008)	(0.008)	(0.011)
Number of Observations	2,240	1,121	1,119	2,240	1,121	1,119	2,240	1,121	1,119
R-Squared	0.8803	0.9116	0.8932	0.8803	0.9123	0.8929	0.8804	0.9128	0.8930
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes. Table 10 presents the results of Equation (4), examining the relationship between FinTech loan size and bank branch market concentration.

$$Y_{s,t} = \alpha + \beta_1 \cdot HHI_{s,t} + \beta_2 \cdot TimePeriod + \beta_3 \cdot HHI_{s,t} \times TimePeriod + \delta \cdot Controls_{s,t} + FEs + \varepsilon_{s,t} \quad (4)$$

Columns 1 to 3 report results for the Pre-COVID period, columns 4 to 6 display findings for the COVID, and columns 7 to 9 illustrate outcomes for the RU-War period. Control variables, as specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Appendix A - Definitions of Variables

Definitions of Variables

Variables	Definition
Dependent Variables	
FinTech Loan Amount (‘000)	The loan amount in thousands of dollars funded to borrower in FinTech platform.
Borrower Interest Rate (%)	Average Annual Percentage Rate (APR) on the loan, as set by Prosper, expressed as a percentage.
Loan Maturity	The length of the loan, in months.
FinTech Daily Loan Origination Numbers	The daily average number of loans issued by Prosper.
Independent Variables	
Refinancing purpose (1/0)	Loan purpose selected by the borrower: Refinancing purpose = 1 indicates that the FinTech loan proceeds will be used for debt refinancing; Refinancing purpose = 0 otherwise.
Repeat Times (1/0)	Dummy Variable = 1 indicates that the borrowers have used the FinTech platform (Prosper) more than once; 0 otherwise.
Debt-to-income	The ratio, expressed in decimal form, of monthly debt as reported by the credit bureau to the monthly income stated by the borrower on the loan application.
FICO score (midpoint)	Midpoint value of the binned FICO score, as reported by the credit bureau.
Homeowner (1/0)	A dummy variable of home ownership that is set to 1 if the borrower either has an outstanding mortgage listed on their credit report or has provided documentation verifying home ownership and set to 0 in all other cases.
Monthly Income ($ ‘000)	Monthly income amounts in thousands of dollars, as declared by the borrower on their loan application
Employment (year)	Duration of employment with the current employer, as self-reported by the borrower and measured in years, encompassing both formal employment and self-employment.
Credit History (years) (Years in Market)	The length of the borrower’s credit history, measured in years. It’s determined by subtracting the date when the oldest account on the borrower’s credit record was opened from the loan application date.

Interest rate	Daily interest rate set by the U.S. government.
HHI Branches	The HHI is calculated by first determining the market share of each bank, defined as the proportion of branches it operates relative to the total number of branches within a state. Each bank's market share is then squared to account for the disproportionate influence of larger shares on overall market concentration. The final HHI value is obtained by summing these squared market shares across all banks operating within the state.
Bank Loan	Total bank loans in a year measured in trillions sourced from the FDIC Call Reports.
Time Variables:	
Pre-COVID	Pre-crisis period; (May 1, 2017 – March 12, 2020)
COVID	Beginning **March 13, 2020**, marked by the U.S. national emergency declaration and WHO's pandemic announcement; (March 13, 2020 – February 23, 2022)
RU-War	Starting from February 24, 2022, when Russia invaded Ukraine, marking the largest attack on a European country since World War II. (February 24, 2022 – December 31, 2022)

Appendix B – Robustness Tests

Table B1: Impact of Refinancing on FinTech Loan Amount Across Periods

	Dependent Variable: FinTech Loan Amount					
	First-Time			Repeat		
	Pre-COVID	COVID	RU-War	Pre-COVID	COVID	RU-War
	(1)	(2)	(3)	(4)	(5)	(6)
Refinance	1.8377***	1.8922***	1.4893***	1.6837***	2.4625***	2.5838***
	(0.081)	(0.091)	(0.064)	(0.069)	(0.106)	(0.108)
FICO Score	0.0370***	0.0271***	0.0396***	0.0308***	0.0222***	0.0255***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Debt-to-income	3.5321***	4.8371***	3.8420***	3.5706***	3.9173***	3.0927***
	(0.130)	(0.139)	(0.167)	(0.128)	(0.101)	(0.227)
Log(Income)	7.4469***	7.7776***	7.1075***	6.5124***	6.9765***	7.4759***
	(0.050)	(0.063)	(0.089)	(0.054)	(0.060)	(0.077)
Log(Years in Market)	0.1948***	0.3452***	0.3442***	0.0694	-0.0656	-0.1286
	(0.033)	(0.049)	(0.036)	(0.049)	(0.055)	(0.080)
Log(Employments)	-0.1295***	-0.0561***	-0.0291***	-0.2355***	-0.0965***	-0.1051***
	(0.012)	(0.018)	(0.011)	(0.017)	(0.020)	(0.019)
Homeowner	0.2213**	0.3617**	0.2970***	-0.0848	0.0977	-0.1693
	(0.083)	(0.153)	(0.079)	(0.093)	(0.086)	(0.167)
Interest Rate	-0.2417*	-0.0667	-0.2937***	-0.2021	0.6880*	-0.1461
	(0.126)	(0.261)	(0.051)	(0.132)	(0.386)	(0.091)
Constant	-27.9107***	-23.9398***	-30.3190***	-22.4759***	-18.6217***	-20.5513***
	(0.518)	(0.815)	(0.939)	(0.614)	(0.607)	(0.772)
Number of Observations	328,343	84,124	133,501	210,516	82,035	48,512
R-Squared	0.2873	0.3199	0.3517	0.2356	0.2502	0.2711
Borrower State FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
State-Year-Month FE	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State

Notes. Table B1 presents the results of Equation (1), showing the effect of refinancing on FinTech loan amounts across different periods.

$$Y_i = a + \beta_1 \cdot Refinance + \delta \cdot Controls_i + FEs + \varepsilon_i \quad (1)$$

Columns 1 to 3 report the results for the First-Time borrowers, columns 4 to 6 display the findings for the Repeat borrowers. Control variables are specified in section 5.1, which includes the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of Credit History (ln(Years in Market)), duration of employment (ln(Employment)), Home Ownership, and the federal interest rate set by the U.S. government. All columns incorporate the year-quarter and state fixed effects. Standard errors are clustered at the state level

Table B2: Impact of Refinancing on FinTech Borrower APR Across Periods

	Dependent Variable: FinTech Interest Rate					
	First-Time			Repeat		
	Pre-COVID (1)	COVID (2)	RU-War (3)	Pre-COVID (4)	COVID (5)	RU-War (6)
Refinance	-0.4428***	-0.4046***	-0.1995***	-0.1748***	-0.1543***	0.0649
	(0.026)	(0.030)	(0.044)	(0.039)	(0.026)	(0.047)
FICO Score	-0.1031***	-0.0697***	-0.1089***	-0.1008***	-0.0743***	-0.0897***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Debt-to-income	4.7545***	1.7882***	3.6705***	5.5003***	2.3139***	3.7267***
	(0.421)	(0.206)	(0.251)	(0.516)	(0.228)	(0.245)
Log(Income)	-1.1873***	-1.3057***	-1.5701***	-0.8532***	-1.1609***	-1.4402***
	(0.030)	(0.048)	(0.033)	(0.028)	(0.033)	(0.056)
Log(Years in Market)	-0.2756***	-0.2503***	-0.4607***	-0.3468***	-0.3907***	-0.7007***
	(0.023)	(0.027)	(0.019)	(0.033)	(0.037)	(0.045)
Log(Employments)	-0.0035	-0.0202	-0.0308***	0.0268**	0.0170	-0.0504***
	(0.010)	(0.014)	(0.011)	(0.012)	(0.012)	(0.018)
Homeowner	-0.3004***	-0.1145**	-0.6618***	-0.2606***	-0.1877***	-0.5589***
	(0.042)	(0.054)	(0.061)	(0.068)	(0.049)	(0.083)
Interest Rate	-0.2174**	-0.4655**	0.7279***	0.0232	-0.1841	0.7773***
	(0.083)	(0.174)	(0.050)	(0.139)	(0.195)	(0.072)
Constant	94.1509***	69.8021***	97.2175***	90.9909***	72.7831***	83.8511***
	(1.817)	(1.097)	(1.610)	(1.405)	(0.958)	(1.409)
Number of Observations	328,343	84,124	133,501	210,516	82,035	48,512
R-Squared	0.3972	0.3935	0.4897	0.3781	0.3824	0.4273
Borrower State FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
State-Year-Month FE	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State

Notes. Table B2 presents the results of Equation (1), showing the effect of refinancing on FinTech loan interest rate across different periods.

$$Y_i = a + \beta_1 \cdot Refinance + \delta \cdot Controls_i + FEs + \varepsilon_i \tag{1}$$

Columns 1 to 3 report the results for the First-Time borrowers, columns 4 to 6 display the findings for the Repeat borrowers. Control variables are specified in section 5.1, which includes the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of Credit History (ln(Years in Market)), duration of employment (ln(Employment)), Home Ownership, and the federal interest rate set by the U.S. government. All columns incorporate the year-quarter and state fixed effects. Standard errors are clustered at the state level.

Table B3: Impact of Refinancing on FinTech Loan Maturity Across Periods

	Dependent Variable: FinTech Loan Maturity					
	First-Time			Repeat		
	Pre-COVID	COVID	RU-War	Pre-COVID	COVID	RU-War
	(1)	(2)	(3)	(4)	(5)	(6)
Refinance	0.0741	-0.3462***	0.9089***	0.1246***	0.4175***	1.4304***
	(0.054)	(0.085)	(0.087)	(0.043)	(0.108)	(0.150)
FICO Score	0.0386***	0.0135***	0.0314***	0.0358***	0.0121***	-0.0179***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Debt-to-income	-0.7903**	3.5216***	6.7911***	-0.6110	3.4278***	4.7098***
	(0.340)	(0.202)	(0.231)	(0.405)	(0.286)	(0.386)
Log(Income)	1.6902***	2.1498***	1.4626***	1.1785***	1.9945***	1.2031***
	(0.059)	(0.082)	(0.089)	(0.062)	(0.112)	(0.098)
Log(Years in Market)	0.8523***	0.7552***	0.8923***	0.7499***	0.3300***	-0.2289
	(0.077)	(0.075)	(0.078)	(0.066)	(0.099)	(0.170)
Log(Employments)	0.0443**	0.0576	0.0102	0.0261	0.0219	-0.1024**
	(0.020)	(0.038)	(0.031)	(0.022)	(0.037)	(0.048)
Homeowner	0.2125*	0.7817***	0.6264***	-0.1145	0.3590*	0.2259
	(0.125)	(0.156)	(0.188)	(0.138)	(0.194)	(0.245)
Interest Rate	-0.9050***	-0.5643	-0.1839**	-0.6768**	0.7083	-0.0709
	(0.188)	(0.487)	(0.085)	(0.268)	(0.483)	(0.100)
Constant	12.0716***	28.9623***	18.6027***	14.2994***	30.4395***	57.6615***
	(0.627)	(0.809)	(1.472)	(0.675)	(0.806)	(1.144)
Number of Observations	328,343	84,124	133,501	210,516	82,035	48,512
R-Squared	0.0358	0.0491	0.0468	0.0270	0.0273	0.0188
Borrower State FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
State-Year-Month FE	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State

Notes. Table B3 presents the results of the Equation (1), showing the effect of refinancing on FinTech loan maturity across different periods.

$$Y_i = a + \beta_1 \cdot Refinance + \delta \cdot Controls_i + FEs + \varepsilon_i \quad (1)$$

Columns 1 to 3 report the results for the First-Time borrowers, columns 4 to 6 display the findings for the Repeat borrowers. Control variables are specified in section 5.1, which includes the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of Credit History (ln(Years in Market)), duration of employment (ln(Employment)), Home Ownership, and the federal interest rate set by the U.S. government. All columns incorporate the year-quarter and state fixed effects. Standard errors are clustered at the state level.

Table B4: Changes in Borrower Quality by Period - Equal Borrower Quintiles

	Dependent Variable: FICO Range														
	Pre-COVID					COVID					RU-War				
FICO Range	20th	40th	60th	80th	100th	20th	40th	60th	80th	100th	20th	40th	60th	80th	100th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Pre-COVID	0.4815***	0.1100***	-0.0065	-0.2273***	-0.2230***										
	(0.042)	(0.037)	(0.036)	(0.036)	(0.034)										
COVID						-0.3416***	-0.0701***	0.0200	0.1778***	0.2111***					
						(0.024)	(0.023)	(0.022)	(0.024)	(0.022)					
RU-War											0.2572***	0.0409	-0.0260	-0.1281***	-0.1813***
											(0.028)	(0.028)	(0.027)	(0.030)	(0.028)
Observations	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091	887,091
Pseudo R-Squared	0.0487	0.0064	0.0024	0.0104	0.0336	0.0488	0.0064	0.0024	0.0104	0.0337	0.0486	0.0064	0.0024	0.0103	0.0336
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State	State	State	State	State	State	State

Notes: Table B4 reports the findings of Equation (3), the overall borrower FICO Score Quintiles change across periods.

$$Logit[P(FICO\_Range_i = 1)] = a + \beta_1 \cdot TimePeriod + \delta \cdot Controls_i + FEs + \varepsilon_i \tag{3}$$

Columns 1 to 5 report the borrower quality in Pre-COVID. Columns 6 to 10 illustrate the COVID. Columns 11 to 15 show RU-War. Control variables are specified in section 5.1, which includes the debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of Credit History (ln(Years in Market)), duration of employment (ln(Employment)), Home Ownership, and the federal interest rate set by the U.S. government. All columns incorporate the year-quarter and state fixed effects. Standard errors are clustered at the state level.

Table B5: Borrower Quality Change Across Periods

	Dependent Variable: Borrower Quality								
	Overall Borrower			First-Time			Repeat		
	Pre-COVID	COVID	RU-War	Pre-COVID	COVID	RU-War	Pre-COVID	COVID	RU-War
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre-COVID	-0.5528***			-0.5891***			-0.4682***		
	(0.037)			(0.047)			(0.062)		
COVID		0.5287***			0.5866***			0.0913**	
		(0.027)			(0.035)			(0.041)	
RU-War			-0.4703***			-0.5436***			0.1271**
			(0.036)			(0.047)			(0.050)
Number of Observations	885,995	885,995	885,995	545,251	545,251	545,251	340,744	340,744	340,744
R-Squared	0.1594	0.1597	0.1595	0.2011	0.2014	0.2012	0.0924	0.0923	0.0923
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes: Table B5 reports the findings of Equation AE1. The overall borrower prosper score change across periods.

$$Prosper\ Score_i = a + \beta_1 \cdot TimePeriod + \delta \cdot Controls_i + FEs + \varepsilon_i \quad \text{(AE1)}$$

Columns 1 to 5 report the borrower quality in Pre-COVID. Columns 6 to 10 illustrate the COVID. Columns 11 to 15 show RU-War. Control variables are specified in section 5.1, which includes the debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of Credit History (ln(Years in Market)), duration of employment (ln(Employment)), Home Ownership, and the federal interest rate set by the U.S. government. All columns incorporate the year-quarter and state fixed effects. Standard errors are clustered at the state level.

Table B6: FinTech Loan Entries and Bank Concentration

	Dependent Variable: FinTech Loan Numbers								
	Pre-COVID			COVID			RU-War		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HHI-Deposit	-12.9028***	-11.5020*	-13.7843***	-6.2960***	-6.9687**	-5.5016***	-3.8566**	-3.4169	-4.0624***
	(4.115)	(6.685)	(2.429)	(2.010)	(3.234)	(1.202)	(1.929)	(3.142)	(1.145)
Pre-COVID	-1.1489**	-1.7318**	-0.5727*						
	(0.536)	(0.872)	(0.326)						
COVID				0.5260	0.8719	0.3166			
				(0.456)	(0.758)	(0.273)			
RU-War							1.0031	1.4970	0.3225
							(0.735)	(1.237)	(0.432)
HHI-Deposit x Pre-COVID	6.6669**	5.3667	7.5329***						
	(2.779)	(4.509)	(1.642)						
HHI-Deposit x COVID				-9.4404***	-11.6877**	-6.5622***			
				(2.827)	(4.557)	(1.687)			
HHI-Deposit x RU-War							4.0370	9.7872*	-2.1559
							(3.584)	(5.754)	(2.158)
Number of Observations	2,240	1,121	1,119	2,240	1,121	1,119	2,240	1,121	1,119
R-Squared	0.7605	0.7976	0.9076	0.7608	0.7980	0.9071	0.7600	0.7977	0.9059
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes. Table B6 presents the results of Equation (4), examining the relationship between FinTech loan entries and bank market concentration (HHI-Deposit).

$$Y_{s,t} = \alpha + \beta_1 \cdot HHI_{s,t} + \beta_2 \cdot TimePeriod + \beta_3 \cdot HHI_{s,t} \times TimePeriod + \delta \cdot Controls_{s,t} + FEs + \varepsilon_{s,t} \quad (4)$$

Columns 1 to 3 report results for the Pre-COVID period, columns 4 to 6 display findings for the COVID, and columns 7 to 9 illustrate outcomes for RU-War period. Control variables, as specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table B7: Average loan size and Bank Market Concentration

	Dependent Variable: FinTech Loan Amount / Numbers								
	Pre-COVID			**COVID**			**RU-War**		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HHI-Deposit	-0.0412^{**}	-0.0679^{***}	-0.0183	-0.0164	-0.0361^{*}	0.0002	-0.0209	-0.0305	-0.0142
	(0.017)	(0.019)	(0.025)	(0.017)	(0.019)	(0.024)	(0.017)	(0.019)	(0.025)
Pre-COVID	-0.2910	-0.5507^{*}	0.0979						
	(0.254)	(0.303)	(0.362)						
COVID				0.2130	0.5354^{**}	-0.0608			
				(0.180)	(0.208)	(0.257)			
RU-War							-0.0646	-0.5203^{*}	0.1312
							(0.256)	(0.292)	(0.367)
HHI-Deposit x Pre-COVID	0.0119^{**}	0.0103^{*}	0.0128^{*}						
	(0.005)	(0.005)	(0.007)						
HHI-Deposit x COVID				-0.0193^{***}	-0.0303^{***}	-0.0072			
				(0.005)	(0.006)	(0.007)			
HHI-Deposit x RU-War							0.0128^{*}	0.0404^{***}	-0.0152
							(0.008)	(0.008)	(0.011)
Number of Observations	2,240	1,121	1,119	2,240	1,121	1,119	2,240	1,121	1,119
R-Squared	0.8803	0.9116	0.8932	0.8803	0.9123	0.8929	0.8804	0.9128	0.8930
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes. Table B6 presents the results of Equation (4), examining the relationship between Average FinTech loan Sizes and bank market concentration (HHI-Deposit).

$$Y_{s,t} = \alpha + \beta_1 \cdot HHI_{s,t} + \beta_2 \cdot TimePeriod + \beta_3 \cdot HHI_{s,t} \times TimePeriod + \delta \cdot Controls_{s,t} + FEs + \varepsilon_{s,t} \quad (4)$$

Columns 1 to 3 report results for the Pre-COVID period, columns 4 to 6 display findings for the COVID, and columns 7 to 9 illustrate outcomes for RU-War. Control variables, as specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table B8: Relationship Between FinTech Loan Amounts and Bank Loan

	Dependent Variable: FinTech Loan Amount								
	Pre-COVID			**COVID**			**RU-War**		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank Loan	-0.0022	0.0251***	-0.0136**	-0.1107***	-0.1095***	-0.1160***	-0.0365***	-0.0361***	-0.0379***
	(0.005)	(0.009)	(0.007)	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)	(0.003)
Pre-COVID	1.0272***	1.4134***	0.9874***						
	(0.049)	(0.103)	(0.075)						
COVID				-2.0358***	-2.1739***	-2.0288***			
				(0.021)	(0.056)	(0.034)			
RU-War							1.4060***	1.4494***	1.3103***
							(0.056)	(0.074)	(0.091)
Bank Loan x Pre-COVID	-0.0903***	-0.1256***	-0.0871***						
	(0.004)	(0.009)	(0.007)						
Bank Loan x COVID				0.1907***	0.2026***	0.1906***			
				(0.002)	(0.005)	(0.003)			
Bank Loan x RU-War							-0.1337***	-0.1376***	-0.1251***
							(0.005)	(0.007)	(0.008)
Number of Observations	2,240	1,121	1,119	2,240	1,121	1,119	2,240	1,121	1,119
R-Squared	0.7471	0.7724	0.7433	0.7702	0.7864	0.7720	0.7189	0.7153	0.7268
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State	State	State	State

Notes. Table B8 presents the results of Equation (5), examining the relationship between total FinTech loan amounts (in millions) and bank loans.

$$Y_{s,t} = \alpha + \beta_1 \cdot BankLoan_{s,t} + \beta_2 \cdot TimePeriod + \beta_3 \cdot BankLoan_{s,t} \times TimePeriod + \delta \cdot Controls_{s,t} + FEs + \varepsilon_{s,t} \quad (5)$$

Columns 1 to 3 report results for the Pre-COVID period, columns 4 to 6 display findings for the COVID, and columns 7 to 9 illustrate outcomes for RU-War. Control variables, as specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table B9: FinTech Loan Activities and Bank Market Concentration

	Dependent Variables					
	FinTech Loan Origination Numbers			FinTech Loan Amount / Numbers		
	Overall	First-Time	Repeat	Overall	First-Time	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)
HHI Branches	0.5328***	0.4969***	0.2586***	0.0205***	0.0350***	0.0044
	(0.036)	(0.043)	(0.070)	(0.004)	(0.005)	(0.011)
Post-COVID	1.9094***	2.8860***	1.2008***	0.3216	0.5772	0.0942
	(0.344)	(0.445)	(0.344)	(0.203)	(0.348)	(0.196)
HHI Branches x Post-COVID	-0.3919***	-0.5368***	-0.2885***	-0.0556**	-0.0514**	-0.0388
	(0.019)	(0.027)	(0.042)	(0.021)	(0.022)	(0.025)
Number of Observations	2,240	1,121	1,119	2,240	1,121	1,119
R-Squared	0.8953	0.9117	0.9365	0.8862	0.9216	0.8982
Constant	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Year-Qtr FE	YES	YES	YES	YES	YES	YES
Borrower State	YES	YES	YES	YES	YES	YES
Cluster	State	State	State	State	State	State

Notes. Table B9 presents the results of Equation (4), examining the relationship between FinTech Loan Origination Numbers and Average FinTech loan Sizes and bank market concentration (HHI-Branches).

$$Y_{s,t} = \alpha + \beta_1 \cdot HHI_{s,t} + \beta_2 \cdot TimePeriod + \beta_3 \cdot HHI_{s,t} \times TimePeriod + \delta \cdot Controls_{s,t} + FEs + \varepsilon_{s,t} \quad (4)$$

Columns 1 to 3 report results for FinTech Loan Origination Numbers, and columns 4 to 6 display findings for Average FinTech loan Sizes. Control variables, as specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.

Table B10: FinTech Loan Activities and Bank Market Concentration

Dependent Variable: FinTech Loan Amount			
	Overall	First-Time	Repeat
	(1)	(2)	(3)
Bank Loan	-0.0992***	-0.1030***	-0.1003***
	(0.002)	(0.003)	(0.002)
Post-COVID	-1.5153***	-1.5897***	-1.4952***
	(0.014)	(0.043)	(0.028)
Bank Loan x Post-COVID	0.1465***	0.1539***	0.1446***
	(0.001)	(0.004)	(0.003)
Number of Observations	2,240	1,121	1,119
R-Squared	0.7288	0.7292	0.7388
Constant	YES	YES	YES
Controls	YES	YES	YES
Year-Qtr FE	YES	YES	YES
Borrower State	YES	YES	YES
Cluster	State	State	State

Notes. Table B10 presents the results of Equation (5), examining the relationship between total FinTech loan amounts (in millions) and bank loans.

$$Y_{s,t} = \alpha + \beta_1 \cdot BankLoan_{s,t} + \beta_2 \cdot TimePeriod + \beta_3 \cdot BankLoan_{s,t} \times TimePeriod + \delta \cdot Controls_{s,t} + FEs + \varepsilon_{s,t} \quad (5)$$

Columns 1 to 3 report results for Post-COVID. Control variables, as specified in Section 5.1, include the FICO credit score (borrower quality), debt-to-income ratio (consumer leverage), the natural logarithm of borrower income (ln(income)), the natural logarithm of credit history (ln(years in market)), employment duration (ln(employment)), home ownership, and the U.S. federal interest rate. All regressions incorporate year-quarter and state fixed effects, with standard errors clustered at the state level.