Working Paper presented at the

Peer-to-Peer Financial Systems 2026 Workshop

June 2026

Credit market competition and the agency costs of tiered loan guarantees

Sonny Biswas

–

Min Park

–

Ziqing Yuan

–

Powered by

Credit market competition and the agency costs of tiered loan guarantees[*]

Sonny Biswas[†] Min Park[‡] Ziqing Yuan [§]

April 3, 2026

Abstract

We study how credit market competition affects loan guarantee programs with tiered guarantee rates. Using staggered peer-to-peer (P2P) lender entry across U.S. states, we find that fintech entry lowers borrower quality in the SBA 7(a) loan guarantee program, raising default probabilities and charge-off rates – consistent with fintech cream-skimming. In response, participating lenders, especially those with greater autonomy, concentrate riskier borrowers in the smaller, more heavily guaranteed loan segment, generating bunching just below the threshold above which the guarantee rate falls. Thus, competition and tiered guarantee design interact in ways that undermine fiscal neutrality and intensify agency frictions.

JEL Classification: G21, H81, G28

Keywords: Banking, Agency Conflict, Government Loan Guarantees, Market Competition, FinTech Entry

[*]Acknowledgments. We are grateful to Hans Degryse, Eli Fich, Andrea Gamba, Julian Neira, Michelle Pelli, Rish Singhania. We are also thankful for the helpful comments received from the participants of 2025 Annual Workshop on Applied Economics (AWAE). All errors remain our own. Declarations of interest: none.

[†]Henley Business School, University of Reading. s.biswas@henley.ac.uk.

[‡]University of Bristol Business School. min.park@bristol.ac.uk.

[§]Henley Business School, University of Reading. ziqing.yuan@pgr.reading.ac.uk.

1 Introduction

Government credit guarantee programs expand access to financing for borrowers who cannot obtain credit from conventional sources. By design, these programs delegate loan origination and screening to private intermediaries while the government absorbs default losses – an arrangement that creates inherent agency frictions and makes program performance sensitive to lenders' incentives and the competitive environment in which they operate. A second layer of agency conflict, less studied, arises when guarantee rates vary across loan segments: lenders may strategically exploit the tiered structure to maximize coverage rather than to allocate credit efficiently. We study how increased competition in credit markets reshapes these incentives, focusing on the interaction between lender screening behavior and tiered guarantee design.

The U.S. Small Business Administration (SBA) 7(a) loan program offers an ideal empirical setting. The program partially guarantees loans originated by private lenders to firms that cannot obtain credit elsewhere, and by statute it must operate on a zero-subsidy basis – making its fiscal integrity a matter of sustained policy attention.[1] We show that fintech entry into local credit markets intensifies competition and erodes the average quality of borrowers remaining in the SBA pool. This deterioration in pool quality induces lenders to strategically reallocate riskier borrowers toward the smaller, more heavily guaranteed loan segment, increasing the program's exposure to losses while shrinking its overall scale.

To organize these ideas, we develop a stylized model of tiered loan guarantees under competition. Banks choose between larger loans with lower guarantee coverage and smaller loans with higher coverage, and acquire information in two stages: an initial screening stage that determines whether to lend, and a second stage that determines loan size. When guarantee rates decline with loan size, second-stage screening introduces a new distortion: banks may strategically downsize loans to access higher coverage. If fintech lenders selectively attract safer borrowers, the residual pool deteriorates, raising the value of second-stage screening and inducing banks to shift more borrowers into the smaller, more heavily guaranteed segment. This produces bunching of loan originations just below guarantee thresholds. The distortion is strongest among lenders with the greatest discretion over lending decisions, and while the guaranteed share per loan rises, total

[1] https://bidenwhitehouse.archives.gov/wp-content/uploads/2023/04/Small-Business-Report.pdf
https://www.sba.gov/article/2025/05/19/sba-overhauls-reckless-biden-era-lending-program

program scale may fall. Our model thus connects competitive entry in credit markets to lender screening incentives and the consequences of tiered guarantee design.

We test these predictions by exploiting the staggered adoption of peer-to-peer (P2P) lending across U.S. states as a source of variation in credit market competition. The SBA 7(a) program is explicitly designed as a lender of last resort, restricting eligibility to borrowers who *"are not able to obtain the desired credit on reasonable terms from non-Federal, non-State, and non-local government sources."*[2] This borrowing hierarchy is central to our identification: if fintech lenders can identify and serve high-quality borrowers who would otherwise turn to SBA-guaranteed lending, their entry mechanically lowers the average quality of the pool ultimately applying to the program. A deteriorating application pool, in turn, alters the screening incentives of participating lenders.

Using the staggered timing of P2P entry across states in a difference-in-differences framework, we find that entry significantly worsens the quality of borrowers in the SBA 7(a) program. SBA-backed loans originated after P2P entry exhibit substantially higher default probabilities – 1.8 percentage points higher at the loan level and 1.5 percentage points higher at the bank level – and higher charge-off rates, while average loan size declines. Because SBA eligibility requires exhausting alternative funding sources, these patterns are consistent with P2P entry drawing away the strongest borrowers and leaving a riskier residual pool for the program.

We then turn to the bunching analysis. The SBA 7(a) program features a tiered guarantee structure, with guarantee rates declining discretely at subprogram-specific loan-size thresholds (e.g., from 85% to 75% for loans above the threshold of $150,000 in 7(a) Small Loans, and from 90% to 75% for loans above the threshold of $350,000 in 7(a) Export Express Loans). Exploiting these discontinuities collectively, we find a pronounced increase in loan originations just below the relevant guarantee cutoffs following P2P entry-consistent with lenders strategically downsizing loans to maximize guarantee coverage as competition erodes pool quality. Default rates rise disproportionately for loans clustered in these regions, confirming that the bunching reflects deteriorating borrower quality rather than benign compositional shifts. Taken together, the results indicate that P2P entry induces both a decline in aggregate borrower quality and intensified within-pool cream-skimming by SBA lenders.

Finally, we sharpen identification by comparing two types of participating lenders that differ

[2]https://www.sba.gov/funding-programs/loans/7a-loans

in their delegated authority. The SBA classifies lenders as Preferred Lender Program (PLP) institutions – which have full authority to make credit decisions independently – and non-PLP institutions, whose applications are evaluated directly by the SBA. This distinction constrains non-PLP lenders' ability to exploit guarantee coverage strategically. We find that the quality deterioration following P2P entry is significantly larger among PLP lenders: default rates rise by 2.14 percentage points for PLP originations versus 1.54 percentage points for non-PLP loans, a difference of roughly 40 percent. A similar pattern holds for charge-off rates. This cross-lender evidence confirms that agency conflicts are amplified when the guarantor delegates the lending decision – and that the distortions we document are not merely compositional, but reflect strategic lender behavior.

Our findings carry broader implications for the design and oversight of government lending programs. When guarantee rates vary with loan size, competition can interact with program structure in ways that undermine fiscal integrity: lenders respond to an eroding borrower pool by exploiting the guarantee schedule to shift risk onto the government. Preserving budget neutrality under competitive pressure may therefore require not only tighter oversight of loan origination but also attention to how guarantee tiers create room for strategic manipulation. The results highlight that competition in credit markets and guarantee design are not independent – their interaction shapes lender behavior in ways that standard models of delegated screening do not capture.

Related literature.

We contribute to two separate strands of literature: government credit guarantees and fintech lending.

A first set of papers examines the effects of government loan guarantees on credit supply and real activity. SBA guarantees increase lending by reducing expected losses and relaxing collateral constraints (Brau and Osteryoung, 2001; Bachas et al., 2021), and regional evidence links SBA lending to positive real outcomes (Craig, Jackson, and Thomson, 2007). However, partial guarantees also reallocate risk and may distort screening incentives: several studies document elevated default rates and risk-shifting under higher guarantee intensity (Glennon and Nigro, 2005; Gropp, Gruendl, and Guettler, 2014), and recent work shows that the incidence of credit guarantees depends on market structure, with benefits accruing disproportionately to lenders rather than borrowers (Martin, Mayordomo, and Vanasco, 2025). Most of this literature takes the competitive landscape as given. We depart from this assumption by showing that competitive entry reshapes the borrower pool and, in turn, lenders' incentives to exploit guarantee structures.

A second strand examines the effects of the rise of fintech lending on credit markets. Digital platforms use alternative screening technologies and non-traditional data sources (Iyer et al., 2016; Berg et al., 2020), and may either substitute for or segment alongside banks depending on the market (De Roure et al., 2022; Tang, 2019; Buchak et al., 2018). Even where banks retain market share, fintech entry induces incumbents to adjust pricing, processing speed, and screening standards (Erel and Liebersohn, 2022). This evidence establishes that competitive entry reshapes equilibrium lender behavior. Our finding that P2P entry materially affects the guaranteed loan segment is consistent with fintech and traditional bank technologies being complements rather than substitutes.

Despite this growing body of work, little research examines how fintech competition interacts with government-guaranteed lending programs. This intersection matters because fintech lenders, by selectively attracting the strongest borrowers, may deteriorate the composition of the residual pool applying for guaranteed credit – altering the screening environment facing program participants. We show that the lenders respond by concentrating riskier borrowers in the more heavily guaranteed loan segment, amplifying agency conflicts and raising the fiscal burden borne by the government.

2 Conceptual Framework

We develop a stylized model of bank screening under the SBA 7(a) loan guarantee program to motivate our empirical analysis. The model illustrates how the interaction between loan size-dependent guarantees and applicant pool quality amplifies agency conflicts, shaping loan allocation and program costs. It generates two key empirical predictions: (i) a concentration of loans just below the guarantee threshold following a decline in applicant pool quality, and (ii) stronger effects among banks with greater autonomy over lending decisions (PLP banks).

There is a continuum of penniless borrowers seeking financing from a bank to undertake a project. A borrower either has a good project or a bad project, but she does not know her type. Each project can be undertaken at a small scale, requiring 1 unit of investment, or at a large scale, requiring 2 units. A good project yields $X > 1$ in pledgeable output per unit of investment; a bad project produces 0. These borrowers cannot obtain credit elsewhere and therefore qualify for the SBA 7(a) program. The SBA covers a fraction of losses in the event of default: 1-unit loans obtain a guarantee covering ϕ_1, while 2-unit loans receive a lower guaranteed portion $\phi_2 < \phi_1 < 1$. The bank thus chooses between a 1-unit loan with a higher guarantee and a 2-unit loan with a lower guarantee. A fraction α of projects are good; because borrowers cannot obtain funds elsewhere, banks extract the full pledgeable output as repayment. We assume unconditional lending is unprofitable:

A1: $\alpha X - 1 < 0$

Given A1, the SBA must prevent unconditional lending to operate on a zero-subsidy basis.

When a borrower applies, the bank screens the project in two stages.

Stage 1 (Hard information). The screening technology entails a fixed installation cost that is sunk before the game begins, so the lending standard remains fixed regardless of applicant pool quality. The signal $s \in \{s_g, s_b\}$ is sufficiently informative that lending is profitable conditional on a favorable signal, and the bank approves the loan if and only if $s = s_g$:

$$\Pr(s = s_g \mid \text{project} = \text{good}) = \Pr(s = s_b \mid \text{project} = \text{bad}) = \beta \in \left(\frac{1}{2}, 1\right) \tag{1}$$

By Bayes' rule, the posterior probability that the project is good after observing s_g is:

$$\Pr(\text{project} = \text{good} \mid s_g) = \frac{\alpha\beta}{\alpha\beta + (1-\alpha)(1-\beta)} \equiv \mu \tag{2}$$

μ is increasing in the unconditional probability of a good project:

$$\frac{\partial \mu}{\partial \alpha} = \frac{\beta(1-\beta)}{(1-\alpha-\beta+2\alpha\beta)^2} > 0 \tag{3}$$

Lemma 1 *Given screening precision β, the posterior probability of a good project given a favorable signal, μ, is increasing in applicant pool quality α.*

We make the following parametric assumption:

A2: $2(\mu X + (1-\mu)\phi_2 - 1) > \mu X + (1-\mu)\phi_1 - 1 > 0$

A2 implies that, absent further screening, the bank prefers the larger 2-unit loan following a favorable first-stage signal.

Stage 2 (Soft information). If the first-stage signal is favorable, the bank may acquire soft information that further refines its estimate of project quality. This produces a second independent signal $\sigma \in \{\sigma_g, \sigma_b\}$ with precision $\gamma \in \left(\frac{1}{2}, 1\right)$. Taking μ as the prior, the updated posteriors are:

$$\Pr(\text{project} = \text{good} \mid s_g, \sigma_g) = \frac{\mu\gamma}{\mu\gamma + (1-\mu)(1-\gamma)} \equiv \mu_H \tag{4}$$

$$\Pr(\text{project} = \text{bad} \mid s_g, \sigma_b) = \frac{(1-\mu)\gamma}{(1-\mu)\gamma + \mu(1-\gamma)} \equiv \mu_L \tag{5}$$

We assume $\mu_L > \alpha$, so that even an unfavorable second-stage signal leaves lending viable, though now optimally at the smaller scale to benefit from the higher guarantee rate. The cost of second-stage screening, k_i, varies across banks, is uniformly distributed on $[0,1]$, and is uncorrelated with project type. If the bank does not screen at the second stage, it extends the larger loan with the smaller guarantee.

The bank screens at the second stage if:

$$\begin{aligned} &2\Pr(\sigma_g)\left[\mu_H(X-1) + (1-\mu_H)(\phi_2 - 1)\right] + \Pr(\sigma_b)\left[\mu_L(\phi_1 - 1) + (1-\mu_L)(X-1)\right] - k_i \\ &\geq 2\left[\mu(X-1) + (1-\mu)(\phi_2 - 1)\right] \end{aligned}$$

The left-hand side is the bank's expected profit from second-stage screening: a favorable signal arrives with probability $\Pr(\sigma_g) = \mu\gamma + (1-\mu)(1-\gamma)$, yielding a large loan with SBA coverage ϕ_2; an unfavorable signal arrives with probability $\Pr(\sigma_b) = (1-\mu)\gamma + \mu(1-\gamma)$, yielding a small loan with higher coverage ϕ_1. The right-hand side is the profit from extending a large loan to all first-stage approvals, saving the screening cost. Simplifying, the bank screens if:

$$k_i \leq \mu(X-1)(\gamma-1) + \gamma(1-\mu)(\phi_1 - 2\phi_2 + 1) \equiv k^* \tag{6}$$

Since $k_i \sim U[0,1]$, a fraction k^* of first-stage approvals are screened at the second stage and receive a large loan only if $\sigma = \sigma_g$; the remaining $1-k^*$ receive large loans unconditionally. Taking the derivative of k^* with respect to α:

$$\frac{dk^*}{d\alpha} = \left[\underbrace{(X-1)(\gamma-1)}_{<0} - \underbrace{\gamma(\phi_1 - 2\phi_2 + 1)}_{>0} \right] \underbrace{\frac{d\mu}{d\alpha}}_{>0} < 0 \tag{7}$$

Proposition 1 *An increase in applicant pool quality reduces second-stage screening and reduces the concentration of bad loans in the high-guarantee segment.*

The key mechanism is the interaction between second-stage screening and the differential guarantee rates. When $\phi_1 = \phi_2$, the bank faces no trade-off between loan sizes and never incurs the cost of second-stage screening — it simply extends a large loan to every first-stage approval. When $\phi_1 > \phi_2$, however, an unfavorable second-stage signal gives the bank an incentive to downsize the loan and access the higher guarantee. This creates two distinct layers of agency cost. The first is standard: guarantees induce the bank to approve loans that would otherwise be unprofitable. The second is novel: differential guarantee rates induce the bank to strategically allocate marginal borrowers into the smaller, more heavily guaranteed segment. Changes in applicant pool quality affect both layers — reducing α not only increases bad lending overall but reshapes its distribution across guarantee tiers, directly affecting program costs.[3]

Empirical mapping. Suppose fintech entry cream-skims a subset of good borrowers, reducing α. This lowers the bank's posterior μ, which raises the second-stage screening cutoff k^*: with fewer good borrowers in the pool, screening becomes more valuable as a means of avoiding large low-guarantee loans to bad borrowers. The fraction of bad borrowers obtaining small loans is $k^* \mu_L$; the fraction of good borrowers obtaining small loans is $k^*(1-\mu_L)$. Taking the derivative of $\Pr(\text{bad small loan})$ with respect to α:

$$\frac{\partial \Pr(\text{bad small loan})}{\partial \alpha} = \frac{\partial k^*}{\partial \alpha}\mu_L + \frac{\partial \mu_L}{\partial \alpha} k^* < 0 \tag{8}$$

Both terms are negative: $\frac{\partial k^*}{\partial \alpha} < 0$ and $\frac{\partial \mu_L}{\partial \alpha} < 0$.[4] As α falls, more bad borrowers concentrate in

[3] A utilitarian regulator may optimally tolerate this distortion if the net social surplus remains positive. From an ex ante perspective, the regulator sets a program access fee to ensure budget neutrality; if α changes, this fee must be adjusted accordingly.

[4] From the expression for μ_L, $\frac{\partial \mu_L}{\partial \alpha} = \frac{-(1-\gamma)\frac{\partial \mu}{\partial \alpha}}{[(1-\mu)\gamma + \mu(1-\gamma)]^2} < 0$.

the small-loan segment. Empirically, fintech entry reduces α, intensifies agency frictions, and generates bunching just below the size cutoff at which the guaranteed portion declines.

Prediction 1: An exogenous decline in α leads to bunching of loans just below the threshold, where the guarantee rate falls discretely from high guarantee to low guarantee.

Whether bunching increases or reduces overall program scale depends on two opposing forces — the gap in guarantee rates between tiers and the extent of loan downsizing — and is an empirical question we investigate below.

Prediction 2: The bunching effect will be stronger among PLP banks, which have full autonomy over lending decisions, than among non-PLP banks, whose loans are subject to direct SBA review. Direct SBA oversight mutes the second layer of agency conflict, limiting the bank's ability to strategically shift borrowers into the smaller, more heavily guaranteed segment.

3 Data and Identification Strategy

3.1 Data

Our primary dataset comprises 1.58 million SBA 7(a) loans obtained from the SBA's Freedom of Information Act (FOIA) database. The sample spans 1991 to 2019; we exclude 2019 onwards because LendingClub ceased small-business lending that year (Fintech Futures, 2019). The dataset records borrower and lender identities, addresses, industry codes, loan terms, guarantee amounts, ex-post performance, and lender delegation status.

Since the introduction dates of P2P lending in each state vary, we follow Cumming et al. (2022)'s work to determine the dates of P2P introduction in some states (for example, Kansas, North Carolina, Indiana, Mississippi, Tennessee, Idaho, Maine, Nebraska, North Dakota, Pennsylvania, West Virginia) by referring to the financial annual reports of Lending Club or Prosper, which are the largest online marketplaces in the US. For those states where the introduction dates of P2P could ont be determined from the annual report of Lending Club and Prosper, we confirmed the dates through the website announcements of WebBank (the intermediary institution through which all P2P loans were facilitated, based on the LendingClub IPO filing). Iowa's P2P introduction date (2023) falls outside the sample window and is therefore treated as a non-adopting state.

Insert Tables 1 here

Table 1 shows the summary statistics of the main variables in regression analysis. We measure the qualities of SBA loans using the detailed information on the loan (loan amount, charge-off rate, guaranteed approval amount, defaults, percentage of loans which amount is above the guaranteed threshold).

3.2 Identification

To examine how P2P entry reshapes incentives and outcomes under government loan guarantees, we employ a quasi-experimental framework that leverages the staggered legalization of P2P lending across U.S. states. Our empirical design evaluates whether P2P entry constitutes a negative composition shock to the SBA 7(a) program and whether participating lenders respond by strategically adjusting origination behavior under the program's guarantee structure. We estimate causal effects using a staggered difference-in-differences (DID) approach following Callaway and Sant'Anna (2021), combined with a border discontinuity design to strengthen identification. Because states adopted P2P lending regulations at different times, the staggered DID framework allows us to account for heterogeneous treatment timing while preserving valid comparisons across treated and not-yet-treated states. The DID framework exploits variation in both the timing and location of P2P market entry. States that legalize P2P lending constitute treated units, while states without adoption during the sample window serve as controls. We identify adoption dates using regulatory filings and financial disclosures from LendingClub, Prosper, and WebBank, complemented by state-level announcements. Since regulatory timing is largely driven by legislative processes rather than contemporaneous SBA loan outcomes, P2P entry generates plausibly exogenous shocks to local traditional credit markets. We estimate the following staggered DID model:

$$\textit{Loan Quality}i,s,t = \alpha + \beta Treatment s,t + \gamma X_{i,t} + \delta_i + \lambda_t + \mu s + \theta i + \varepsilon_{i,t} \tag{9}$$

where $\textit{Loan Quality}_{i,s,t}$ measures the performance and risk characteristics of a loan issued by bank i in borrower state s at time t. Loan quality is captured using ex post outcomes-including default rates, charge-off rates, realized loss amounts borne by banks and by the SBA-as well as loan size and guarantee intensity. A deterioration in these measures following P2P entry would indicate that higher-quality borrowers migrate to alternative credit channels, leaving a weaker applicant pool within the guaranteed segment. $Treatment_{s,t}$ equals one if P2P lending has entered state s by time t. Identification relies on differences in loan outcomes before and after P2P entry relative to states that have not yet experienced entry. $X_{i,t}$ includes time-varying bank characteristics and macroeconomic controls. Bank fixed effects δ_i absorb time-invariant heterogeneity across lenders; year fixed effects λ_t capture aggregate trends; and borrower-state fixed effects μ_s control for persistent cross-state differences. In loan-level regressions, we further include industry and bank-location fixed effects to mitigate concerns about differential industry composition or geographic exposure.

To sharpen identification, we implement a border discontinuity design that restricts the sample to borrowers located within a 10-mile radius of borders separating treated and untreated states (Cumming et al., 2022). This restriction ensures that treatment and control observations are drawn from geographically proximate and economically comparable regions, strengthening the counterfactual and alleviating concerns that unobserved state-level heterogeneity drives the results.

To examine whether lenders engage in cream-skimming of good quality borrowers by strategically securing higher guarantee level for poorer quality loans, we analyze origination behavior around the loan size thresholds that separate high guarantee and low guarantee coverages. If intensified screening is disproportionately directed toward protecting lenders' unguaranteed exposure, we expect loan originations to cluster just below the higher-coverage threshold. Such behavior would be consistent with selective origination designed to maximize guarantee protection within a deteriorating borrower pool.

Following Bachas et al. (2021), we conduct a bunching analysis by fitting a smooth counterfactual distribution of loan amounts and estimating excess density around the threshold. We exclude a narrow symmetric window around the cutoff when fitting the counterfactual to avoid mechanical mass-point distortions. Beyond loan density, we examine whether defaults and realized losses also cluster around the threshold. Because losses on the guaranteed portion are borne by the SBA, evidence of excess origination and elevated default risk just below the cutoff would indicate that competitive pressure amplifies the strategic use of guarantee coverage and shifts incremental downside risk toward the government.

By linking changes in overall loan quality to threshold-level origination behavior and realized loss allocation, this framework allows us to assess whether P2P entry intensifies agency conflicts embedded in the guarantee structure.

4 Results

4.1 Loan Size and Performance

P2P entry significantly reshapes SBA 7(a) lending along three dimensions: loan size, loan performance, and the distribution of loans across guarantee tiers. We document each in turn.

Table 2 reports the effect of P2P entry on SBA lending volume and average loan size. At the bank-borrower state level, P2P introduction is associated with a coefficient of -0.182 on log total gross approval amount, statistically significant at the 1 percent level. This estimate implies an economically significant decline of approximately 16.6 percent ($e^{-0.182} - 1$ = -0.166) in aggregate SBA loan volume following P2P entry. At the loan level, average loan size falls by about 6 percent points after P2P entry, also statistically significant.

To validate these findings, Panel B implements the border discontinuity design by restricting the sample to borrowers located within 10 miles of state borders separating treated and untreated states. Within this geographically narrow band-where local economic and demographic conditions are plausibly comparable-the reductions in aggregate loan volume and average loan size remain quantitatively similar and statistically significant. This consistency strengthens the causal interpretation by mitigating concerns that differential state-level economic trends drive the results. Overall, the decline in loan size is consistent with stronger borrowers migrating to P2P platforms, leaving a smaller-loan residual pool in the SBA program.

Table 3 turns to loan performance. At the bank-borrower state level, P2P entry increases the SBA default rate by 1.5 percentage points and the average charge-off rate by 1.1 percentage points, both significant at the 1 percent level. Relative to a baseline default rate of approximately 1 percent in the full sample, these effects represent a substantial proportional increase in realized credit risk. Loan-level estimates reinforce this pattern: loans originated after P2P entry are 1.8 percentage points more likely to default and exhibit charge-off rates higher by 1.7 percentage points, with strong statistical significance. The border discontinuity results again mirror the baseline estimates in magnitude and significance, confirming that the deterioration in performance is not driven by broader state-level shocks. Taken together, the evidence indicates that credit risk within the SBA program rises following P2P introduction, consistent with a worsening of the borrower pool remaining in the guaranteed segment.

Insert Tables 2, 3 and 4 here

Table 4 examines whether P2P entry alters the distribution of lending across guarantee categories. At the bank-borrower state level, the share of large loans-those receiving lower guarantee coverage-declines by 1.9 percentage points after P2P entry, significant at the 1 percent level. This result holds in both the full sample and the 10-mile border sample. The shift away from larger, lower-guarantee loans toward smaller, more heavily guaranteed loans suggests that competitive pressure interacts with the program's stepwise guarantee structure. As relatively stronger firms migrate to P2P platforms, demand for larger SBA loans may weaken, while the guarantee schedule may incentivize lenders to concentrate originations in segments with higher public coverage.

Across Tables 2-4, P2P entry is associated with (i) a significant contraction in loan size, (ii) a marked deterioration in loan performance, and (iii) a reallocation of lending toward more heavily guaranteed loans. The consistent results within the geographically restricted border sample strengthen the causal interpretation. Collectively, the findings indicate that fintech entry reshapes the composition of SBA lending and increases realized credit risk within the guaranteed segment, while shifting a greater share of exposure into loans with higher public protection.

4.2 Bank losses vs. SBA losses

We next examine how P2P entry affects the allocation of losses between banks and the SBA. Using the data on SBA loans' charge-off amount, we calculate the losses to banks and SBA in the following way:

$$\mathit{BankLoss} = \min\left(\mathit{TotalChargeOff},\ \mathit{Nonguaranteed\ Portion\ of\ Loan}\right)$$

$$SBALoss = \max\left(TotalChargeOff - BankLoss,\ 0\right)$$

Table 5 reports the impact of P2P entry on bank and SBA loss rates at the bank-borrower state-year level. In the full sample, P2P entry increases bank losses by 0.449 percentage points and SBA losses by 0.672 percentage points, both significant at the 1 percent level. The magnitude of the effect on the SBA is roughly 50 percent larger than that on banks, indicating that a disproportionate share of the incremental credit deterioration is absorbed by the government guarantor.

Insert Table 5 here

The border discontinuity results are consistent, with effects even more pronounced: within 10 miles of state borders, bank losses rise by 0.468 percentage points, while SBA losses increase by 0.723 percentage points, again highly significant. The persistence and amplification of the asymmetry in geographically proximate areas strengthens the causal interpretation and mitigates concerns that the baseline estimates reflect cross-state heterogeneity.

This asymmetric allocation of losses is consistent with the model: banks bear initial losses only up to the unguaranteed portion, after which the SBA covers remaining defaults. Yet rather than screening more rigorously, the evidence suggests that banks respond to the deterioration in borrower quality by selectively intensifying screening and origination toward smaller, highly guaranteed loans, effectively offloading substantial downside risk to the SBA. In other words, competition-induced screening favors private lenders while the residual risk and associated fiscal burden is shifted to the public sector.

From a policy perspective, this dynamic raises concerns: while partial guarantees are intended to stabilize credit for underserved markets, P2P competition amplifies adverse selection within the SBA pool, increasing expected losses potentially borne by taxpayers. In practice, this raises the possibility that the 7(a) program may fall short of its intended zero-subsidy design, as competition clearly increases losses borne by the guarantor.

4.3 Preferred Lenders Programme (PLP) versus non-PLP

This section investigates how varying levels of delegation in SBA loan approvals between PLP and non-PLP lenders shape lending outcomes under competitive pressure. PLP lenders exercise broad authority over credit decisions, servicing, and liquidation, while non-PLP lenders must submit each loan for SBA review, creating natural variation in incentive alignment and exposure to moral hazard.

Using a staggered DID framework on split samples of PLP and non-PLP lenders, we find that P2P entry reduces SBA loan sizes and worsens ex-post loan performance across both groups, consistent with our hypothesis that fintech entry deteriorates the borrower pool in the guaranteed segment. Tables 6 and 8 show that, at the bank-borrower state level, total SBA gross approvals and guaranteed volumes decline by roughly 30% for PLP lenders versus 16.7% for non-PLP lenders, with large-loan incidence declining significantly only for PLP lenders. Loan-level results similarly show smaller average loan sizes for both groups, but the contraction is markedly stronger among PLP lenders.

Table 7 documents the deterioration in ex-post performance. Defaults increase by a larger magnitude for PLP lenders than non-PLP lenders, and charge-off rates follow the same pattern, indicating that delegated lenders face a weaker screening incentive under partial risk absorption. The results suggest that as higher-quality borrowers migrate to P2P platforms, the residual SBA pool becomes lower quality. PLP lenders, enjoying delegated authority and partial risk coverage, appear to respond by maintaining origination activity while focusing on smaller, highly guaranteed loans, effectively transferring a disproportionate share of downside risk to the government. Non-PLP lenders, constrained by SBA review requirements, show less pronounced adjustments in loan size and distribution.

Taken together, these patterns highlight a dual mechanism. First, competitive entry reallocates borrowers: better-qualified, growth-oriented firms self-select into P2P platforms, thinning the pool for SBA loans. Second, banks endogenously adjust lending behavior, particularly those with delegated authority, strategically concentrating on loans with higher guarantee coverage. This strategic downsizing protects banks from default risk but increases the fiscal exposure of the guarantor.

Table 9 explores the impact on SBA loss rates. Following P2P entry, SBA losses rise for both lender types, but the increase is substantially larger for PLP lenders. In the full sample, PLP lenders' SBA loss rates increase more than non-PLP lenders, and the Chow test confirms the differential effect is statistically significant. The border discontinuity estimates, restricting the sample to borrowers within 10 miles of state borders, reinforce these findings and show even more pronounced effects, lending credence to a causal interpretation that isolates competitive entry as the driver.

Insert Tables 6, 7, 8, and 9 here

Overall, these results are consistent with the predicted agency-cost channel. When banks hold delegated authority and only partially internalize loan losses, heightened screening under competition does not improve overall loan performance. Instead, it disproportionately favors the lender by concentrating on safer, smaller, highly guaranteed loans while residual risk is transferred to the SBA. From a policy perspective, this wedge highlights a tension inherent in the tiered guarantee design of 7(a) loans: while delegation encourages efficiency and faster loan processing, it can exacerbate moral hazard in competitive markets, amplifying fiscal exposure and reducing program effectiveness.

4.4 Bunching Analysis

To examine how institutional design interacts with P2P entry, we analyze loan distributions around the threshold separating high and low guarantee coverages. Figures 1-3 show a pronounced spike in loan originations just below the threshold in both the full sample and PLP/non-PLP subsamples, consistent with banks strategically resizing loans to maximize guarantee protection. We implement a structured bunching design, estimating a smooth counterfactual density by excluding a narrow symmetric band around the notch (e.g., \$143k-\$150k) to avoid mechanical clustering at exact threshold values, ensuring valid estimation of excess mass.

Insert Figures 1-3 here

Table 10 reports that although the absolute number of loans near the threshold is stable or slightly lower post-entry–reflecting reduced total SBA originations–the normalized bunching intensity rises materially. We use two measures of bunching intensity: Share CF (excess loans in the window divided by the counterfactual count) and Share Alt (excess mass divided by the expected mass if each bin equaled the average unaffected-region count). Share CF rises by 0.093, 0.091, and 0.325 and Share Alt rises by 0.146, 0.154, and 0.585 for the \$15k, \$10k, and \$5k window respectively, with narrower windows exhibiting more concentrated resizing.

Subsample analysis (Table 11) highlights heterogeneity across lender types. For PLP lenders, absolute excess loans in the bunching region decline, but ratio-based measures increase (e.g., Share Alt rises from 2.43 to 2.94 within the $5k window), reflecting tighter concentration among remaining originations. Non-PLP lenders, by contrast, show both higher absolute bunching and larger normalized measures, indicating broader shifts of originations toward the notch.

To assess risk implications, we examine default rates within the bunching windows, comparing observed rates to counterfactual benchmarks from unaffected regions (Figures 4-6; Tables 12-13). In the full sample, loans near the notch are safer than counterfactuals (negative uplift), but the safety advantage diminishes post-P2P entry, producing a positive pre-post differential across all window widths. This indicates that although notched loans remain comparatively safer, their relative quality deteriorates following competitive entry.

Subsample results underscore the role of delegation: for PLP lenders, post-entry loans near the notch not only concentrate more sharply (Figure 5) but also become riskier relative to the counterfactual, yielding large, positive Post-Pre differentials. For non-PLP lenders, default risk remains low in the notch region, with consistently negative Post-Pre differentials, suggesting that tighter SBA oversight preserves loan quality even under competition.

Insert Figures 4-6 here

Insert Tables 10, 11, 12 and 13 here

Together, the bunching results show that P2P entry intensifies strategic loan sizing around the guarantee notch. Lenders concentrate originations just below the loan size threshold to maximize guarantee coverage on loans of deteriorating quality, a pattern consistent with the second-stage screening mechanism in Section 2. The effect is particularly pronounced among PLP lenders, where delegated authority allows sharper notch targeting and produces an observable rise in default rates within the bunching region. Non-PLP lenders, subject to greater SBA oversight, exhibit less concentrated resizing and no corresponding deterioration in default risk near the notch.

5 Conclusion

We examine how competition in credit markets affects the performance of government-backed loan guarantee programs. Using the SBA 7(a) program as our empirical setting, we show that fintech entry into local credit markets deteriorates the composition of the SBA borrower pool, which in turn, reshapes the screening incentives of participating lenders. Our results reveal a novel mechanism: when guarantee rates vary with loan size, competition not only erodes the average borrower quality, but it also redirects lender effort toward coverage maximization, thereby amplifying agency frictions and potentially raising the fiscal burden borne by the guarantor. These findings highlight that competitive entry and tiered guarantee design interact in ways that standard models of delegated screening do not capture, with direct implications for the fiscal oversight of government-backed lending.

References

[1] Bachas, N., Kim, O. S., & Yannelis, C. (2021). Loan guarantees and credit supply. Journal of Financial Economics, 139(3), 872-894.

[2] Barrot, J. N., Martin, T., Sauvagnat, J., & Vallee, B. (2024). The labor market effects of loan guarantee programs. The Review of Financial Studies, 37(8), 2315-2354.

[3] Berg, T., Burg, V., Gombovic, A., & Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. The Review of Financial Studies, 33(7), 2845-2897.

[4] Bertoni, F., Colombo, M. G., & Quas, A. (2023). The long-term effects of loan guarantees on SME performance. Journal of Corporate Finance, 80, 102408.

[5] Brau, J. C., & Osteryoung, J. S. (2001). An empirical examination of SBA guaranteed loans: Rates, collateral, agency costs, and the time to obtain the loan. Journal of Entrepreneurial Finance, 6(1), 1-23.

[6] Broecker, T. (1990). Credit-worthiness tests and interbank competition. Econometrica: Journal of the Econometric Society, 429-452.

[7] Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. Journal of financial economics, 130(3), 453-483.

[8] Craig, B. R., Jackson III, W. E., & Thomson, J. B. (2007). Small firm finance, credit rationing, and the impact of SBA-guaranteed lending on local economic growth. Journal of small business management, 45(1), 116-132.

[9] Cumming, D., Farag, H., Johan, S., & McGowan, D. (2022). The digital credit divide: Marketplace lending and entrepreneurship. Journal of Financial and Quantitative Analysis, 57(7), 2659-2692.

[10] Dell'Ariccia, G., & Marquez, R. (2004). Information and bank credit allocation. Journal of financial Economics, 72(1), 185-214.

[11] Dell'Ariccia, G., & Marquez, R. (2006). Lending booms and lending standards. The journal of finance, 61(5), 2511-2546.

[12] DeYoung, R., Glennon, D., & Nigro, P. (2008). Borrower-lender distance, credit scoring, and loan performance: Evidence from informational-opaque small business borrowers. Journal of Financial Intermediation, 17(1), 113-143.

[13] De Roure, C., Pelizzon, L., & Thakor, A. (2022). P2P lenders versus banks: Cream skimming or bottom fishing?. The Review of Corporate Finance Studies, 11(2), 213-262.

[14] Erel, I., & Liebersohn, J. (2020). Does fintech substitute for banks? evidence from the paycheck protection program (No. w27659). National Bureau of Economic Research.

[15] Glennon, D., & Nigro, P. (2005). Measuring the default risk of small business loans: A survival analysis approach. Journal of Money, Credit and Banking, 923-947.

[16] Glennon, D., & Nigro, P. (2005). An analysis of SBA loan defaults by maturity structure. Journal of Financial Services Research, 28(1), 77-111.

[17] Gropp, R., Gruendl, C., & Guettler, A. (2014). The impact of public guarantees on bank risk-taking: Evidence from a natural experiment. Review of Finance, 18(2), 457-488.

[18] Hauswald, R., & Marquez, R. (2006). Competition and strategic information acquisition in credit markets. The Review of Financial Studies, 19(3), 967-1000.

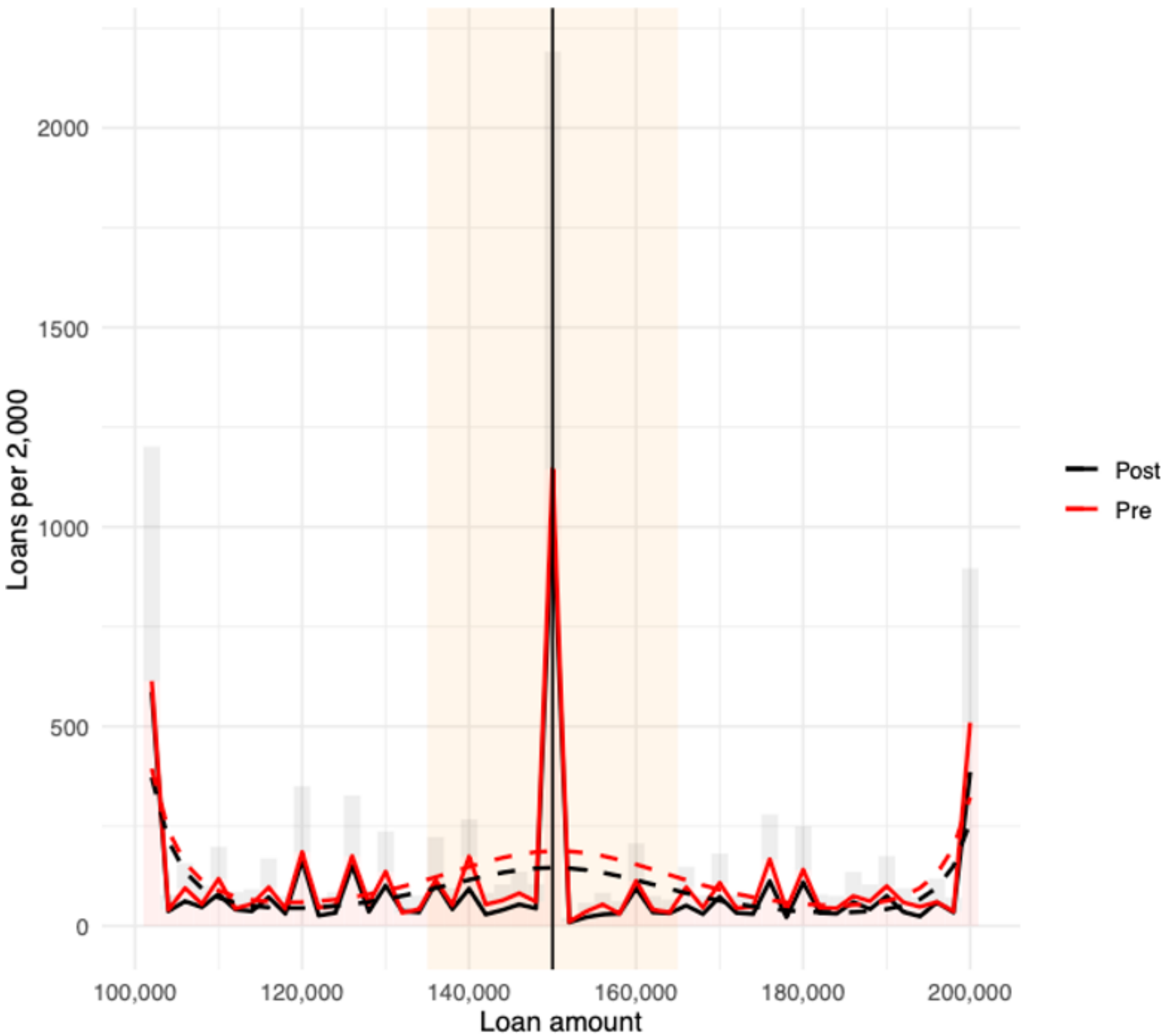
[19] Iyer, R., Khwaja, A. I., Luttmer, E. F., & Shue, K. (2016). Screening peers softly: Inferring the quality of small borrowers. Management Science, 62(6), 1554-1577.

[20] Lelarge, C., Sraer, D., & Thesmar, D. (2010). Entrepreneurship and credit constraints: Evidence from a French loan guarantee program. In International differences in entrepreneurship (pp. 243-273). University of Chicago Press.

[21] Martin, A., Mayordomo, S., & Vanasco, V. (2025). Banks vs. firms: who benefits from credit guarantees?. Working Paper.

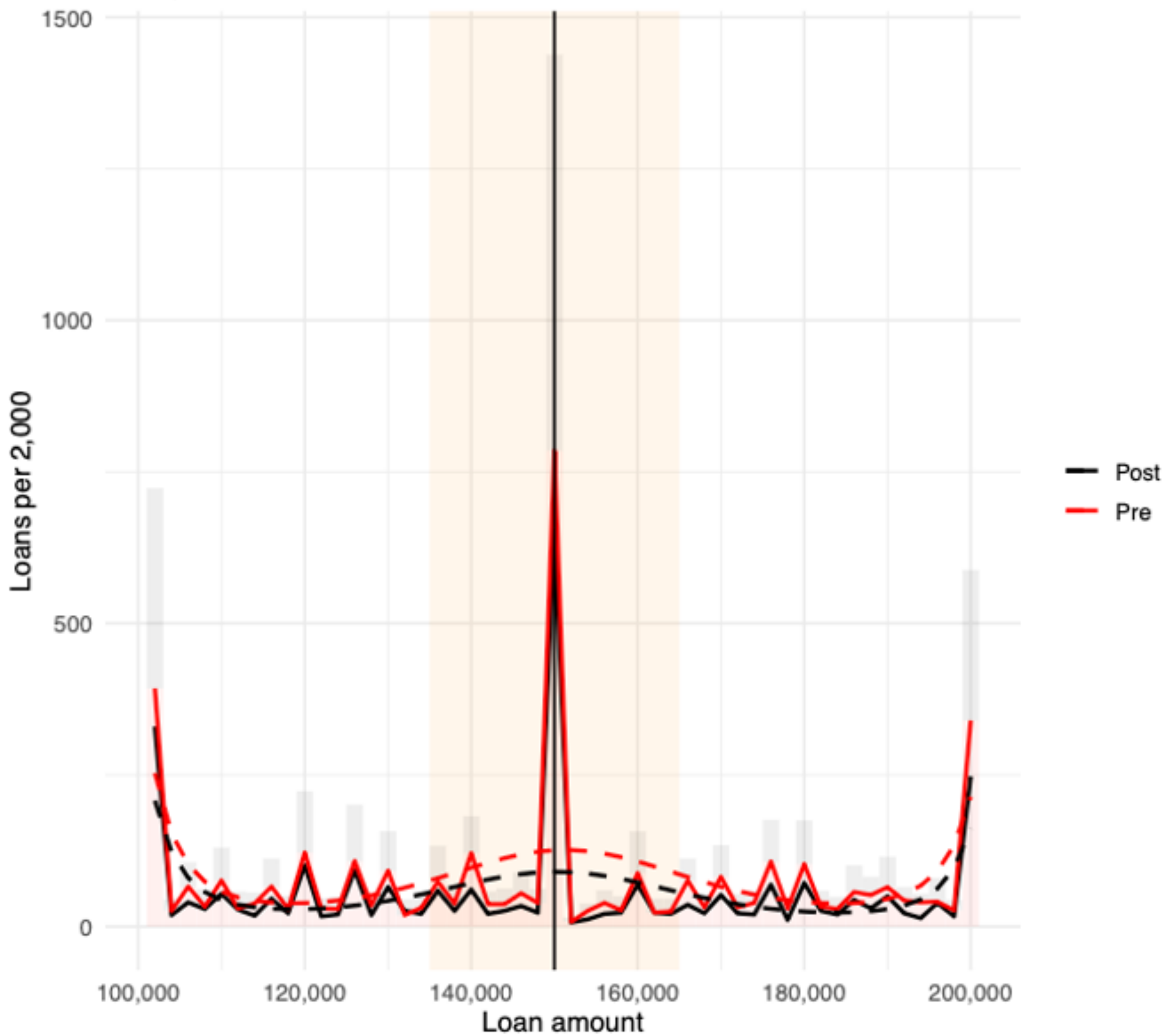
[22] Tang, H. (2019). Peer-to-peer lenders versus banks: substitutes or complements?. Review of Financial Studies, 32(5), 1900-1938.

Figure 1: Bunching at the guaranteed notch in full sample (number of loans)



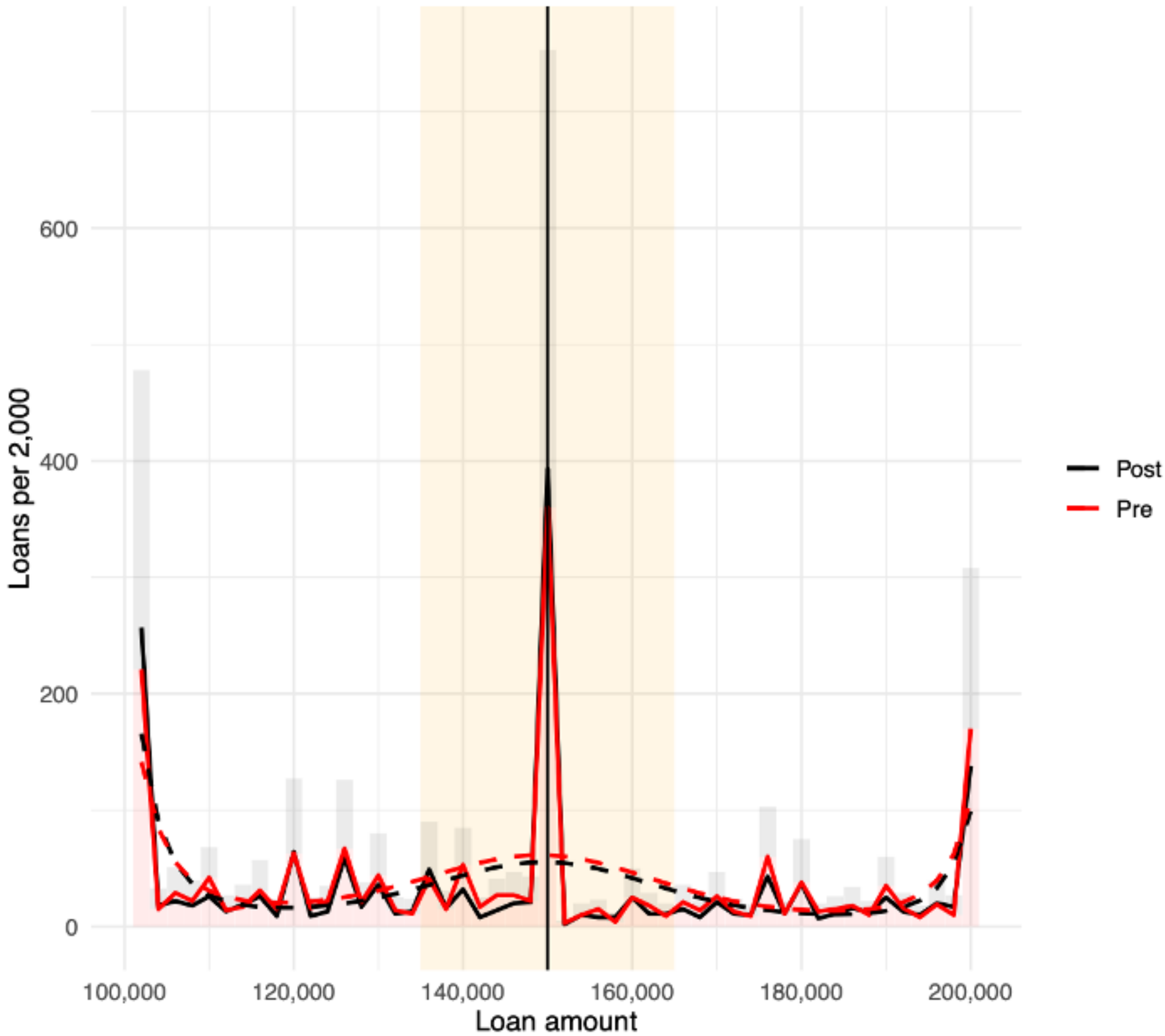
Notes: This figure plots the distribution of SBA loan amounts around the $150,000 guarantee notch for the full sample, which separates loans with a 85 percent SBA guarantee from those with a 75 percent guarantee. The figure reports the number of loans per $2,000 bin for the full sample, separately for the pre- and post-P2P entry periods. The vertical line indicates the $150,000 threshold.The figure reports the number of loans per bin separately for the pre- and post-P2P entry periods. Shaded bins denote a symmetric exclusion band around the notch, within which observations are excluded from the estimation of the counterfactual density.

Figure 2: Bunching at the guaranteed notch in PLP sample (number of loans)



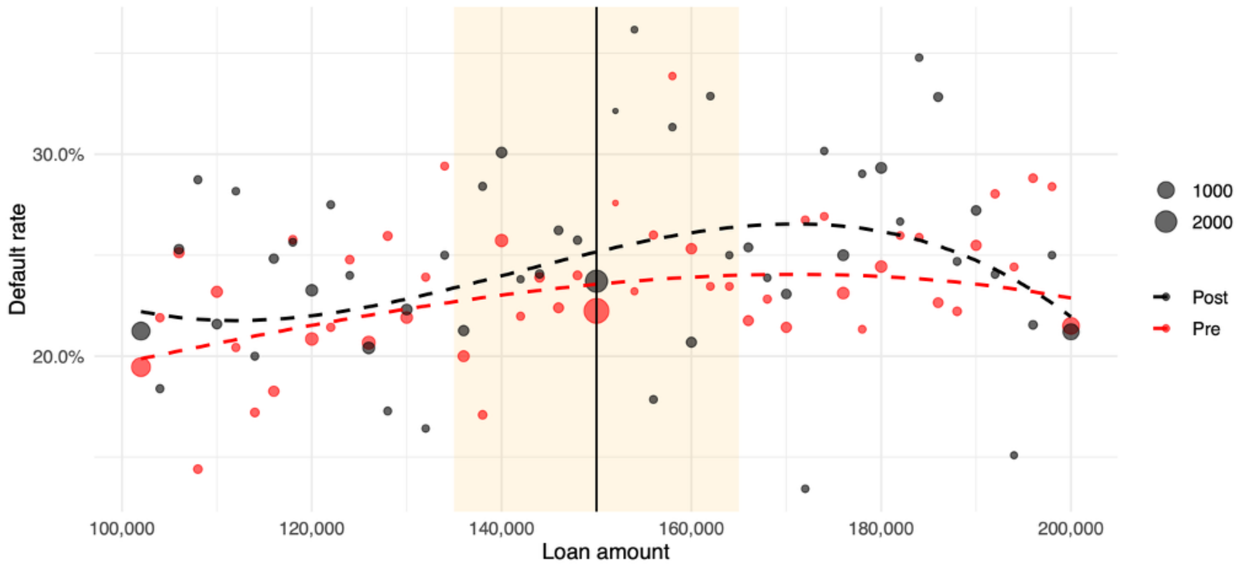
Notes: This figure plots the distribution of SBA loan amounts around the $150,000 guarantee notch for the subsample with PLP lenders, which separates loans eligible for a 85 percent SBA guarantee from those eligible for a 75 percent guarantee. Loan amounts are grouped into $2,000 bins, and the vertical line indicates the $150,000 threshold. The figure reports the number of loans per bin separately for the pre- and post-P2P entry periods. Shaded bins denote a symmetric exclusion band around the notch, within which observations are excluded from the estimation of the counterfactual density.

Figure 3: Bunching at the guaranteed notch in non-PLP sample (number of loans)



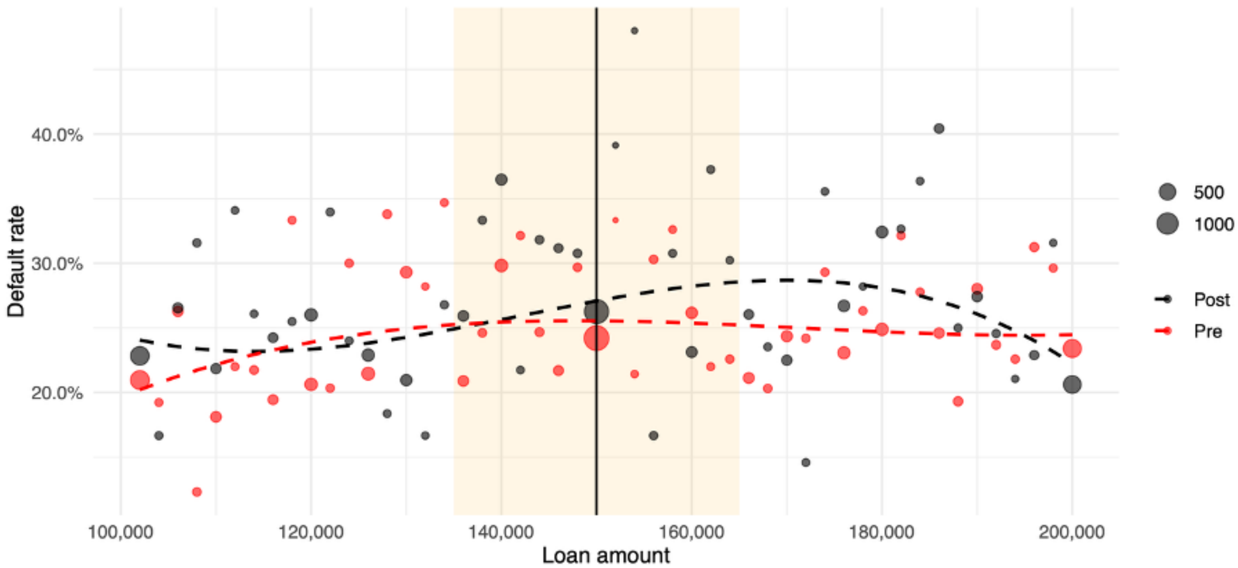
Notes: This figure plots the distribution of SBA loan amounts around the $150,000 guarantee notch for the subsample with non-PLP lenders, which separates loans eligible for a 85 percent SBA guarantee from those eligible for a 75 percent guarantee. Loan amounts are grouped into $2,000 bins, and the vertical line indicates the $150,000 threshold. The figure reports the number of loans per bin separately for the pre- and post-P2P entry periods. Shaded bins denote a symmetric exclusion band around the notch, within which observations are excluded from the estimation of the counterfactual density.

Figure 4: Default Rate: Full Sample



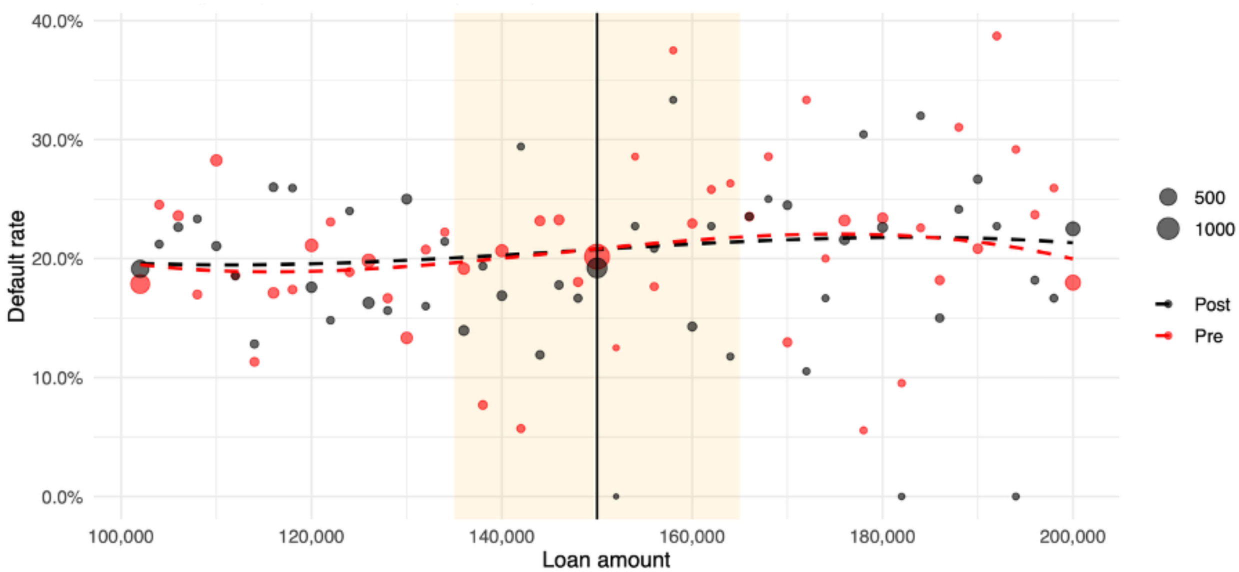
Notes: This figure shows how default risk varies with loan size around the $150,000 SBA guarantee notch in the full sample. The default rate is computed as the number of defaulted loans divided by the total number of loans within each loan-amount bin. Each dot corresponds to a loan-amount bin (e.g., $100k–$105k, $105k–$110k), and its vertical position indicates the observed default rate in that bin. Dot size reflects the number of loans in the bin. The solid points plot the observed default rates, while the dashed lines report smooth counterfactual default rates predicted from unaffected regions using the structured bunching framework. The vertical line marks the $150,000 threshold. Shaded bins denote a symmetric exclusion band around the notch that is excluded when fitting the counterfactual to avoid mechanical mass points at and immediately below the threshold, which would otherwise contaminate the fitted counterfactual. The figure is shown separately for the pre- and post-P2P entry periods.

Figure 5: Default Rate: PLP Lenders



Notes: This figure shows how default risk varies with loan size around the $150,000 SBA guarantee notch in subsample with PLP lender. The default rate is computed as the number of defaulted loans divided by the total number of loans within each loan-amount bin. Each dot corresponds to a loan-amount bin (e.g., $100k–$105k, $105k–$110k), and its vertical position indicates the observed default rate in that bin. Dot size reflects the number of loans in the bin. The solid points plot the observed default rates, while the dashed lines report smooth counterfactual default rates predicted from unaffected regions using the structured bunching framework. The vertical line marks the $150,000 threshold. Shaded bins denote a symmetric exclusion band around the notch that is excluded when fitting the counterfactual to avoid mechanical mass points at and immediately below the threshold, which would otherwise contaminate the fitted counterfactual. The figure is shown separately for the pre- and post-P2P entry periods.

Figure 6: Default Rate: Non-PLP Lenders



Notes: This figure shows how default risk varies with loan size around the $150,000 SBA guarantee notch in subsample with non-PLP lender. The default rate is computed as the number of defaulted loans divided by the total number of loans within each loan-amount bin. Each dot corresponds to a loan-amount bin (e.g., $100k–$105k, $105k–$110k), and its vertical position indicates the observed default rate in that bin. Dot size reflects the number of loans in the bin. The solid points plot the observed default rates, while the dashed lines report smooth counterfactual default rates predicted from unaffected regions using the structured bunching framework. The vertical line marks the $150,000 threshold. Shaded bins denote a symmetric exclusion band around the notch that is excluded when fitting the counterfactual to avoid mechanical mass points at and immediately below the threshold, which would otherwise contaminate the fitted counterfactual. The figure is shown separately for the pre- and post-P2P entry periods.

Table 1: Variable Descriptive Statistics

Variable	Obs.	Mean	Min	P5	P95	Max	SD
Panel A. Full sample							
Loan-level variables							
Loan size ($)	1,511,552.000	252,341.100	75.000	10,000.000	1,025,000.000	5,000,000.000	459,052.200
Charge-off amount ($)	1,511,552.000	13,002.040	0.000	0.000	55,385.900	4,254,436.000	72,032.650
Initial interest rate (%)	533,935.000	6.431	0.000	4.500	9.750	56.000	1.486
Jobs supported (count)	1,511,552.000	7.378	0.000	0.000	30.000	9,500.000	29.108
Revolver status (0/1)	1,511,552.000	0.255	0.000	0.000	1.000	1.000	0.436
SBA guaranteed amount ($)	1,511,552.000	185,622.600	50.000	5,000.000	750,000.000	5,400,000.000	348,879.000
Loan maturity (months)	1,511,552.000	110.981	0.000	22.000	300.000	847.000	77.263
Default (0/1)	1,511,552.000	0.132	0.000	0.000	1.000	1.000	0.338
SBA guarantee rate (share)	1,511,552.000	0.674	0.010	0.500	0.900	2.250	0.154
Charge-off rate (share)	1,511,552.000	0.095	0.000	0.000	0.870	8.979	0.260
Treatment timing (year)	1,495,681.000	2,007.963	2,007.000	2,007.000	2,015.000	2,020.000	2.577
Bank-borrower state level variables							
Number of SBA loans (count)	122,456.000	12.344	1.000	1.000	45.000	3,545.000	52.914
Number of loans $>$ $150k (count)	122,456.000	4.347	0.000	0.000	18.000	566.000	12.603
Number of loans $\leq$ $150k (count)	122,456.000	7.997	0.000	0.000	27.000	3,539.000	48.503
Share of loans $>$ $150k (0–1)	122,456.000	0.513	0.000	0.000	1.000	1.000	0.415
Share of loans $\leq$ $150k (0–1)	122,456.000	0.487	0.000	0.000	1.000	1.000	0.415
Panel B. Bunching-analysis subsample							
Loan size ($)	10,213.000	147,315.400	100,000.000	100,000.000	200,000.000	200,000.000	30,925.140
Charge-off amount ($)	10,213.000	24,344.300	0.000	0.000	136,816.400	207,725.000	48,005.850
Revolver status (0/1)	10,213.000	0.016	0.000	0.000	0.000	1.000	0.124
SBA guaranteed amount ($)	10,213.000	118,046.100	17,220.000	85,000.000	150,000.000	180,000.000	20,712.760
Loan maturity (months)	10,213.000	107.413	0.000	34.000	240.000	360.000	57.130
Default (0/1)	10,213.000	0.235	0.000	0.000	1.000	1.000	0.424
SBA guarantee rate (share)	10,213.000	0.808	0.150	0.750	0.850	0.960	0.055
Charge-off rate (share)	10,213.000	0.165	0.000	0.000	0.897	1.346	0.317
Treatment timing (year)	10,213.000	2,008.003	2,007.000	2,007.000	2,015.000	2,016.000	2.602

Notes: This table reports descriptive statistics for the main variables used in the analysis. Panel A reports the full sample. Within Panel A, the first block contains loan-level variables, and the second block contains variables defined at the bank-borrower state level. Panel B reports the bunching-analysis subsample. This subsample restricts attention to loans from 7(a) delivery methods for which $150,000 is the relevant statutory threshold and excludes products subject to alternative thresholds. Within Panel B, variables are again reported separately at the loan level and at the bank-borrower state level. "Loan size" is the gross SBA loan approval amount. "SBA guaranteed amount" is the dollar amount guaranteed by the SBA. "Charge-off amount" is the dollar amount charged off. "Charge-off rate" is the charge-off amount divided by loan size. "Initial interest rate" is the loan's initial interest rate. "Loan maturity" is measured in months. "Jobs supported" is the number of jobs reported by the borrower. "Revolver status" equals one if the loan is classified as a revolver and zero otherwise. "Default" equals one if the loan is charged off and zero otherwise. "Treatment timing" is the year in which the relevant treatment is assigned to the borrower's state. "Number of SBA loans" is the number of loans in a given bank-borrower state cell. "Number of loans $>$ $150k" and "Number of loans $\leq$ $150k" are the corresponding counts above and at or below $150,000, and the associated share variables report the corresponding fractions within the cell. P5 and P95 denote the 5th and 95th percentiles. Dollar-denominated variables are reported in U.S. dollars.

Table 2: Staggered Difference-in-Differences Regression Results: Loan Size

	Bank-Borrower State Level		Loan Level	
	ln(Total Gross Approval Loan Amount)		ln(Gross Approval Loan Amount)	
	Full Sample	Sample within 10 miles buffer	Full Sample	Sample within 10 miles buffer
	(1)	(2)	(3)	(4)
P2P Introduction	−0.182***	−0.177***	−0.060***	−0.060***
	(−6.188)	(−6.003)	(−9.545)	(−11.202)
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Borrower State FE	YES	YES	YES	YES
Industry FE			YES	YES
Bank location FE			YES	YES
N	122,451	121,494	1,309,246	1,277,447

Notes: This table reports staggered difference-in-differences estimates of the effect of P2P introduction on SBA loan size. Columns (1)–(2) use a bank-borrower state level panel; Columns (3)–(4) use loan-level data. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Staggered Difference-in-Differences Regression Results: Default

Panel A. Full Sample

	Bank-Borrower State Level		Loan Level	
	Default Rate	Average Charge-off Rate	Default Indicator	Charge-off Rate
	(1)	(2)	(3)	(4)
P2P Introduction	0.015***	0.011***	0.018***	0.017***
	(4.526)	(3.891)	(10.032)	(12.165)
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Borrower State FE	YES	YES	YES	YES
Industry FE			YES	YES
Bank Location FE			YES	YES
N	122,456	122,456	1,309,246	1,309,246

Panel B. Sample Within 10-Mile Buffer

	Bank-Borrower State Level		Loan Level	
	Default Rate	Average Charge-off Rate	Default Indicator	Charge-off Rate
	(1)	(2)	(3)	(4)
P2P Introduction	0.016***	0.011***	0.023***	0.022***
	(4.833)	(4.176)	(15.584)	(19.049)
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Borrower State FE	YES	YES	YES	YES
Industry FE			YES	YES
Bank Location FE			YES	YES
N	121,494	121,494	1,277,447	1,277,447

Notes: This table reports staggered difference-in-differences estimates of the effect of P2P introduction on loan performance. Panel A uses the full sample. Panel B restricts the sample to bank-borrower pairs located within a 10-mile buffer of P2P entry. Columns (1) and (2) use bank-borrower state-level data, where the dependent variables are the default rate and the average charge-off rate. Columns (3) and (4) use loan-level data, where the dependent variables are the default indicator and the charge-off rate. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Staggered Difference-in-Differences Regression Results: Share of Large Loans (Low SBA Guarantee Level)

	Bank-Borrower State Level	
	Share of Large Full Sample (1)	Share of Large Within 10-Mile Buffer (2)
P2P Introduction	−0.019***	−0.019***
	(−3.321)	(−3.281)
Bank FE	YES	YES
Year FE	YES	YES
Borrower State FE	YES	YES
N	122,456	121,494

Notes: This table reports staggered difference-in-differences estimates of the effect of P2P entry on the share of large loans for the subsample with low SBA guarantee levels. Column (1) uses the full sample, and Column (2) restricts the sample to bank-borrower pairs located within a 10-mile buffer of P2P entry. The unit of observation is a bank-borrower state-by-year cell. Bank, year, and borrower-state fixed effects are included. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Staggered Difference-in-Differences Regression Results: Losses (Bank–Borrower State Level)

	Bank-Borrower State Level			
	Full Sample		Within 10-Mile Buffer	
	Bank Loss Rate	SBA Loss Rate	Bank Loss Rate	SBA Loss Rate
	(1)	(2)	(3)	(4)
P2P Introduction	0.449***	0.672***	0.468***	0.723***
	(3.956)	(3.622)	(4.146)	(3.886)
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Borrower State FE	YES	YES	YES	YES
N	122,456	122,456	121,494	121,494

Notes: This table reports staggered difference-in-differences estimates of the effect of P2P introduction on loss outcomes using a bank–borrower state-level panel. The dependent variables are the bank loss rate and the SBA loss rate aggregated within a bank–borrower state–year cell. Columns (1)–(2) use the full sample, while Columns (3)–(4) restrict the sample to bank–borrower pairs located within a 10-mile buffer of P2P entry. Bank, year, and borrower-state fixed effects are included. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Staggered Difference-in-Differences Regression Results: Loan Size (PLP vs. Non-PLP)

	Bank-Borrower State Level		Loan Level	
	ln(Total Gross Approval Loan Amount)		ln(Gross Approval Loan Amount)	
	PLP	Non-PLP	PLP	Non-PLP
	(1)	(2)	(3)	(4)
P2P Introduction	−0.307***	−0.167***	−0.043***	−0.051***
	(−7.895)	(−6.775)	(−3.960)	(−8.144)
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Borrower State FE	YES	YES	YES	YES
Industry FE			YES	YES
Bank Location FE			YES	YES
N	33,344.000	88,899.000	332,532.000	976,490.000

Notes: This table reports staggered difference-in-differences estimates of the effect of P2P introduction on loan size, separately for PLP and non-PLP lenders. Columns (1)–(2) use a bank-borrower state-level panel in which the dependent variable is the logarithm of the total gross approval loan amount aggregated within a bank-borrower state–year cell. Columns (3)–(4) use loan-level data in which the dependent variable is the logarithm of the gross approval loan amount for each individual loan. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Staggered Difference-in-Differences Regression Results: Default (PLP vs. Non-PLP)

	Loan Level			
	Default Rate		Average Charge-off Rate	
	PLP	Non-PLP	PLP	Non-PLP
	(1)	(2)	(3)	(4)
P2P Introduction	0.021***	0.015***	0.017***	0.016***
	(6.085)	(7.443)	(7.024)	(9.460)
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Borrower State FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Bank location FE	YES	YES	YES	YES
N	332,532.000	976,490.000	332,532.000	976,490.000

Notes: This table reports staggered difference-in-differences estimates of the effect of P2P introduction on loan performance, separately for PLP and non-PLP lenders. The sample consists of loan level obeservations. Columns (1)–(2) report default rates, and Columns (3)–(4) report charge-off rates aggregated within a bank-borrower state–year cell. Bank, year, borrower-state, industry and bank location fixed effects are included. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Staggered Difference-in-Differences Regression Results: Share of Large Loans (PLP vs. Non-PLP)

	Bank-Borrower State Level	
	Share of Large Loans	
	PLP	Non-PLP
	(1)	(2)
P2P Introduction	−0.015***	−0.008
	(−1.972)	(−1.399)
Bank FE	YES	YES
Year FE	YES	YES
Borrower State FE	YES	YES
N	33,344.000	88,904.000

Notes: This table reports staggered difference-in-differences estimates of the effect of P2P introduction on the share of large loans, separately for PLP and non-PLP lenders. The sample consists of bank-borrower state-level observations. The dependent variable is the share of large loans within a bank-borrower state–year cell. Bank, year, and borrower-state fixed effects are included. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Staggered Difference-in-Differences Regression Results: Losses (PLP vs. Non-PLP)

	Bank-Borrower State Level			
	Bank Loss Rate		SBA Loss Rate	
	PLP	Non-PLP	PLP	Non-PLP
	(1)	(2)	(3)	(4)
P2P Introduction	0.465 ***	0.551***	0.917***	0.643***
	(3.437)	(4.867)	(3.422)	(3.210)
Bank FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Borrower State FE	YES	YES	YES	YES
Chow Test (Non-PLP − PLP)	0.157*		−0.367**	
p-value	0.054		0.012	
N	33,344	88,899	33,344	88,899

Notes: This table reports staggered difference-in-differences estimates of the effect of P2P introduction on lender (bank) losses and government (SBA) losses, separately for PLP and non-PLP lenders. Columns (1)–(4) use bank-borrower state-year level data. The Chow test evaluates whether the treatment effect differs between PLP and non-PLP lenders. The reported difference corresponds to the coefficient on the interaction term between *treatment_post* and the non-PLP indicator (Non-PLP − PLP). t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Estimated Left-Side Bunching Below the $150,000 Cutoff: Full Sample

Window	Group	Excess Loans	Share CF	Share Alt.	Observed Loans in Bunch	Counterfactual Loans in Bunch
	Pre	459	0.356	0.554	1,748	1,289
-15k	Post	451	0.449	0.701	1,456	1,005
	Post–Pre	-7.57	0.0932	0.146	-292	-284
	Pre	548	0.532	0.884	1,580	1,032
-10k	Post	501	0.623	1.040	1,306	805
	Post–Pre	-47.3	0.0909	0.154	-274	-227
	Pre	736	1.330	2.370	1,288	552
-5k	Post	714	1.660	2.960	1,144	430
	Post–Pre	-22.2	0.325	0.585	-144	-122

Notes: This table summarizes estimated left-side bunching just below the $150,000 cutoff in the full sample. For each window ($15k/$10k/$5k), *Excess Loans* is the difference between the observed number of loans and the counterfactual number predicted by the fitted (unaffected-region) density model. *Observed Loans in Bunch* is the total observed count in the bunching window, while *Counterfactual Loans in Bunch* is the model-predicted count absent bunching. *Share CF* is defined as the excess number of loans in the bunching window divided by the counterfactual number of loans. *Share Alt.* is defined as the excess mass in the bunching window divided by the counterfactual mass that would be present in that window if each bin had the same height as the average predicted count in the unaffected region. Rows labeled *Post–Pre* report the change in these bunching measures from the Pre to the Post period.

Table 11: Estimated Left-Side Bunching Below the $150,000 Cutoff: PLP vs. Non-PLP

Subsample	Window	Group	Excess Loans	Share CF	Share Alt.	Observed Loans in Bunch	Counterfactual Loans in Bunch
PLP	-15k	Pre	334	0.392	0.596	1,186	852
		Post	280	0.450	0.696	903	623
		Post–Pre	-53.7	0.0582	0.0999	-283	-229
	-10k	Pre	390	0.571	0.929	1,074	684
		Post	320	0.643	1.060	818	498
		Post–Pre	-70.3	0.0717	0.1310	-256	-186
	-5k	Pre	511	1.390	2.430	879	368
		Post	444	1.670	2.940	710	266
		Post–Pre	-66.8	0.282	0.508	-169	-102
Non-PLP	-15k	Pre	126	0.288	0.470	562	436
		Post	171	0.446	0.707	553	382
		Post–Pre	44.9	0.158	0.238	-9	-53.9
	-10k	Pre	159	0.459	0.794	506	347
		Post	181	0.590	1.000	488	307
		Post–Pre	21.9	0.131	0.208	-18	-39.9
	-5k	Pre	226	1.240	2.250	409	183
		Post	270	1.650	2.990	434	164
		Post–Pre	43.9	0.410	0.731	25	-18.9

Notes: This table summarizes estimated left-side bunching just below the $150,000 cutoff for PLP and non-PLP subsamples. For each window ($15k/$10k/$5k), *Excess Loans* is the difference between the observed number of loans and the counterfactual number predicted by the fitted (unaffected-region) density model. *Observed Loans in Bunch* is the total observed count in the bunching window, while *Counterfactual Loans in Bunch* is the model-predicted count absent bunching. *Share CF* is defined as the excess number of loans in the bunching window divided by the counterfactual number of loans. *Share Alt.* is defined as the excess mass in the bunching window divided by the counterfactual mass that would be present in that window if each bin had the same height as the average predicted count in the unaffected region. Rows labeled *Post–Pre* report the change in these bunching measures from the Pre to the Post period.

Table 12: Default-Rate Bunching Below the $150,000 Cutoff: Full Sample

Window	Group	Observed Default Rate in Bunch	Counterfactual Default Rate in Bunch	Uplift Rate
	Pre	0.2240	0.2340	-0.00999
-15k	Post	0.2430	0.2480	-0.00513
	Post–Pre	0.0193	0.0144	0.00486
	Pre	0.2270	0.2350	-0.00729
-10k	Post	0.2440	0.2500	-0.00540
	Post–Pre	0.0171	0.0152	0.00188
	Pre	0.2230	0.2350	-0.0122
-5k	Post	0.2390	0.2510	-0.0121
	Post–Pre	0.0161	0.0159	0.000183

Notes: This table summarizes default-rate bunching just below the $150,000 cutoff in the full sample. For each window ($15k/$10k/$5k), the default rate is computed as the number of defaulted loans divided by the total number of loans. *Observed Default Rate in Bunch* is the realized default rate among loans originated within the bunching window. *Counterfactual Default Rate in Bunch* is the smooth default rate that would prevail in the same window absent local manipulation at the cutoff. *Uplift Rate* is defined as the difference between the observed default rate in the bunching window and its counterfactual counterpart. Rows labeled *Post–Pre* report changes from the Pre to the Post period.

Table 13: Default-Rate Bunching Below the $150,000 Cutoff: PLP vs. Non-PLP Subsamples

Subsample	Window	Group	Observed Default Rate in Bunch	Counterfactual Default Rate in Bunch	Uplift Rate
PLP	-15k	Pre	0.2490	0.2550	-0.00663
		Post	0.2770	0.2670	0.00982
		Post–Pre	0.0282	0.0118	0.0165
	-10k	Pre	0.2510	0.2550	-0.00412
		Post	0.2760	0.2690	0.00769
		Post–Pre	0.0250	0.0132	0.0118
	-5k	Pre	0.2430	0.2550	-0.0129
		Post	0.2670	0.2700	-0.00338
		Post–Pre	0.0244	0.0149	0.00949
Non-PLP	-15k	Pre	0.1980	0.2060	-0.00846
		Post	0.1840	0.2060	-0.0224
		Post–Pre	-0.0136	0.000339	-0.0140
	-10k	Pre	0.2010	0.2070	-0.00549
		Post	0.1870	0.2070	-0.0195
		Post–Pre	-0.0140	0.0000662	-0.0140
	-5k	Pre	0.2020	0.2080	-0.00553
		Post	0.1900	0.2070	-0.0172
		Post–Pre	-0.0121	-0.000478	-0.0117

Notes: This table summarizes default-rate bunching just below the $150,000 cutoff for PLP and non-PLP subsamples. For each window ($15k/$10k/$5k), the default rate is computed as the number of defaulted loans divided by the total number of loans. *Observed Default Rate in Bunch* is the realized default rate among loans originated within the bunching window. *Counterfactual Default Rate in Bunch* is the smooth default rate that would prevail in the same window absent local manipulation at the cutoff. *Uplift Rate* is defined as the difference between the observed default rate in the bunching window and its counterfactual counterpart. Rows labeled *Post–Pre* report changes from the Pre to the Post period.

A Appendix

A.1 Institutional Background

The SBA seeks to empower entrepreneurs and small business owners by facilitating their access to credit. Under its flagship 7(a) loan guarantee program, commercial banks extend credit to small businesses while the SBA acts as the guarantor, covering a portion of lenders' losses in the event of borrower default. Participating banks pay guarantee and servicing fees upon entering the program. 7(a) program is composed of multiple subprograms and a key feature in some of them is a nonlinear guarantee structure. For example, in the 7(a) Small Loan program, the maximum guarantee rate is 85 percent for loans at or below the $150,000 threshold, declining to 75 percent for larger loans, accompanied by a discrete increase in guarantee fees. In the 7(a) Export Express program, the threshold is $350,000, with guarantee rates of 90 percent for loans below the threshold and 75 percent for those above it.

The 7(a) program, designed specifically for small businesses, functions as a lender of last resort when firms have exhausted all other potential sources of financing. To qualify, borrowers must be for-profit entities that fall within SBA size standards[5], be independently owned and not nationally dominant, operate within U.S. territories, and demonstrate both a financing need and prior attempts to obtain alternative funding, as documented through application history, firm financial statements, and personal equity contributions (Bachas et al., 2021).

To participate, lenders must be public-facing institutions with operational capacity across the full small business lending lifecycle, including underwriting, processing, closing, disbursement, servicing, and liquidation. They must demonstrate sustained integrity and reputation and be supervised and examined by state or federal authorities acceptable to the SBA. Lender performance is monitored through SBA on-site reviews and examinations and historical indicators such as default, purchase, and loss rates, as well as loan volume. The 7(a) program comprises two lender types: Preferred Lenders Program (PLP) and non-PLP lenders. PLP lenders are delegated authority for final credit decisions and most servicing and liquidation functions. In PLP processing, the SBA's role is limited to an eligibility review and loan-number assignment, with PLP lenders preparing

[5] Industry-specific criteria based on headcount or annual receipts, with the latter defined as total income plus cost of goods sold

and executing the SBA guarantee authorization without prior SBA review. By contrast, non-PLP lenders are subject to SBA review for every originated loan. Despite their delegated authority, PLP lenders must comply fully with all SBA eligibility rules, credit standards, procedures, and program requirements. The SBA assigns PLP lenders a quarterly composite risk rating and may conduct enhanced reviews for those with outstanding SBA balances of at least $10 million (Gupta and Ongena, 2023).

Because the SBA 7(a) program serves as a lender of last resort, borrowers are required to provide sufficient evidence that they have exhausted alternative funding sources, including personal wealth and other bank loans. In recent years, financing options available to small businesses have become increasingly diversified, reflecting rapid innovation in financial intermediation. One prominent development is peer-to-peer (P2P) marketplace lending, which emerged in the United States in the mid-2000s as an alternative credit channel that connects borrowers directly with individual or institutional investors through online platforms. These platforms typically use algorithmic credit assessments based on borrower financial information, transaction histories, and alternative data to price and allocate credit, often enabling faster approval and funding than traditional bank loans. P2P lenders generally operate without deposit funding and do not benefit from public guarantees, instead relying on risk-based pricing and investor diversification to manage credit risk. These platforms originate substantial volumes across small-business and consumer segments, typically offering three- to five-year terms and loan sizes up to $50,000 at Lending Club (average $11,744; Cumming et al., 2022). The expansion of P2P lending also has important implications for the SBA 7(a) program. Because 7(a) functions as a lender of last resort, the availability of an additional private financing channel may exacerbate adverse selection: relatively stronger borrowers may obtain funding through P2P platforms, while weaker borrowers who are unable to secure either bank or P2P financing are more likely to sort into SBA-backed loans. As a result, the introduction and growth of P2P lending may deteriorate the average credit quality of borrowers entering the 7(a) program, with potential consequences for default rates and guarantee costs. In light of recent developments in the financial industry, while the 7(a) program plays a central role in supporting small businesses, its effectiveness and long-term viability depend critically on the interaction among borrower selection, bank screening, and the design of public guarantees.