Back to Banks: Nonbank Price Transparency, Substitution, and Small Business Lending

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Abstract:

This paper examines how nonbank loan transparency affects substitution between nonbank and bank credit and, in turn, bank lending. In the absence of disclosure regulation, nonbank lenders often shroud the true cost of small business loans, misleading not only borrowers with limited access to traditional banking but also those with access to bank credit. Exploiting California's nonbank loan cost transparency mandate — the Commercial Financing Disclosure Law (SB1235) as a natural experiment, I show that standardized Annual Percentage Rate (APR) disclosure increased banks' share of small business lending by 25%, driven by both reduced nonbank credit and expanded bank originations. This reverse substitution is explained by borrowers shifting away from nonbank lenders, prompted by greater sensitivity to loan pricing under standardized disclosure, as well as by a contraction in nonbank credit due to higher compliance costs. Banks responded selectively, tightening standards, raising markups, and concentrating new lending in counties with higher education and numeracy levels and lower poverty. As a result, disadvantaged areas experienced limited increase in bank credit, highlighting potential unintended consequences of transparency regulation.

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1. Introduction

Small and medium-sized enterprises (SMEs) are the backbone of the U.S. economy and have become increasingly dependent on nonbank credit.[1] By 2016, nonbanks accounted for more than 60% of small business lending (Gopal & Schnabl, 2022). Prior research attributes this shift largely to the contraction in bank lending to small businesses following post-crisis regulatory changes, as well as to differences in funding models, technology, and screening practices (Tang, 2019; Chernenko et al., 2022; Erel & Liebersohn, 2022; Gopal & Schnabl, 2022; Howell et al., 2024). Yet one important dimension remains underexplored: the role of price transparency. Nonbank lenders face limited disclosure requirements when issuing commercial loans: they often advertise alternative interest rate metrics that appear low while concealing additional fees. Borrowers may be enticed by these seemingly inexpensive loans even when they qualify for bank credit, causing substitution away from banks. In reality, however, such loans often entail substantially higher effective borrowing costs, resulting in inefficient credit allocation and, in some cases, severely harm businesses (L. M. Palladino, 2021). To address the lack of price transparency and the risk of predatory lending, the state of California enacted the Commercial Financing Disclosure Law (SB1235), which requires nonbank lenders to disclose standardized loan cost information before borrowers enter a contract. I exploit this nonbank price transparency mandate to investigate (i) whether greater transparency in nonbank loan pricing reallocates small business credit between nonbanks and banks; (ii) how banks adjust their screening and pricing in response; and (iii) the implications for underserved small businesses' access to bank credit.

In small business lending, this lack of transparency is particularly salient compared to consumer lending. Consumer loans, such as mortgages, from both banks and nonbanks are subject to the Truth in Lending Act (TILA) of 1968, which mandates upfront and standardized disclosure of borrowing costs. However, no equivalent disclosure requirements exist for small business loans. Banks, subject to prudential regulation and supervisory standards, typically disclose interest rates and costs transparently and upfront.[2] In contrast, nonbank lenders, including FinTech firms, have considerable latitude in how

[1] These loans include small business loans issued by non-depository institutions such as online lenders, FinTech lenders, and finance companies.

[2] Banks are subject to federal rules that explicitly prohibit misleading borrowers. In particular, the OCC enforces the Unfair or Deceptive Acts or Practices (UDAP) and Unfair, Deceptive, or Abusive Acts or Practices (UDAAP)

they present loan terms due to the absence of standardized disclosure rules. They often advertise ostensibly low interest rates using language such as "*fixed simple interest rates starting at…"* or "*factor rates as low as…*" while obscuring the true cost of borrowing. Borrowers may mistakenly interpret these metrics as equivalent to an annual percentage rate (APR), even though they are not. In addition, large service and origination fees, sometimes amounting to thousands of dollars, as well as prepayment penalties, are frequently omitted from initial advertisements and disclosed only after the borrower has entered into a lending relationship (Lipman & Wiersch, 2019; Mills, 2016; Stango & Zinman, 2011). This practice parallels the broader phenomenon of "shrouded" pricing, in which lenders or intermediaries exploit borrowers' misunderstanding of cost structures (Gabaix & Laibson, 2006).

This lack of transparency creates an additional channel for the substitution from bank loans into nonbank credit, distinct from the supply-side factors emphasized in prior research, such as regulatory constraints, funding structures, and technological advantages (Erel & Liebersohn, 2022; Gopal & Schnabl, 2022; Howell et al., 2024). Specifically, it shapes borrower demand. While borrowers can voluntarily choose nonbank credit from finance companies or FinTech lenders because of faster disbursement or the convenience of online applications, price shrouding amplifies this demand channel by making these loans appear even "cheaper" than bank loans. As a result, not only do less creditworthy borrowers with limited access to bank credit turn to nonbanks, but even those who could qualify for bank loans are lured by these "favorable terms" (Lipman & Wiersch, 2019). The extent to which this demand-driven mechanism contributes to the broader shift toward nonbank lending, however, is unclear.

Increased nonbank price transparency could cause borrowers to substitute nonbank loans with bank loans for two reasons. First, the mandated APR disclosure now includes all costs, such as service and origination fees, making previously low-appearing rates substantially higher. This higher disclosed APR could deter SME borrowers from taking nonbank loans (Bertrand & Morse, 2011; Wang & Burke, 2022). Additionally, the APR disclosure effectively standardizes the pricing format of SME loan

standards, based on Section 5 of the Federal Trade Commission Act and Dodd-Frank §§ 1031 and 1036, which require clear and non-misleading presentation of loan terms. For SBA-guaranteed small business loans, the SBA's Standard Operating Procedure 50 10 and related regulations further prescribe allowable fees, cap interest rates, and specify the documentation and disclosures that must be provided to borrowers.

products, making previously difficult-to-compare prices easier to compare. This standardization increases borrowers' price sensitivity, i.e., their responsiveness to differences in loan interest rates (Ellison & Ellison, 2009). Compared to nonbank lenders who often charge APRs ranging from 20% to 100%, bank loans typically offer lower average interest rates of 8% to 15%.[3] Borrowers discouraged by the high cost of nonbank loans may seek more affordable financing alternatives through banks. Second, heightened compliance costs and legal risks may lead nonbank lenders to withdraw from markets like California, reducing the supply of nonbank capital to small businesses.

However, greater transparency in nonbank small business loans may have little impact on bank loans. Compared to bank loans, FinTech lenders have easier online applications, higher approval rates, and faster disbursement (L. Palladino, 2019), which attract borrowers, but at the same time, some borrowers are discouraged by possible hidden fees, as highlighted by the Federal Reserve Small Business Survey (Corcoran et al., 2023). By reducing concerns about such fees, transparency could further increase borrowers' likelihood of selecting FinTech loans.

Given the reasons above, whether greater price transparency, brought about by regulations requiring nonbanks to disclose standardized cost information, including APR, induces a reverse substitution effect in small business credit markets is, thus, an empirical question. In other words, does greater transparency in nonbank loan discourage borrowers from choosing nonbanks and redirect demand back toward banks?

Conditional on borrowers increasing their demand for bank loans, it is also unclear whether banks are able or willing to accommodate this additional demand. *Ex-ante*, banks could: (i) relax screening to expand access, (ii) maintain credit standards and keep the composition of borrowers unchanged, or (iii) tighten credit standards to prioritize safer applicants. Prior literature suggests that FinTech small business credit often complements bank lending by serving borrowers with weaker access to banks, for example, riskier firms or those located in minority-concentrated, lower-income, or poorly banked areas (Erel & Liebersohn, 2022; Howell et al., 2024). How banks adjust in response, therefore, also raises important questions about access to bank credit for these borrowers.

[3] See https://fred.stlouisfed.org/categories/22 up-to-date interest rates.

To provide evidence on these questions, I exploit California's nonbank transparency mandate—the CFDL, which took effect on December 9, 2022. The CFDL requires nonbank lenders offering commercial financing products, such as term loans, commercial open-end credit plans, lease financing, factoring transactions, and sales-based financing transactions ranging from $5,000 to $500,000, to provide standardized cost disclosures, including the APR, total funding amount, and repayment terms. These disclosures must be presented to borrowers before they enter into a lending agreement. Although several states including New York, Virginia, and Utah have enacted similar regulations, California provides an ideal setting due to its comprehensive coverage of commercial loan products and early adoption, allowing sufficient time and data to observe the effects of such regulations.[4]

Measuring small business lending is challenging due to the absence of a comprehensive dataset that captures both bank and nonbank small business lending. To overcome this limitation, I employ Uniform Commercial Code (UCC) filings, which are public records of secured lending contracts that creditors file with state authorities when making collateralized loans to businesses, as a proxy for small business loans by banks and nonbanks (Gopal & Schnabl, 2022; Minnis et al., 2024). However, UCC filings cover only secured lending and do not report loan amounts. To address this, I supplement the bank lending analysis with two additional data sources. First, I use the Community Reinvestment Act (CRA) data, which, under mandatory reporting requirements, provide annual aggregates of all small business loans of $1 million or less at the bank–county–year level (Cortés et al., 2020). Second, I draw on the SBA 7(a) loan-level data, which cover a subset of bank-issued, SBA-guaranteed small business loans and include detailed information on loan terms, loan status, and borrower characteristics. The SBA data offer a granular view of banks' small business lending and allow me to examine additional dimensions such as pricing and risk (Granja et al., 2022).

I start my analyses by examining the effect of the CFDL on the share of bank loans using UCC filings from January 1, 2022, to December 31, 2023, capturing one year before and after the regulation. I aggregate these filings at the state–county–quarter level and compute the share

[4] Concurrently, states including New York, Virginia, and Utah have enacted similar regulations. However, Virginia's law applies only to sales-based loans, which do not overlap with the term loans that dominate bank lending. Utah's law does not require APR disclosure. New York's regulation only recently became effective in August 2023, leaving limited time and data to observe its effects, specifically, no CRA data were available for 2024 when this paper was written in September 2025.

attributable to banks. On average, banks account for approximately 50% of small business loans. This is roughly consistent with Gopal and Schnabl (2022), who report slightly higher shares (60%) in 2016.[5] Using a difference-in-differences research design, I find that, relative to the control group, (treated) counties in California experienced a 25% increase in the share of small business lending by banks following the regulation. This effect is estimated relative to a pre-shock mean of 32% after controlling for county–time-varying market structure, macroeconomic conditions, county fixed effects, and time trends. Further examining the level of UCC filings, I find that the increase in banks' lending share reflects both a contraction in nonbank lending and an expansion in bank lending.

To provide a more comprehensive view of bank lending on both secured and unsecured loans, I turn to CRA data. Consistent with the UCC findings, I observe a comparable post-regulation increase in bank lending, particularly concentrated in smaller loans under $250,000, which fall within the regulatory threshold.[6] To sharpen identification, I leverage SBA 7(a) loan-level data with precise loan amount information and find an increase in lending for loans under $500,000, which are covered by the mandate, and a simultaneous decline in larger, exempt loans. Together, these findings provide additional evidence that the observed effects are driven by the disclosure requirement.

Next, I examine whether the observed substitution is driven by increased demand for bank loans following the price transparency mandate. Because application-level data on bank small business loans, which would provide a direct measure of demand, are not publicly available, I rely on two indirect but complementary proxies. First, I use weekly Google Trends search intensity for bank business loan–related terms (Drake et al., 2012; Saxa, 2014; Oehl et al., 2017). Specifically, I estimate changes in search intensity for the term "*Bank Business Loan*" and the topic "*SBA Loan*," and find increases of approximately 6% and 11%, respectively, after controlling for state–time-varying macroeconomic conditions and market structures. Second, I draw on data from the Federal Reserve's Small Business

[5] With the rise of FinTechs and the expansion of open banking, the nonbank lending share may have increased in more recent years.
[6] The CRA reports only three loan size categories: below $100,000, $100,000 to $250,000, and $250,000 to $1 million. The only brackets that fall entirely within the regulation threshold are loans below $100,000 and those between $100,000 and $250,000; thus, I aggregate these two categories.

Credit Survey (SBCS),[7] an annual survey that collects information on SME financing conditions, including where firms apply for financing, and publishes tabulations at the state level. These state-level results show that the share of California SMEs applying to bank lenders increased from 59% in 2022 to 61% in 2023, while the average across other reporting states declined from 72% to 70%. Together, these two analyses indicate a post-mandate increase in demand for bank small business loans in California.

Having documented a demand-induced increase in both bank share and overall bank lending, I next examine how banks respond to these migrating borrowers. Specifically, I test whether banks adjust their credit standards by analyzing the distribution of borrower risk. Because UCC and CRA data lack loan-level information and default outcomes, I rely on SBA 7(a) loan-level data, which include *ex-post* default status, to construct an *ex-ante* measure of borrower risk (probability of default). I train a machine learning (*XGBoost* classification) model on historical loans to predict the probability of default based on loan terms, borrower characteristics, and local macroeconomic conditions.[8] I then apply the model to loans in my sample period and use the predicted probabilities to compare average risk and risk distributions (e.g., quantiles) for new loans in California versus other states after the regulation.

Two observations emerge. First, average *ex-ante* risk declines among bank originations. Second, the upper tail of the risk distribution, specifically the 75th to 95th percentiles, contracts. This pattern is consistent with banks tightening credit standards rather than screening relaxation: had banks loosened, the risky tail would have expanded. Instead, originations are safer, especially at the margin, suggesting that banks may be replacing riskier borrowers with safer ones migrating from nonbanks. I acknowledge that SBA 7(a) loans represent only a subset of bank small business lending. However, because they are government-guaranteed, SBA loans often serve smaller, younger, and riskier borrowers, making them a closer substitute for nonbank credit than conventional bank loans, which target larger and safer borrowers (Gopal & Schnabl, 2022; Jeong, 2023).[9] If risky borrowers were shifting to banks and obtaining loans, we would expect to observe

[7] https://www.fedsmallbusiness.org/ publishes the state level results for around 20 states. Firms surveyed have less than 500 employees.
[8] See Appendix E for detailed construction of the risk measure *PD* (Probability of Default).
[9] Program design and practice suggest that SBA 7(a) loans tend to reach borrowers who face frictions in conventional bank markets. In particular, the "credit elsewhere" requirement asks lenders to document why the

this first in SBA lending, where they are most likely to qualify. The fact that SBA loans have become safer suggests that such risky borrowers are unlikely to be obtaining other types of bank loans.

Beyond borrower risk, I also examine how other contract terms change. Quintile tests on loan size and maturity show that, on average, loan sizes decrease, and maturities shorten after the mandate. This pattern may reflect two mechanisms: borrowers returning from nonbanks may have preferred smaller, shorter-term loans and are bringing those preferences with them (Tang, 2019); alternatively, on the supply side: banks facing increased demand may tighten terms to manage lending capacity and liquidity. However, with the data available, I cannot distinguish between these channels.

I then turn to pricing. At the loan level, holding the *ex-ante* risk measure constant, SBA loans in California carry higher interest rates after the mandate than contemporaneous loans in other states issued by the same banks. This increase reflects higher markups rather than a higher risk premium. This pattern is consistent with demand pushing: more bank-eligible borrowers switching to banks, allowing banks to raise prices at a given risk. The resulting increase in per-loan margins provides banks with an incentive to expand originations rather than keep lending constant.

These credit standard and pricing adjustments raise important questions about distributional impacts: who gains access to bank credit under the new equilibrium, and who might be left behind? Disadvantaged small businesses, such as minority borrowers or borrowers in less-developed areas, are often served by FinTech lenders (Buchak et al., 2018; Bartlett et al., 2022; Erel & Liebersohn, 2022; Howell et al., 2024). Can these borrowers obtain bank credit if they also migrate, given that banks are further tightening standards and raising prices? To provide evidence on these questions, I utilize cross-sectional county characteristics, including numeracy and literacy levels, poverty rates,

applicant cannot obtain comparable credit on reasonable terms without an SBA guarantee (e.g., limited operating history, collateral shortfalls, cash-flow constraints, or needed term length). Empirically, SBA borrowers are, on average, smaller and younger and exhibit weaker observed credit proxies than recipients of conventional bank loans, consistent with the program easing access at the margin (see Gopal & Schnabl, 2022; Cortés, De Roure & Santos, 2020; Granja, Matvos & Seru, 2022; Jeong, 2023). These patterns align with the program's guarantee structure rather than an explicit targeting of "marginal" borrowers.

educational attainment, and minority shares, to examine which groups gain greater access to bank credit. Using a triple-differences research design, I find that counties with lower poverty rates, higher education levels, and stronger numeracy skills obtain more bank credit. However, I do not find evidence that high-minority areas receive less bank credit. These findings highlight important heterogeneity in how the regulation affects access to credit across communities. Although the regulation is intended to curtail predatory lending and support small-business financing, it primarily benefits relatively advantaged borrowers by redirecting them toward bank loans and helping them avoid unnecessarily high financing costs caused by price shrouding.

Taken together, the evidence suggests that a lack of price transparency played an important role in the substitution between bank and nonbank small business credit. With greater transparency, SMEs shifted back from nonbank loans toward bank loans. Banks responded by selectively issuing credit to more creditworthy borrowers while tightening standards for risky applicants. The increase in bank lending was concentrated in areas with higher education levels, lower poverty, stronger numeracy skills, and greater banking access, raising concerns about disparities in bank credit availability across borrowers.

This paper contributes to the literature on the relationship between bank and nonbank credit (Buchak et al., 2018; Tang, 2019; Fuster et al., 2019; Di Maggio & Yao, 2021; Erel & Liebersohn, 2022; Howell et al., 2024). Distinct from previous studies, I emphasize the role of price transparency in understanding the rise of nonbank small business lending and its substitutability with bank loans. In doing so, it also extends the literature on product disclosure, price transparency, and economic behavior, particularly the consequences of price shrouding (Gabaix & Laibson, 2006; Bertrand & Morse, 2011; Morse, 2011; Restoy, 2021; Agarwal et al., 2015; Kielty et al., 2023; Nicoletti & Zhu, 2023). I show that price disclosure regulation influences consumer decisions not only for the directly regulated product but also spills over to other products in the market.

This paper also adds to the literature on uneven regulation and financial intermediation. While large banks face stringent regulatory requirements, including Basel III liquidity rules and the Federal Reserve's stress tests, nonbank lenders, including FinTech firms, remain largely

unregulated and have expanded rapidly, filling gaps in small business finance (Buchak et al., 2018; Carter & McNulty, 2005; L. Palladino, 2019; Cortés et al., 2020; Breuer & Breuer, 2022; Gopal & Schnabl, 2022; Srivastav & Vallascas, 2022; Chernenko et al., 2022). I highlight that "leveling the playing field" would have consequences for both banks and nonbanks, with effects that are both intended and unintended. This paper also contributes to the broader literature on credit supply to small businesses by underscoring the importance of transparency (Berger & Black, 2011; Ertan et al., 2017; Balakrishnan & Ertan, 2019; Granja et al., 2022, 2022).

Finally, this paper informs regulators by providing preliminary evidence on the effects of such nonbank price transparency laws. The issue is particularly relevant now, as multiple states have adopted similar rules and federal legislation is under consideration (the Small Business Financing Disclosure Act of 2023, S.2021/H.R.4192). The findings suggest that while banks absorb additional demand from borrowers migrating from nonbanks, they do so by lending more selectively to less risky borrowers, and thus raise concerns about disparities in access to bank credit.[10]

2. Institutional Background

2.1 Nonbank Lending

In the past decade, small businesses have increasingly turned to nonbank lenders, especially nonbank online lenders (Tang, 2019; L. Palladino, 2019; L. M. Palladino, 2021; Chernenko et al., 2022; Erel & Liebersohn, 2022; Gopal & Schnabl, 2022; Howell et al., 2024). These lenders are also referred to as FinTech lenders and typically use algorithm-driven decision-making instead of relying on conventional credit scores and income verification (Wiersch et al., 2016). Although FinTech lenders can provide credit access to a broader range of borrowers including riskier businesses and minority-owned businesses, they often have less favorable rates and terms, and borrowers generally report a lower satisfaction compared to traditional bank lending.

Online lenders frequently impose unfair, deceptive, or abusive loan terms on small business borrowers, partly due to the absence of clear regulations governing nonbank lenders (Odinet, 2021).

[10] https://www.congress.gov/crs_external_products/R/HTML/R48281.web.html

They obfuscate the true cost of lending by not disclosing a standardized APR and by hiding important cost information, such as payment terms and payment frequencies, in footnotes (Wiersch et al., 2016). They often use alternative metrics like factor rate, annual interest rate, or fixed annual interest rate, which, though appearing similar to APR, can represent significantly higher costs when converted. Research by the Opportunity Fund shows that some small businesses in California faced average APRs as high as 94%, with extremes reaching 350% (Chandler & Wial, 2022). For instance, an online lender might advertise their "interest rate" as being "as low as 1.15". Yet, upon closer examination of the product, it becomes apparent that they apply a weekly factor rate of 1.15. This means that for a six-month loan, the APR could rise to 56.09%, even before considering any additional fees. As a result, many small business borrowers enter the transaction unaware of the true costs and end up paying exorbitantly high fees that can cripple their businesses.

Despite their high interest rates, nonbank online lenders offer benefits that traditional banks cannot offer. First, they provide faster credit decisions and fund disbursements. Mills & McCarthy (2016) emphasize the efficiency of many FinTech lenders, pointing out that they typically make funding decisions within a 48–72 hour window. In practice, the process can be even swifter. The online lender FundingCircle, for example, claims that borrowers can receive a decision within an hour and obtain funding within 48 hours. This pace is significantly faster than the quickest SBA loan type, the SBA Express, which usually requires at least two to three days for a response and an additional 20 to 30 days to disburse the funds post-approval. Another strength of online lenders lies in their ability to cater to businesses that may struggle to access traditional banking systems (Jagtiani & Lemieux, 2018). FinTech lenders can be particularly beneficial in areas with fewer bank branches, those with lower incomes or higher numbers of minority households, and industries that have limited banking relationships (Erel & Liebersohn, 2022). Furthermore, FinTech lenders can offer credit to young firms and startups, which traditional banks often view as high-risk (Chemmanur et al., 2020). These firms frequently face challenges securing financing from traditional banks and obtaining SBA loans due to their perceived risk, absence of credit history, and unstable revenue streams.

2.2 Commercial Financing Disclosure Law (SB1235) California

Although several states, including Virginia, New York, and Utah, have enacted comparable regulations, California is the primary focus of this study due to its expansive regulatory scope, early adoption, and the prominent role of SBA loans and banks within the state. Thus, California provides an ideal setting for me to empirically test the effects of the mandate. In this section, I explain my setting and the regulation change in detail. The disclosure mandate in California, SB1235, which took effect on December 9th, 2022, was first introduced by the California Department of Financial Protection and Innovation (DFPI) in September 2018. The law requires non-depository institutions, including nonbank lenders like finance companies, online lenders, and FinTechs, who offer commercial financing products, to disclose key borrowing costs in a standardized format.[11] Banks are exempt from the disclosure mandate because regulators believe that these institutions do not present the same risk to borrowers as other entities might, given that they are already subject to rigorous federal oversight. Nonbank lenders are mandated to disclose the following: the financed amount, its breakdown, the APR, complete and itemized finance charges, payment specifics (including method, frequency, and terms for both fixed and variable rates), the projected transaction term, and prepayment conditions. California's SB1235 covers an array of small business commercial loan products valued below $500,000, such as term loans, credit lines, lease financing, factoring arrangements, sales-based financing (e.g., merchant cash advances), and asset-backed loans.

It is worth noting that although the final rule of SB1235 clarifies that nonbank entities providing technical support to a bank's commercial financing program are not obligated to disclose these details, this exemption applies only if the nonbank entity neither possesses nor intends to possess a share in the financing, and the program does not feature the nonbank's brand mark. Still, due to the narrow conditions of this exemption, many FinTech firms engaged in routine collaborations with banks could

[11] According to SB1235, a financial provider is defined as "a person who extends a specific offer of commercial financing to a recipient." It includes "a non-depository institution, which enters into a written agreement with a depository institution to arrange for the extension of commercial financing by the depository institution to a recipient via an online lending platform administered by the non-depository institution." In other words, it covers nonbank lenders, brokers, and lead generators.

be classified as providers of commercial loans and thus subject to the mandate.

Similar commercial financing disclosure regimes now exist in New York (23 NYCRR 600), Virginia (Va. Code § 6.2-22.1 et seq.), and Utah (SB 183; Utah Code § 7-27-101 et seq.), as well as in Florida, Georgia, Connecticut, and Kansas. New York's rule applies to loans of up to $2.5 million and imposes civil penalties for noncompliance, including fines of up to $2,000 per violation and up to $10,000 for intentional violations, along with potential restitution or injunctive relief. The Consumer Financial Protection Bureau (CFPB) has separately determined that these state business-lending disclosure regimes are consistent with the Truth in Lending Act framework, which does not extend to commercial credit.

3. Data

3.1 Data Sources

Data that systematically cover bank and nonbank small business lending are scarce. To construct measures of small business lending activity, I draw on three complementary datasets: (1) Uniform Commercial Code (UCC) filings; (2) Community Reinvestment Act (CRA) small business loan data; and (3) loan-level records from the SBA 7(a) program.

UCC filings are public notices that creditors submit to a state's filing office (typically the Secretary of State) when they make a loan secured by a borrower's non–real estate assets. Prior literature such as Gopal & Schnabl (2022) and Minnis et al. (2024) use UCC as a proxy for small business lending. Under Article 9 of the Uniform Commercial Code, lenders record a "financing statement" when they take a security interest in a borrower's assets. These filings identify the debtor, the secured party, and the collateral, providing public notice of the secured party's interest. They establish the lender's legal claim in the event of borrower default. In bankruptcy, priority of repayment is determined by the order of UCC filings: the lender with the earliest filing date typically has first claim on the collateral. Because failing to file often leaves a creditor legally unsecured, lenders have strong incentives to record these transactions. All types of lenders, including banks, finance companies, FinTech lenders, and credit unions, file UCCs when they make secured lending. Each U.S. state maintains its own UCC registry. A creditor must file in the state where the borrower is legally incorporated or headquartered. Importantly,

UCC filings only cover secured, non–real estate lending; unsecured lending and lending secured by real estate are not included. Gopal & Schnabl (2022) estimate that the UCC data covers about 95% of non-real-estate U.S. business loan and 73% of total small business lending.

I obtain UCC filings from a commercial vendor that aggregates records across all 50 states and the District of Columbia for the period January 1, 2022, to December 31, 2023. The dataset includes information on lenders and borrowers, such as names and addresses, along with the filing date and selected borrower characteristics, including industry classification and firm size. The filings do not report loan-level details such as loan amount, maturity, or pricing. Therefore, I use them as a proxy for loan origination activity by banks and nonbanks.

Because of the limitations of the UCC data and my focus on bank small business lending, I supplement the analysis with data from the Community Reinvestment Act (CRA). The CRA was enacted in 1977 to encourage banks to help meet the credit needs of the communities in which they operate, particularly low- and moderate-income neighbourhoods. As part of compliance, banks with more than $1 billion in assets are required to file annual reports with their federal regulators (FDIC, OCC, or Federal Reserve). These reports are compiled and published by the Federal Financial Institutions Examination Council (FFIEC). For small business lending, covered banks must report all loans with an original amount of $1 million or less. The data include both the number of loans and the dollar volume, reported separately for loans of (i) $100,000 or less, (ii) between $100,000 and $250,000, and (iii) between $250,000 and $1 million. Reporting is mandatory and covers virtually all small business loans made by these banks, including both secured and unsecured lending. CRA data are reported at the aggregate bank–county–year level and do not include loan-level information such as contract terms.

To obtain loan-level information that is absent from the CRA data, I turn to the SBA 7(a) dataset, which is publicly accessible under the Freedom of Information Act (FOIA). This dataset provides comprehensive details for every loan originated under the SBA's 7(a) program, including gross approval amounts, guaranteed amounts, initial interest rates, loan maturities, and *ex-post* loan performance (e.g., charge-offs and defaults). It also includes information on the lending institutions (identity and location) and selected borrower characteristics such as name, location, and business age.

These features allow me to analyze detailed loan terms, including pricing, maturity, and size, and to construct measures of loan risk. It is worth noting that the SBA 7(a) dataset does not cover all small business loans. Instead, it includes only 7(a) loans that are partially guaranteed by the SBA in case of borrower default. The program is explicitly designed to facilitate credit access for borrowers who might not otherwise obtain financing on reasonable terms. Applicants are required to demonstrate a "credit elsewhere" condition, that is, they cannot secure comparable credit without SBA support. For this reason, 7(a) loans serve underserved borrowers and are particularly well suited to capturing potential substitution effects when nonbank borrowers switch into bank-originated credit.

Additionally, I employ a set of granular macroeconomic controls, including state-level house price growth, per capita income, and employment rates, obtained from the Federal Housing Finance Agency (FHFA) and the Bureau of Labor Statistics (BLS). To capture local credit market structures, I incorporate county-level data from the FDIC's Summary of Deposits (SOD) and construct the local Herfindahl–Hirschman Index (HHI), the number of bank branches, total deposits, the share of national banks, and the share of small banks. Because the SOD is reported annually, these market structure controls are available only at the county–year level.

3.2 Sample Construction

I conduct my main analysis at the county–year–quarter level. I begin with the UCC filing–level data and classify lenders by type. To identify bank lenders, I flag creditors whose names contain terms such as "bank" or "banco" (and other equivalent terms in other languages). In addition, I compile official lists of depository institutions from the FDIC, OCC, and CFPB. I first exact match creditor names in the UCC data with these lists. For unmatched cases, I employ OpenAI's embedding model to generate vector representations of creditor names in both the UCC data and the regulatory lists, from which I compute cosine similarity scores. I classify a UCC filer as a bank if the similarity score exceeds 0.75 and then confirm classifications through manual validation. To identify nonbank lenders, I exclude all entities classified as banks and remove filings by government agencies, municipalities, universities, and other non-lending entities. I also exclude credit unions, as they are exempt from the regulation of interest and operate under a membership-based cooperative structure that differs fundamentally from

commercial banks. After these steps, my nonbank category consists of finance companies, FinTech lenders, and other private non–credit union lenders. With this classification, I retain only UCC filings by banks and nonbanks. I then aggregate the data to the county–quarter level and construct my primary measures: the share of UCCs filed by banks, the number of bank UCCs, and the number of nonbank UCCs. After constructing this main dataset, I turn to the SBA 7(a) loan-level data and similarly aggregate it to the county–quarter level. Because the SBA data do not directly report county identifiers, I use the borrower address and ZIP code provided in the data and crosswalk them to counties using the official U.S. Postal Service ZIP-to-county dataset.

I restrict the sample to four quarters of county–level data prior to the regulation's effective date (December 9, 2022), beginning in 2022Q1, and four quarters after the regulation, ending in 2023Q4. I define the post-period as starting in 2023Q1, since the regulation took effect in the final month of 2022Q4 and may only partially affect that quarter. To avoid confounding effects from concurrent state-level regulations, I exclude counties located in New York, Utah, and Virginia. The final dataset contains 21,194 county–quarter observations, including 448 county–quarter observations from California. I provide further details on the sample selection procedure in the Online Appendix A.

3.3 Descriptive Statistics

I report the county–quarter–level summary statistics in Table 1. On average, bank small business lending accounts for approximately 51% of total small business lending. This finding is consistent with Gopal & Schnabl (2022), who documented that nonbank lenders accounted for around 60% of lending in 2016. The higher nonbank share in my sample may reflect the continued expansion of FinTech lending and the broader adoption of open banking in recent years. Because the distributions of loan counts are highly skewed, I transform the raw counts by taking the natural logarithm of one plus the number of loans. For UCC filings, counties record on average 93 bank filings and 120 nonbank filings per quarter. These correspond to log-transformed means of 3.66 for bank filings and 3.69 for nonbank filings. For CRA loans, which are reported only at the county–year level, the average number of loans under $1 million is 2,489. After applying the log transformation, the mean is 6.1, which corresponds to roughly 600 loans per county–quarter. As expected, the CRA dataset captures a broader

set of small business loans than the UCC, since the CRA includes all loans under $1 million originated by large banks, while the UCC only records secured transactions.

Because I employ a difference-in-differences research design, I also report summary statistics for the dependent variables measuring bank share and bank lending in Table 2. In California (the treated state), the average bank share of small business lending increased from 0.32 in the pre-regulation period to 0.35 after the mandate. In contrast, in the control states without concurrent regulations, the average bank share declined from 0.54 to 0.48 over the same period. These descriptive statistics provide preliminary evidence that the transparency regulation may have increased the relative share of bank lending by shifting borrowers away from nonbank lenders.

4. Research Design and Results

4.1 Substitution and Bank Lending

To identify the effects of the nonbank loan price-transparency mandate (CFDL) on bank–nonbank substitution and, in turn, on bank lending, I estimate the following regression:

$$Y_{c,t} = \beta Treated_c \times Post_t + X_{c,t} + \gamma_c + \sigma_t + \varepsilon_{ct} \quad (1)$$

where c denotes counties and t denotes time: quarters when using UCC and SBA data and years when using CRA data. *Treated* is an indicator equal to 1 if the county is in California and 0 otherwise. *Post* is an indicator equal to 1 for periods after December 9, 2022, the effective date of the CFDL. X_{ct} includes state-time macroeconomic variables: home price index growth (*HPI Growth*), the natural logarithm of income per capita (*PI Capita*), and the employment rate (*%Employment*), and county–time market-structure variables: total deposits (*Deposit*), small-bank share (*%Small Bank*), national-bank share (*%National Bank*), deposit-based bank concentration (*HHI*), the number of bank branches (*#Bank Branch*), and the log number of small businesses (*#SME*) (Tang, 2019; Erel & Liebersohn, 2022).

The first set of dependent variables captures bank–nonbank substitution in small business lending. I use state–county–quarter UCC filing counts as a proxy for loan originations and construct three measures: (1) *%Bank Loan UCC*, the share of loans recorded by banks out of all loans (banks + nonbanks); (2) *#Bank Loan UCC*, the number of loans recorded by banks; and (3) *#NonBank Loan UCC,* the number of loans recorded by nonbanks.

The second set of dependent variables directly measures the number of bank small business loan origination. I start with the CRA lending data. Because the CRA discloses loan counts only annually, I construct these variables at the county–year level. The transparency regulation applies to nonbank loans between $5,000 and $500,000, so any substitution into banks should occur primarily within this range. Ideally, I would measure the exact number of bank loans within this threshold, but the CRA provides only three size bins: below $100,000, between $100,000 and 250,000, and between $250,000 and $1 million. In light of this limitation, I construct three measures. (1) *#Bank Loan CRA* < 1m, the number of bank loans less than $1 million; (2) *#Bank Loan CRA < 250*, the number of bank loans below $250,000, used a proxy for the treated range under the regulation; and (3) *#Bank Loan CRA 250–1m***,** the number of bank loans between $250,000 and $1 million, which serves as an above-threshold comparison group. Finally, to align exactly with the regulation threshold, I use SBA loan data, which report exact loan amounts and approval dates. I aggregate these loans to the county–quarter level and construct two measures: the number of SBA loans less than $500,000 *(#Bank Loan SBA < 500*, within the threshold) and the number of SBA loans larger than $500,000 *(#Bank Loan SBA* > 500, above the threshold). All count variables are expressed in natural logarithms.

Table 3 reports the estimates of equation (1). Column (1) includes state and quarter fixed effects without controls; column (2) adds the full set of controls. Columns (3) – (4) re-estimate the specification with county fixed effects to absorb time-invariant county heterogeneity. Across all specifications, treated counties experience an increase of about 8 percentage points in the share of small business loans issued by banks, relative to a pre-mandate mean of 32% in the treated group (overall mean 51%), this is roughly a 25% increase. The estimates are stable across columns and statistically significant at the 1% level. In the regression sample, the within–county–time standard deviation of the dependent variable is 0.122; thus the 0.08 coefficient estimate equals 0.65 standard deviations, indicating a large within-unit effect after netting out county and time fixed effects.

The rise in bank share could reflect higher bank originations, lower nonbank originations, or both. To examine levels of loan origination, I re-estimate equation (1) using as dependent variables the natural log of the number of UCC filings by banks and by nonbanks. Columns (5) – (6) report the results: bank filings increase while nonbank filings decline, indicating that the substitution is driven by both an

expansion in bank lending and a contraction in nonbank lending.

To visualize the timing of the mandate's effect, I re-estimate equation (1) by replacing the *Post* dummy with year–quarter dummies interacted with the treatment indicator. I then plot the estimated coefficients together with 95% confidence intervals in Figure 2. Figure 2a presents the results for the dependent variable *%Bank Loan UCC*, corresponding to the specification in Table 3, column (4). Time *t-4* (the quarter beginning 2022Q1) is used as the reference point. The results indicate no significant differences between treated and control counties prior to the transparency mandate, with the exception of period *t-1*, where the treated counties exhibit a positive deviation. This finding is not unexpected for two reasons. First, the regulation became effective on December 9, 2022, which falls within the last month of the *t-1* quarter; thus, some contamination may arise from the quarterly aggregation of outcomes. Second, it is plausible that nonbank lenders began to adjust their disclosure practices in anticipation of the mandate, leading to early responses that appear prior to the official implementation date. Figures 2b and 2c present analogous event-study plots, using *#Bank Loan UCC* and *#NonBank Loan UCC* as the dependent variables, corresponding to columns (5) and (6) of Table 3, respectively.

4.2 Demand for Bank Loan

Next, I provide additional evidence on whether the observed substitution is driven by increased borrower demand for bank loans in response to the transparency mandate. Ideally, such demand would be measured directly using application-level data for bank loans. However, no comprehensive dataset of this kind is publicly available. I therefore rely on two indirect and complementary approaches to gauge borrower interest: (1) Google Trends search activity, and (2) borrower-reported responses from the SBCS, administered by the Federal Reserve Bank of Cleveland and regional partners. The first approach captures changes in borrower search behavior, while the second provides insights into self-reported financing experiences and preferences from a representative sample of small businesses.

I begin this analysis by examining Google Trends search index data. Prior research has validated the use of Google search intensity as a proxy for demand in contexts such as information acquisition, mortgage activity, and policy engagement (Drake et al., 2012; Saxa, 2014; Oehl et al., 2017). Google Trends provides normalized indices (ranging from 0 to 100) of the popularity of specific

search terms and topics across time and geographic regions, which I use to construct a state–time panel for empirical analysis. I first analyze the search term "*Bank Business Loan*", which is expected to proxy for borrower interest in small business loans from banks. Yet, Google does not provide a "topic" category for bank business loans, limiting this measure's coverage. More specifically, this key term search is relatively narrow and only captures exact-match queries; similar searches such as "*Bank Business Credit*" are not included. To complement this measure, I examine the broader Google topic "*SBA Loan*," which aggregates various related queries such as "*Small Business Administration Loan*," "*SBA 7(a)*," and "*SBA Financing*." The combination of term and topic based indices allows for a more comprehensive assessment of borrower search behavior surrounding the policy intervention. I estimate the following regression:

$$Google\ Search\ Index_{s,t} = \beta Treated_s \times Post_t + X_{s,t} + \gamma_s + \sigma_t + \varepsilon_{st} \quad (2)$$

where *s* identifies a state, and *t* refers to the week of google search. The unit of analysis is at the state–week level, in alignment with Google Trends data's weekly time interval. The dependent variable in this analysis is either the Google search term index for "*Bank Business Loan*" or the broader search topic index for "*SBA Loan*." To control for shifts in general small business financing demand, I also include the Google topic "*Small Business Financing*". This index captures a wide range of relevant queries, including "*Small Business Loans*," across different languages. I include the same set of control variables used in previous analyses. These controls comprise state-time macroeconomic conditions: home price index growth (*HPI Growth*), the natural logarithm of per capita personal income (*PI Capita*), and the employment rate *(%Employment*). Since the unit of analysis here is at the state–time level (rather than county–time), I construct corresponding state–time measures of market structure by aggregating from county–level data. These include total deposits (*Deposit*), small-bank market share (*%Small Bank*), national-bank market share (*%National Bank*), deposit-based bank concentration (*HHI*), the number of bank branches (*#Bank Branch*), and the log number of small businesses (*#SME*).

Table 5 presents the results of this analysis. Column (1) shows estimates using the Google Search Index for the term "*Small Business Loan*." The coefficient on *Treated×Post* is positive and statistically significant at the 5% level, with a magnitude of 3.71. This corresponds to an 8% increase relative to the pre-shock mean of 49.077. Column (2) reports results using the Google Search Index for

the topic "*SBA Loan*," where the estimated effect translates to a 15% increase relative to the pre-shock mean of 66.615. This is consistent with the interpretation that borrowers substitute away from nonbank loans, with SBA loans representing the closest alternative. The greater rise in searches for SBA loans relative to general small business loans further supports this substitution channel.

Google Trends search intensity can be a crude measure for credit demand: it does not observe loan applications directly and can be sensitive to keyword choice. Additionally, Google Search Index reportedly return inconsistent results based on the location and time of queries (Cebrián & Domenech, 2024). To provide additional evidence on demand, I turn to the Federal Reserve's Small Business Credit Survey (SBCS). The SBCS asks firms whether, in the past 12 months, they applied for a loan, line of credit, or merchant cash advance and, if so, to which provider type: "large bank," "small bank," "online lender," "finance company," "credit union," or "CDFI." The Federal Reserve publishes aggregate results and, for roughly 20 states each year, state-level tabulations. I manually collect these state reports and compile application shares (Online Appendix T2 documents data construction and presents the raw tabulations). The patterns are consistent with the search-based results. In California, the share of firms applying to banks (large + small) rose by 2 percentage points (from 59% to 61%), while the average across other states declined (from 72.6% to 71.7%). Conversely, applications to nonbank providers in California fell sharply (from 63% to 41%), whereas the average across other states increased (from 34.1% to 36.0%). Because the state-level SBCS sample is small, I do not estimate regressions with these data; instead, Figure 3 visualizes the year-over-year changes (e.g., 2022-2023) and shows a clear reorientation toward banks in California relative to other states. 2023 as compared to other reported states average for both the demand for banks and nonbanks. Overall, the evidence from both Google search activity and SBCS responses points to a consistent conclusion: the transparency mandate significantly increased borrower demand for bank-provided small business loans, especially for SBA loans.

4.3 Risk

The increase in bank lending only partially reveals how banks respond to the additional demand. To shed light on banks' screening and pricing adjustments, I examine the distribution of borrower risk-

measured by the model predicted *ex-ante* probability of default (*PD*). For each county–quarter, I compute the mean *PD* and the deciles from the 5th to the 95th percentile. I then estimate equation (1) separately for the mean and for each percentile including county and quarter fixed effects and the full control set.

To ensure meaningful distributional estimates, I drop county-quarters with fewer than ten loans. Small cells produce unstable tail percentiles and incomplete decile coverage, which can spuriously inflate coefficients and standard errors; requiring at least ten observations mitigates this problem. Table 6 shows that the average *PD* declines after the mandate ($Treated \times Post = -0.264$, $p<0.10$), indicating that borrowers obtaining bank credit become safer on average. The distributional evidence is sharper: effects are negligible through the 65th percentile, but the upper tail falls significantly. The 75th and 95th percentiles decline by 0.559 and 1.340, statistically significant at the 10% level, respectively, and the 85th declines by 0.428 (though not statistically significant at conventional levels). Relative to the pre-shock means: 4.086 at the 75th percentile, 4.705 at the 85th, and 6.463 at the 95th, the estimated declines of 0.559, 0.428, and 1.340 imply reductions of 13.7%, 9.1%, and 20.7%, respectively. Figure 4a plots the coefficients with 90% confidence intervals, highlighting minimal movement below the 65th percentile and a pronounced downward shift in the upper tail. Taken together, the results are inconsistent with a relaxation of credit standards (which would raise risk broadly across the distribution). Instead, they suggest reallocation toward safer borrowers at the margin, consistent with banks meeting higher demand under funding or risk constraints by trimming the riskiest tail of originations.

4.4 Size and Maturity

Following the same distributional test as in the risk analysis, I examine how loan size and maturity adjust after the CFDL using SBA 7(a) loan-level data. For each county–quarter, I compute the mean size and maturity, as well as the deciles from the 5th to the 95th percentile, excluding cells with fewer than ten loans to avoid instability in the tails. Table 6 and Figures 4b–4c show that maturities shorten on average and particularly at the upper end of the distribution. The mean maturity declines by 5.45 months. The effect is modest and not statistically significant across most percentiles but becomes pronounced in the upper tail: maturities fall by 7.91 months at the 85th percentile and by 46.0 months

at the 95th percentile, relative to pre-shock means of 50.5 and 55.1 months, respectively. These declines correspond to reductions of roughly 15% and 84%. Loan sizes also contract, though the pattern differs. The mean size declines by $5,860. The largest reductions occur in the middle of the distribution: sizes fall by $13,200 at the 35th percentile, $10,300 at the 45th, $12,000 at the 55th, and $15,900 at the 65th. By contrast, effects in the lower tail are negligible, and the top of the distribution shows an increase: the 95th percentile rises by $12,400 relative to a pre-shock mean of $95,000.

These results suggest two potential mechanisms. First, borrowers previously drawn to nonbank FinTech loans may tend to prefer smaller, shorter-maturity products and they carry those preferences with them when they switch to banks, implying a demand-driven channel. This interpretation aligns with Tang (2019), who finds that P2P FinTech lenders in consumer credit primarily serve smaller, shorter-term loans. Second, banks may be tightening contract terms facing increased demand to manage capital and liquidity. Specifically, maturities are cut substantially for relatively longer-term loans, while loan sizes decline for marginal borrowers in the middle of the distribution. However, with the current test, I am unable to disentangle these two explanations.

4.5 Pricing

To test the demand-driven substitution mechanism on prices, I utilize the loan-level SBA 7(a) data to examine the effect of CFDL on loan interest rates. Specifically, I estimate the following regression:

$$Interest\ Rate_{ictl} = \beta Treated_c \times Post_t + X_{ct} + Z_l + \gamma_{it} + \sigma_c (+\zeta_z)(+\eta_k) + \varepsilon_{ictl}, \quad (3)$$

Where i indexes banks, c denotes counties (or ZIP codes z), t represents quarters, and l denotes loans. The dependent variable is the initial loan spread charged by the lender, net of the prime rate (the SBA base rate). X_{ct} includes county–year market-structure and state–quarter macroeconomic controls, as in the previous analyses. Z_l includes standard loan-level and borrower-level characteristics (Cortés et al., 2018). Specifically, I control for the log-transformed loan size (*Loan Size*), the log-transformed loan maturity (*Loan Maturity*), an indicator for whether the loan is an "Express" loan (*Express Loan*), and the model-predicted probability of default as a risk measure (*PD*). Additionally, I include borrower characteristics: an indicator for firms that have existed for less than two years (*Young Business*), the

log-transformed number of jobs supported *(#Jobs Supported*), and a *New Borrower* indicator for firms without a prior relationship with the lender in the past five years. The fixed-effects design isolates within-bank, within-time pricing differences across locations while holding borrower and contract characteristics constant. Bank-by-quarter fixed effects (γ_{it}) absorb all bank-level time-varying factors, such as funding costs, risk taking, and pricing policies, so identification comes from comparing loans made by the same lender in the same quarter across locations. County fixed effects (σ_c) control for time-invariant local characteristics, including borrower mix and market structure. In a stricter specification, I replace county fixed effects with ZIP-code fixed effects (ζ_z) to capture finer geographic variation. I also include industry fixed effects (η_k) to account for sector-specific differences in risk and pricing.

Table 8 Panel B presents the results. Across all specifications, the coefficient on *Treated*×*Post* is positive and statistically significant at the 5% level, ranging from 0.045 to 0.120. This suggests that, holding borrower and loan characteristics constant, loans in California became more expensive after the mandate, relative to similar loans issued by the same bank in the same quarter outside California. The pattern is consistent across fixed effects specifications, indicating that the result is not driven by unobserved differences in location or industry composition. The coefficients on the control variables are as expected. The probability of default (*PD*) is positively and precisely estimated across all models, validating its use as a risk proxy. Loan size (*Loan Size*) is strongly negatively associated with interest rates, reflecting scale economies or lower perceived risk for larger loans. Express loans (*Express Loan*) carry higher spreads, likely due to faster processing or higher borrower risk. The *Young Business* indicator is positively associated with interest rates in most models. The number of jobs supported *(#Jobs Supported*) does not exhibit a consistent effect. The results support the interpretation that the transparency mandate increased demand for bank loans, which in turn allowed banks to raise loan prices. The pricing response, conditional on risk and borrower observables, reinforces the demand-driven nature of the substitution effect rather than a loosening of credit standards.

4.4 Bank Loan Geography

The regulation raises concerns about credit access for disadvantaged SMEs. High compliance and litigation costs may induce nonbank lenders to retrench or exit California, reducing overall credit

supply. At the same time, disclosure of higher nonbank rates redirects applicants toward bank small business loans, intensifying competition for a limited pool of guaranteed credit. This crowding pressure is likely to fall most heavily on SMEs already disadvantaged in traditional financing — businesses in low-income areas, minority-owned firms, and firms led by less-educated owners (Erel & Liebersohn, 2022; Howell et al., 2024). As shown earlier, banks accommodate the inflow by substituting safer borrowers for riskier ones; similar sorting may occur along these disadvantage margins. In particular, SMEs with limited financial literacy or numeracy, or lower formal education, may be disproportionately affected. In the absence of an expansion of lending capacity or targeted support, the mandate could unintentionally widen disparities in access to bank credit.

To examine whether the regulation had uneven effects across communities, I study the geography of bank loan originations. Specifically, I re-estimate equation (1), interacting the *Treated*×*Post* variable with a set of county-level characteristics obtained from the NCES PIAAC State and County Estimates, which are based on the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), a survey of adults (ages from 16 to 74) that measures proficiency in foundational skills. NCES applies model-based methods that combine PIAAC responses with auxiliary data to generate small-area estimates, producing county-level measures of both adult skill levels and key socioeconomic characteristics. From this dataset, I use measures of *Numeracy* (average proficiency in quantitative reasoning, e.g., interpreting numbers, ratios, and simple calculations) and *Literacy* (average proficiency in reading comprehension and written communication). Both are measured on a 0-500 scale, with higher values indicating greater proficiency. In addition, I draw on estimates of socioeconomic composition: the poverty rate *(%Poverty*), the share of adults with a bachelor's degree or higher *(%High Edu*), and the share of racial/ethnic minority residents *(%Minority*). These variables allow me to test whether the regulation's effects on loan originations vary systematically across counties with weaker skills, higher poverty, higher education, or larger minority populations.

I report the results in Table 9, where the dependent variable is the number of loans originated in a county-quarter. To align with the regulation's coverage threshold of $5,000–$500,000, I consider

three measures: (i) all CRA loans below $1 million[12] and (ii) SBA loans below $500,000. The results show modest evidence that banks issue more loans in counties with higher numeracy scores, although the effect is small in magnitude. By contrast, counties with higher poverty rates experience significantly smaller increases in lending across all three measures, suggesting that disadvantaged areas benefit less from the post-mandate expansion of bank credit. At the same time, bank lending appears to increase more in counties with higher shares of college-educated adults, consistent with a reallocation of credit toward better-educated communities. With respect to racial composition, I do not find evidence of reduced access in higher-minority counties; in fact, the results indicate more bank loans in these areas, as the interaction with *%Minority* is positive and highly significant across all specifications. Finally, I explore the role of local banking presence by interacting *Treated*×*Post* with the number of bank branches. The estimates are positive, particularly for SBA loans, indicating that counties with greater branch coverage experienced larger loan increases, consistent with banks using their local branch networks to accommodate the additional demand.

5. Conclusion

Nonbank small business lending expanded rapidly after the financial crisis, sparking debate about its impact on credit markets. Compared with banks, nonbanks and FinTech lenders are subject to less regulation and rely more heavily on technology and data-driven screening in their loan issuance. Many borrowers to substitute bank loans with nonbank credit. I highlight an additional force behind this substitution: the lack of transparency in nonbank loan pricing. Seemingly low advertised rates attract not only borrowers without access to bank credit, who have little choice but to turn to nonbanks, but also borrowers who could qualify for bank loans but are enticed by seemingly cheaper financing. I find that, with increased nonbank price transparency, borrowers refrain from applying for nonbank loans and shift back toward banks. In response, banks selectively issue credit to less risky borrowers while raising loan prices. Moreover, the effects of the regulation are uneven: bank lending increases disproportionately in less disadvantaged areas, those with higher education levels, lower poverty rates,

[12] In untabulated analysis, I repeat the test for all CRA loans below $250,000 and find consistent results.

and residents with stronger numeracy skills, raising concerns about potential increased disparities in access to bank credit.

The extent to which a regulation spills over to other financial instruments (regulatory whack-a-mole) is a key consideration in crafting effective regulation (Wang & Burke, 2022). With ongoing state-level initiatives, at least eight states, including New York, Virginia, Utah, Connecticut, Florida, Georgia, Texas, and New Jersey, have passed or proposed similar commercial financing disclosure laws, and a federal regulation is currently under consideration.[13] This study provides preliminary evidence on the effects of such regulations, focusing not only on the direct impact of disclosure requirements on small business lending but also on their broader consequences for credit market allocation.

[13] https://www.congress.gov/crs_external_products/R/HTML/R48281.web.html

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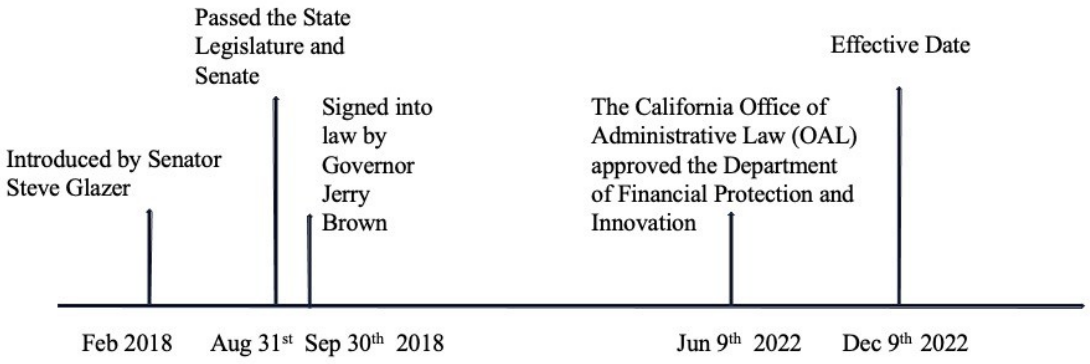
APPENDIX

Appendix A–Variable Definitions

Variable Name	Variable Definition	Data Source
%Bank Loan UCC $_{ct}$	Share of small business loans recorded by banks out of total loans (banks + nonbanks) in county *c*, quarter *t*; proxied by UCC filing counts.	State UCC Filings
#NonBank Loan UCC $_{ct}$	Natural logarithm of one plus the number of loans recorded by banks in county *c,* quarter *t*; proxied by UCC filing counts.	State UCC Filings
#Bank Loan UCC $_{ct}$	Natural logarithm of one plus the number of loans recorded by nonbanks in county *c,* quarter *t*; proxied by UCC filing counts.	State UCC Filings
#Bank Loan CRA <250 $_{ct}$	Natural logarithm of one plus the number of bank loans ≤ $250,000 in county *c,* year *t* (CRA size bin).	FFIEC Community Reinvestment Act (CRA)
#Bank Loan CRA 250-1m $_{ct}$	Natural logarithm of one plus the number of bank loans between $250,000 and $1,000,000 in county *c,* year *t* (CRA size bin).	CRA
#Bank Loan CRA <1m $_{ct}$	Natural logarithm of one plus the number of bank loans ≤ $1,000,000 in county *c,* year *t* (CRA size bin).	CRA
#Bank Loan SBA <500 $_{ct}$	Natural logarithm of one plus the number of SBA 7(a) loans ≤ $500,000 in county *c,* quarter *t*.	U.S. Small Business Administration (SBA)
#Bank Loan SBA >500 $_{ct}$	Natural logarithm of one plus the number of SBA 7(a) loans > $500,000 in county *c,* quarter *t*.	SBA
Treated $_{c}$	Indicator equal to 1 for counties in California subject to SB1235 (Commercial Financing Disclosure Law).	
Post $_{t}$	Indicator equal to 1 for quarters after December 9, 2022 (CFDL effective date).	
HPI Growth $_{st}$	Year-over-year growth rate of the house price index in state *s*, time *t*.	FHFA
PI Capita $_{st}$	Natural logarithm of one plus state personal income per capita in state *s*, time *t*.	BEA
%Employment $_{st}$	Employment rate in state *s*, time *t*.	BLS
HHI $_{ct}$	Herfindahl–Hirschman Index of deposit market concentration in county *c,* year *t* (deposit-share weighted).	FDIC Summary of Deposits (SOD)
#SME $_{ct}$	Natural logarithm of one plus the number of small businesses (establishments) in county *c,* year *t*.	U.S. Census Bureau
%Small Bank $_{ct}$	Share of banks with total assets < $1 billion in county *c,* year *t*.	FDIC Summary of Deposits (SOD)
%National Bank $_{ct}$	Share of banks chartered as national banks in county *c,* year *t*.	SOD
Deposits $_{ct}$	Total deposits in all county bank branches divided by the number of small businesses in county *c,* year *t*.	SOD + U.S. Census Bureau
#Bank Branch $_{ct}$	Number of bank branches in county *c,* year *t*.	SOD
"Bank Business Loan" $_{st}$	Google Search Index for the term “bank business loan” in state *s*, week *t* (0–100 normalized).	Google Trends
"SBA Loan" $_{st}$	Google Search Index for the topic “SBA loan” in state *s*, week *t* (0–100 normalized).	Google Trends

"Small Business Financing" $_{st}$	Google Search Index for the topic "small business financing" in state *s*, week *t* (0–100 normalized).	Google Trends
PD $_{l}$	Predicted borrower probability of default based on SBA 7(a) loan features and borrower geography (zip-level income, minority share, education, local macro).	Constructed from SBA + Census + BEA + BLS
Loan Size $_{l}$	Natural logarithm of one plus the SBA loan amount.	SBA
Loan Maturity $_{l}$	Natural logarithm of one plus the SBA loan maturity (months).	SBA
Young Business $_{l}$	Indicator equal to 1 if the business is a start-up or ≤ 2 years old at origination.	SBA
#Job Supported $_{l}$	Natural logarithm of one plus the number of jobs supported by the SBA loan.	SBA
Literacy $_{c}$	Average literacy level of residents in county *c*.	National Center for Education Statistics (NCES)
Numeracy $_{c}$	Average numeracy level of residents in county *c*.	NCES
%Poverty $_{c}$	Share of residents in poverty in county *c*.	NCES
%High Edu $_{c}$	Share of residents with education beyond high school in county *c*.	NCES
%Minority $_{c}$	Share of non-white population in county *c*.	NCES

Appendix B–California Commercial Finance Disclosure Regulation Timeline



Appendix C. CFDL Sample Disclosure

This financing has multiple payment options. This disclosure assumes you will make the minimum payments permitted under the contract.		
Funding Provided	$____	(i) This is how much funding [name of financer] will provide. (ii) If the amount financed is greater than the recipient funds: "Due to deductions or payments to others, the total funds that will be provided to you directly is [recipient funds]. For more information on what amounts will be deducted, please review the attached document "Itemization of Amount Financed."" As applicable, include short explanations if: ®) any portion of the amount financed will be used to pay down or pay off other amounts owed by the recipient that may change over time; and (ii) the amount paid to the recipient may change if an unknown amount of the financing must be used to pay down or pay off amounts owned to third parties. The Final Regulations do not specify any specific disclosure language for these explanations.
Annual Percentage Rate (APR) or Estimated Annual Percentage Rate (APR) if the contract provides for an adjustable interest rate or rates that are not predetermined by the contract	____%	APR is the cost of your financing expressed as a yearly rate. APR includes the amount and timing of the funding you receive, interest and fees you pay and the payments you make. Your APR is not an interest rate. Your interest rate is [interest rate]. Your APR may be higher than your interest rate because APR incorporates interest costs and other finance charges.
Finance Charge or Estimated Finance Charge	$____	This is the dollar cost of your financing.
Total Payment Amount or Estimated Total Payment Amount	$____	This is the total dollar amount of payments you will make during the term of the contract. or This is our estimate of the total dollar amount of payments you will make during the term of the contract.

<table>
<tr><td>Payment

or

Initial Payment
If the periodic payment amounts will vary over the term of the transaction and it is not possible to calculate the payment amounts in advance</td><td>.</td><td>A short explanation of the payment frequency and any irregular payments. The provider may also include a short explanation describing when each periodic payment will become due.
e.g.,

Months 1-12: $600/month Months 13-24: $1200/month Maintenance Fee Due 2/1/2021: $500. Maintenance Fee Due 8/1/2022: $300.

or

Payments 1-23: $600/month Payment 24: $2000. Maintenance Fee Due 2/1/2021: $500. Maintenance Fee Due 8/1/2022: $300.</td></tr>
<tr><td>Term</td><td>____</td><td>.</td></tr>
<tr><td rowspan="2">Prepayment</td><td colspan="2">If you pay off the financing early, you will still need to pay all or a portion of the finance charge, up to $[maximum non-interest finance charge].

or

“If you pay off the financing early, you will not need to pay any portion of the finance charge other than unpaid interest accrued (if applicable).”</td></tr>
<tr><td colspan="2">If you pay off the financing early you must also pay the following additional fees: followed by the amounts and descriptions of each additional fee and charge.

If you pay off the financing early you will not pay additional fees.</td></tr>
<tr><td>Average Monthly Cost</td><td>$____</td><td>Although this financing does not have monthly payments, this is our calculation of your average monthly cost for comparison purposes</td></tr>
</table>

Appendix E. Construction of *PD* (probability of default)

To construct the *PD* variable, I employed a machine learning model using an XGBoost classifier to predict the likelihood of loan default with historical SBA 7(a) data as well as geographic data. First, I prepared the dataset by dividing it into two segments: data from 2018 and earlier was used for training and evaluation, while data from after 2018 was reserved for prediction. This split was chosen because the loan status for post-2018 data is often incomplete, as most loans are still within their maturity period. I defined the target variable, Default, as a binary indicator where loans marked as 'CHGOFF' in the LoanStatus field were assigned a value of 1, representing default, and non-default loans were assigned a value of 0.

For model features, I selected a combination of numerical and categorical variables based on their relevance to loan and borrower characteristics. The numeric features include GrossApproval (total amount approved for the loan), SBAGuaranteedApproval (portion of the loan guaranteed by the SBA), TermInMonths (loan term in months), JobsSupported (jobs directly supported by the loan), and interest rate prime (interest rate adjusted for prime rate) from SBA 7(a) data. Additionally, demographic data were obtained from the Census, the American Community Survey, the National Center for Education Statistics, and the Federal Reserve Bank of Philadelphia. These variables include: coindex (coincident index, representing economic conditions at the regional level), population zip (population in the borrower's zip code), population nonwhite zip (nonwhite population percentage in the zip code), poverty perc zip (percentage of population living below poverty level in the zip code), high edu zip (percentage with a high school diploma or higher in the zip code), LitA (average literacy level in the county), NumA (average numeracy level in the county), Unemployed (unemployment rate in the county), Eng not well (percentage with limited English proficiency in the county). Categorical features encompassed BusinessType, subpgmdesc, NaicsCode, BusinessAge, RevolverStatus, relationship loan.

For numeric features, I used median imputation for missing values and standardized them with a scaler. For categorical variables, I applied constant imputation for missing values and transformed them into one-hot encoded vectors to make them compatible with the model. The final preprocessing steps were integrated into a ColumnTransformer, which I included within an XGBoost model pipeline. This structure ensured that all transformations occurred as part of the training process, thus preventing data leakage. XGBoost works by building a sequence of decision trees, where each tree attempts to correct the errors made by the previous one, thus reducing bias and capturing complex patterns in the data. For this model, I used the following key parameters in XGBoost: use label encoder=False, which disables the older version's label encoder requirement for the target variable; eval metric='logloss', which uses logarithmic loss to evaluate model performance (a suitable choice for binary classification as it penalizes incorrect probability predictions); and random state=42, which ensures reproducibility of results.

I split the pre-2018 data into training and validation subsets to evaluate the model's predictive performance. Using the validation data, I calculated key metrics: a ROC-AUC of 0.9715 indicated high discriminative power. While an accuracy of 0.9640 demonstrated the model's overall correctness, this high accuracy may be misleading. Since the dataset is imbalanced, the model could achieve high accuracy by mostly predicting non-defaults, even if it misses many defaults. The precision is 0.7192, which is relatively low, indicating that when the model predicts a default, it's only correct 71.92% of the time. The model has a recall of 0.5788, meaning that it correctly identifies 60% of actual defaults. The F1 Score, balancing these aspects, was 0.6414, suggesting a moderate balance between precision and recall. After training and validation, I used the model to predict the probability of default (*PD*) for each loan in the post-2018 data. These predicted probabilities were merged back into the original dataset, creating the *PD* variable as a continuous measure of each loan's likelihood of default.

Figure 1 Bank Share in California by County Pre vs Post CFDL

This figure plots the share of bank loans relative to total small business loans across California counties before and after the implementation of the California Commercial Financing Disclosure Law (CFDL). The top-left map shows the pre-CFDL period, the top-right map shows the post-CFDL period, and the bottom map reports the county-level change (post minus pre, measured in percentage points). Darker shades indicate higher bank share, while in the bottom map red (blue) shading corresponds to increases (decreases) in bank share. County boundaries are based on U.S. Census TIGER/Line cartographic shapefiles.

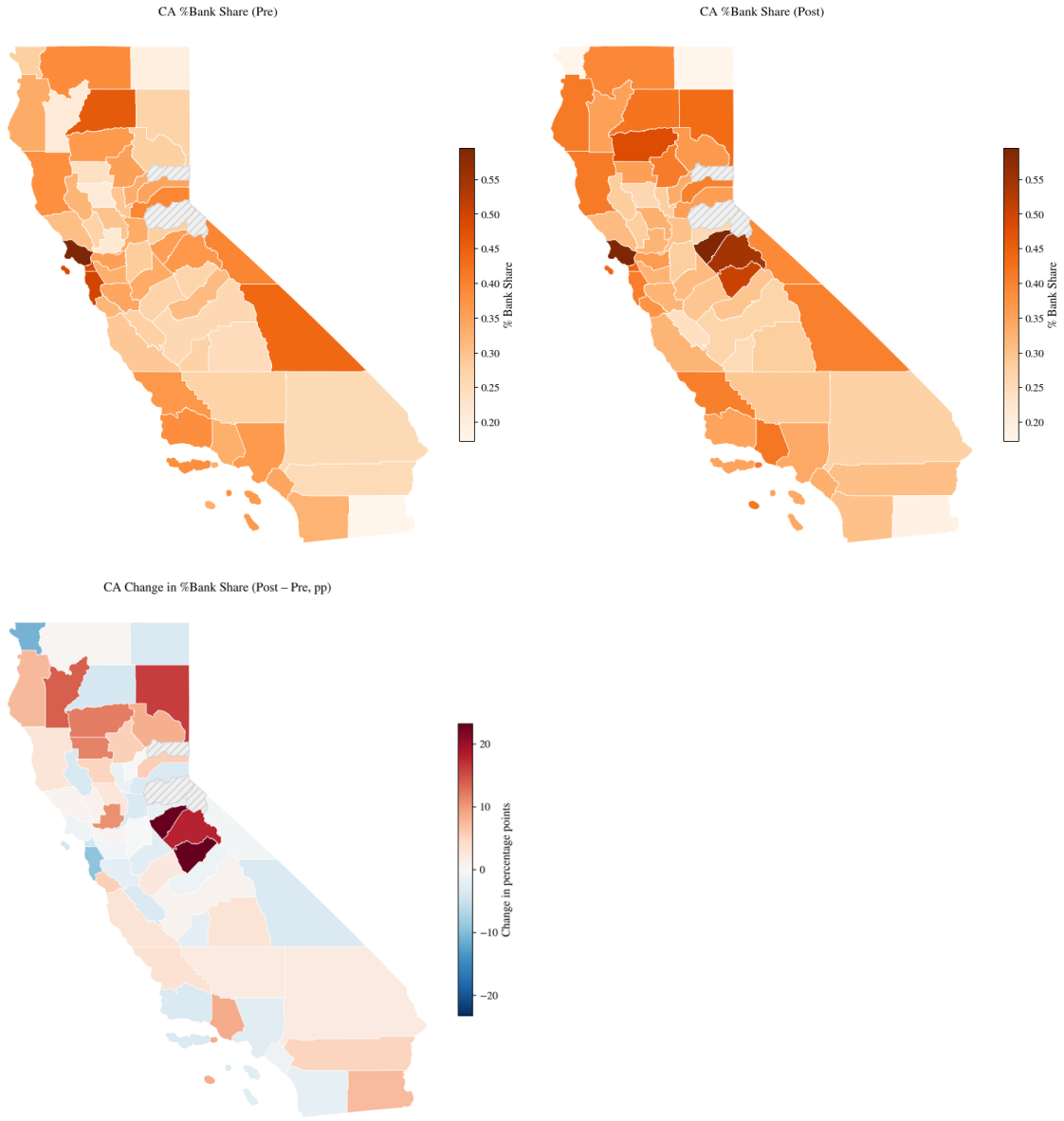


Figure 2 Dynamic Treatment Effects of CFDL

This figure reports the effects of the California Financing Disclosure Law (CFDL) on bank–nonbank substitution and bank lending, as obtained from estimating Equation (1) using county–quarter level data. Each dot represents the estimated treatment effect, and the vertical bars indicate 95% confidence intervals. Figure 2a shows the effect on the share of bank loans in total small business lending *(% Bank Loan UCC*). Figure 2b shows the effect on the number of nonbank loans (*#NonBank Loan UCC*). Figure 2c shows the effect on the number of bank loans (*#Bank Loan UCC*). Figures 2d and 2e report the effects on bank small business lending under the SBA 7(a) program, split by loan size: loans below $500,000 (*#Bank Lon SBA <500*) and loans above $500,000 (*#Bank Loan SBA >500*), respectively. Quarter t = −4 (2022Q1) is the reference period. The vertical dashed line marks the effective date of CFDL (December 9, 2022).

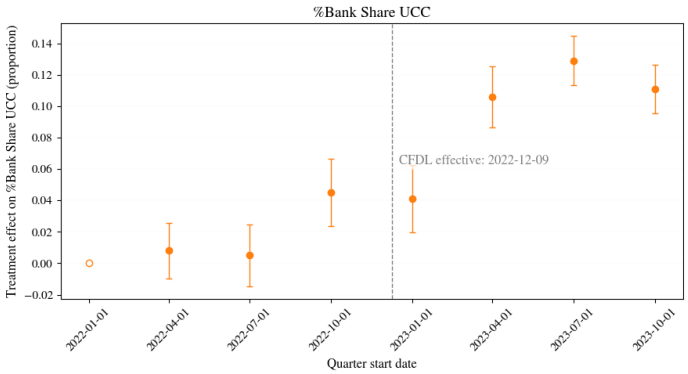


Figure 2a. *%Bank Loan UCC*

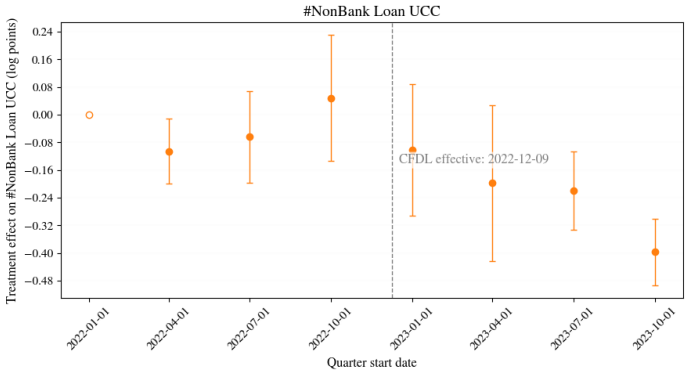


Figure 2b. *#NonBank Loan UCC*

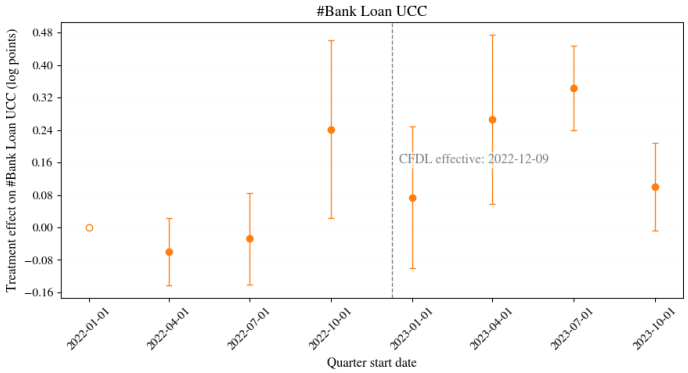


Figure 2c. *#Bank Loan UCC*

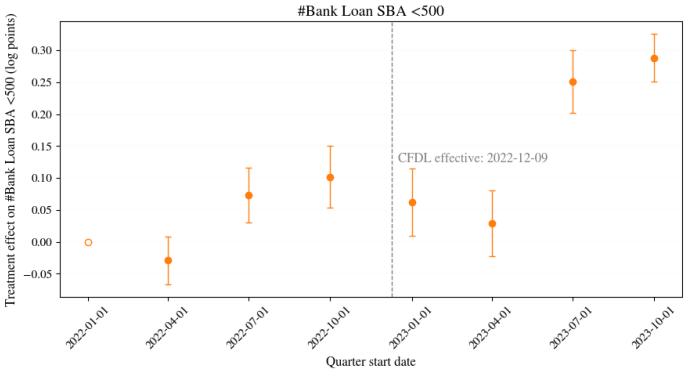


Figure 2d. *#Bank Loan SBA<500*

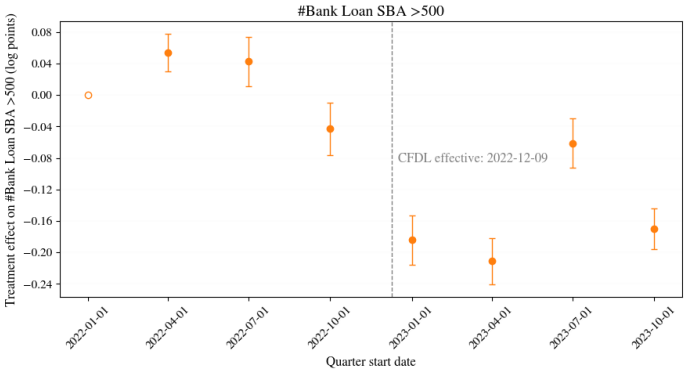


Figure 2e. *#Bank Loan SBA>500*

Figure 3 Demand for Bank vs. Nonbank Loans, California vs. Other States (2023–2022)

This figure plots the change in the share of small businesses applying to different lender types using data from the Federal Reserve's Small Business Credit Survey (SBCS). The left panel shows the year-over-year (2023 minus 2022) change in applications to banks (large + small), while the right panel shows the change in applications to nonbank providers (e.g., online lenders, finance companies). Each dot represents a state; California is highlighted in orange, and all other reported states are shown in light blue. Dashed horizontal lines mark the average change across other states.

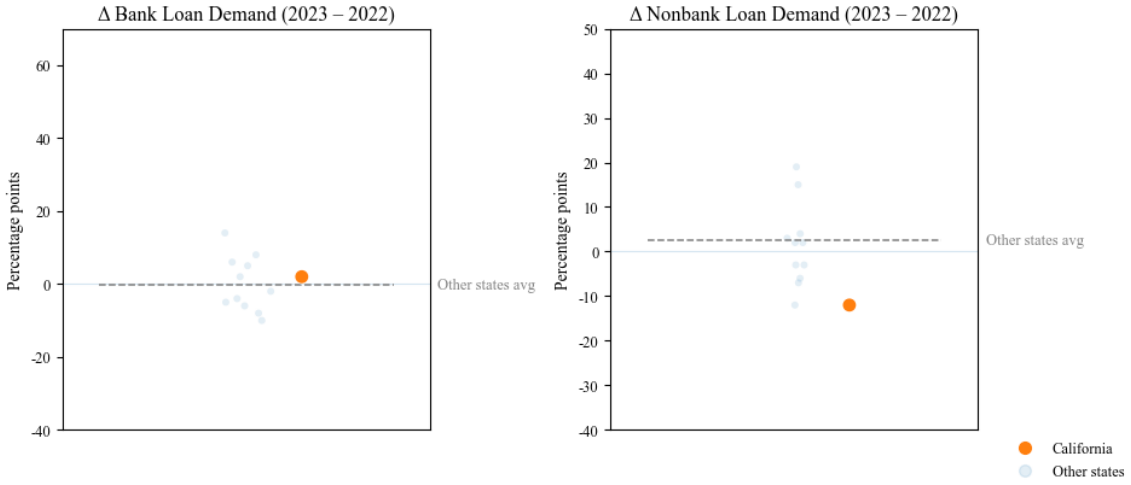


Figure 4 Distribution

This figure reports the effects of the California Financing Disclosure Law (CFDL) across the distribution of loan characteristics, estimated from Equation (1) with county and quarter fixed effects and the full control set. Each line plots the estimated treatment effect by percentile of the outcome distribution, with shaded areas denoting 90% confidence intervals. Figure 3a shows the distribution of borrower risk, measured by the ex-ante probability of default (*PD*). Figure 3b shows the distribution of loan size, and Figure 3c shows the distribution of loan maturity.

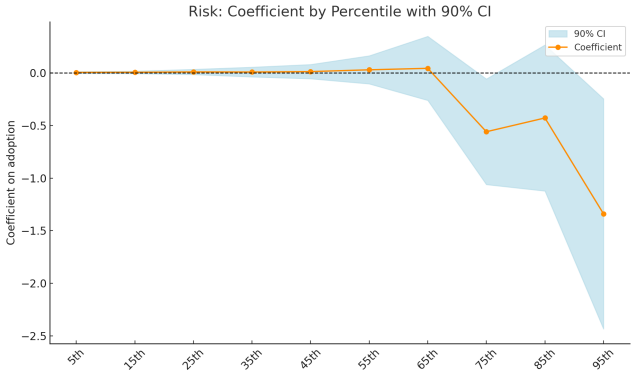


Figure 4a. Risk Distribution

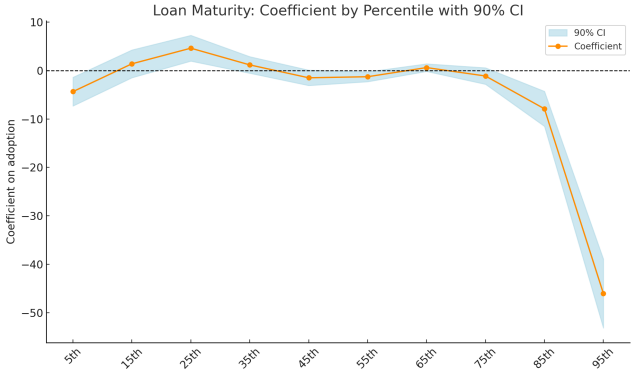


Figure 4a. Size Distribution

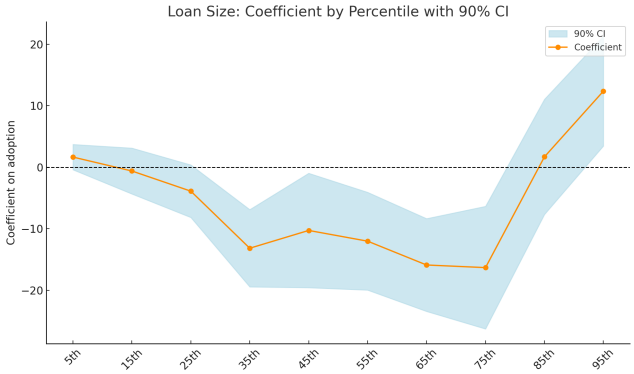


Figure 4a. Maturity Distribution

Table 1 Summary Statistics

This table presents summary statistics for the dependent and control variables. The dependent variables include measures of small business lending from UCC filings, CRA data, and SBA loans. Explanatory variables capture treatment status, time period, and county-level characteristics such as housing price growth, per capita income, employment, banking concentration (HHI), SME counts, deposit shares by bank type, total deposits, and bank branch density. Reported statistics include the number of observations (*N*), mean, standard deviation (std), and the 25th, 50th, and 75th percentiles.

	N	mean	std	25%	50%	75%
Dep. Var.						
%Bank Loan UCC	21194	0.506	0.195	0.377	0.500	0.633
#NonBank Loan UCC	21194	3.655	1.418	2.833	3.638	4.431
#Bank Loan UCC	21194	3.688	1.340	2.944	3.784	4.522
#Bank Loan CRA <250	5878	6.039	1.702	4.890	5.844	6.978
#Bank Loan CRA 250-1m	5878	6.010	1.700	4.860	5.811	6.945
#Bank Loan CRA <1m	5878	2.545	1.668	1.386	2.398	3.555
#Bank Loan SBA <500	21194	0.598	0.945	0.000	0.000	1.099
#Bank Loan SBA >500	21194	0.315	0.635	0.000	0.000	0.693
Explanatory & Control Var.						
Treated	21194	0.021	0.144	0.000	0.000	0.000
Post	21194	0.500	0.500	0.000	0.000	1.000
HPI Growth	21194	9.813	5.874	5.813	8.364	13.801
PI Capita	21194	11.043	0.116	10.973	11.035	11.109
%Employment	21194	60.467	3.858	58.633	60.733	62.033
HHI	21194	0.339	0.219	0.185	0.274	0.418
#SME	21194	6.496	1.471	5.447	6.340	7.378
%Small Bank	21194	0.415	0.296	0.200	0.364	0.625
%National Bank	21194	0.277	0.232	0.000	0.273	0.429
Deposits	21194	28.124	16.719	17.184	24.092	34.273
#Bank Branch	21194	1.958	0.683	1.386	1.946	2.398

Table 2 Diff in Diff Summary Statistics

This table reports descriptive statistics for the main outcome variables used in the difference-in-differences analysis. The sample is split into treated and control groups, and further into pre- and post-periods relative to the implementation of the policy. For each variable, the table presents the number of observations (N), mean, standard deviation (std), and median (50%).

Treated - Pre	*%Bank Loan UCC*	*#NonBank Loan UCC*	*#Bank Loan UCC*	*#Bank Loan CRA <1m*	*#Bank Loan CRA <250*	*#Bank Loan CRA 250-1m*	*#Bank Loan SBA <500*	*#Bank Loan SBA >500*
N	224	224	224	58	58	58	224	224
mean	0.322	4.632	5.392	8.267	8.248	4.302	1.535	1.327
std	0.108	1.786	1.699	2.036	2.035	2.089	1.316	1.164
50%	0.320	4.732	5.474	8.391	8.360	4.655	1.386	1.099

Treated - Post	*%Bank Loan UCC*	*#NonBank Loan UCC*	*#Bank Loan UCC*	*#Bank Loan CRA <1m*	*#Bank Loan CRA <250*	*#Bank Loan CRA 250-1m*	*#Bank Loan SBA <500*	*#Bank Loan SBA >500*
N	224	224	224	58	58	58	224	224
mean	0.349	4.458	5.099	8.189	8.171	4.166	1.703	1.134
std	0.122	1.737	1.729	2.060	2.061	1.948	1.480	1.173
50%	0.332	4.575	5.247	8.258	8.232	4.542	1.609	0.693

Control - Pre	*%Bank Loan UCC*	*#NonBank Loan UCC*	*#Bank Loan UCC*	*#Bank Loan CRA <1m*	*#Bank Loan CRA <250*	*#Bank Loan CRA 250-1m*	*#Bank Loan SBA <500*	*#Bank Loan SBA >500*
N	10383	10383	10383	2881	2881	2881	10383	10383
mean	0.535	3.822	3.662	6.049	6.020	2.569	0.554	0.307
std	0.191	1.321	1.392	1.655	1.652	1.655	0.894	0.612
50%	0.533	3.951	3.689	5.869	5.844	2.398	0.000	0.000

Control - Post	*%Bank Loan UCC*	*#NonBank Loan UCC*	*#Bank Loan UCC*	*#Bank Loan CRA <1m*	*#Bank Loan CRA <250*	*#Bank Loan CRA 250-1m*	*#Bank Loan SBA <500*	*#Bank Loan SBA >500*
N	10363	10363	10363	2881	2881	2881	10363	10363
mean	0.484	3.518	3.579	5.941	5.912	2.453	0.598	0.283
std	0.196	1.308	1.388	1.674	1.672	1.628	0.945	0.594
50%	0.472	3.611	3.584	5.759	5.733	2.303	0.000	0.000

Table 3 Substitution

This table presents county–quarter regressions estimating the effect of California's Commercial Financing Disclosure Law (CFDL) on substitution between banks and nonbanks in small business lending. All specifications are estimated using equation (1). The dependent variable in Columns (1) – (4) is the share of UCC filings attributed to banks *(%Bank Loan UCC*), while Columns (5) – (6) use the natural logarithm of the number of UCC filings by banks *(#Bank Loan UCC*) and by nonbanks (*#NonBank Loan UCC*), respectively. The key regressor is *Treated×Post*, equal to one for California counties after December 9, 2022. Control variables include home price index growth (*HPI Growth*), income per capita (*PI Capita*), employment rate (*%Employment*), bank concentration (*HHI*), the number of small businesses *(#SME*), the share of small banks (*%Small Bank*), the share of national banks (*%National Bank*), total deposits (*Deposits*), and the number of bank branches *(#Bank Branch*). Columns (1) – (2) include state and quarter fixed effects, Columns (3) – (4) include county and quarter fixed effects, and Columns (5) – (6) include county and quarter fixed effects with the full set of controls. Standard errors, clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Dep. Var.	*%Bank Loan UCC*				*#Bank Loan UCC*	*#NonBank Loan UCC*
	(1)	(2)	(3)	(4)	(5)	(6)
Treated×Post	0.078***	0.081***	0.079***	0.082***	0.157***	-0.199***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.038)	(0.038)
HPI Growth		0.001		0.000	0.002	0.000
		(0.001)		(0.001)	(0.006)	(0.006)
PI Capita		0.160		0.143	0.872	0.439
		(0.250)		(0.234)	(1.188)	(1.396)
%Employment		0.015**		0.016**	0.080	0.009
		(0.007)		(0.007)	(0.051)	(0.040)
HHI		-0.008		-0.050	0.083	0.146
		(0.025)		(0.058)	(0.219)	(0.252)
#SME		-0.024**		-0.021	0.051	0.254
		(0.009)		(0.103)	(0.332)	(0.328)
%Small Bank		0.063***		0.035	-0.138	-0.265***
		(0.011)		(0.024)	(0.105)	(0.097)
%National Bank		-0.005		-0.002	-0.090	-0.074
		(0.015)		(0.050)	(0.158)	(0.174)
Deposits		0.000		0.001	0.000	-0.001
		(0.000)		(0.001)	(0.003)	(0.002)
#Bank Branch		0.001		-0.071**	-0.027	0.191
		(0.015)		(0.034)	(0.149)	(0.145)
State FE	Y	Y	N	N	N	N
Quarter FE	Y	Y	Y	Y	Y	Y
County FE	N	N	Y	Y	Y	Y
Adj. R^2	0.254	0.290	0.551	0.552	0.913	0.931
N	21,218	21,218	21,194	21,194	21,194	21,194

Table 4 Bank Loan

This table reports estimates of equation (1) examining the effect of the California Financing Disclosure Law (CFDL) on bank small business lending. The dependent variables are the natural logarithm of the number of bank loans. Columns (1) – (3) use Community Reinvestment Act (CRA) data, which are available only at the county–year level: (1) *#Bank Loan CRA <1m* (loans ≤ $1 million), (2) *#Bank Loan CRA* < 250 (loans ≤ $250,000, within the CFDL disclosure range), and (3) *#Bank Loan CRA* 250–1m (loans between $250,000 and $1 million, partially above the threshold). Columns (4) – (5) use SBA 7(a) loan-level data aggregated to the county–quarter level: (4) *#Bank Loan SBA < 500* (loans ≤ $500,000, within the threshold) and (5) *#Bank Loan SBA* > 500 (loans above $500,000, placebo group). The key independent variable is *Treated×Post*, equal to one for California in weeks after December 9, 2022. All regressions include the same set of state–quarter macroeconomic and county–year market-structure controls as in the previous tables. All regressions include county and quarter fixed effects. Standard errors, clustered at the state level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

	CRA			SBA	
Dep. Var.	*#Bank Loan CRA <1m* (1)	*#Bank Loan CRA <250* (2)	*#Bank Loan CRA 250-1m* (3)	*#Bank Loan SBA<500* (4)	*#Bank Loan SBA>500* (5)
Treated×Post	0.030***	0.031***	-0.019	0.121***	-0.170***
	(0.006)	(0.006)	(0.018)	(0.012)	(0.008)
HPI Growth	-0.003**	-0.003***	-0.000	-0.006***	0.000
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
PI Capita	-0.005	-0.005	-0.028*	-0.177	0.140
	(0.005)	(0.005)	(0.015)	(0.595)	(0.346)
%Employment	0.005	0.006	-0.023	0.039**	-0.006
	(0.006)	(0.006)	(0.027)	(0.019)	(0.008)
HHI	0.099	0.100	0.240	0.192	-0.137
	(0.111)	(0.115)	(0.369)	(0.189)	(0.112)
#SME	0.195*	0.207*	-0.041	0.318*	0.141
	(0.111)	(0.117)	(0.191)	(0.164)	(0.108)
%Small Bank	0.043	0.031	0.115	-0.067	0.029
	(0.056)	(0.052)	(0.140)	(0.047)	(0.041)
%National Bank	0.053	0.049	0.055	-0.018	-0.023
	(0.043)	(0.042)	(0.171)	(0.085)	(0.049)
Deposits	0.001	0.001	0.003	-0.002	-0.001
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
#Bank Branch	0.005	0.012	-0.107	0.101	0.061
	(0.063)	(0.064)	(0.201)	(0.153)	(0.104)
Quarter FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
Adj. R^2	0.997	0.997	0.962	0.850	0.772
N	5,470	5,470	5,470	21,194	21,194

Table 5 Demand for Bank Loans

This table reports estimates of equation (2), which examines whether the California Financing Disclosure Law (CFDL) increased borrower demand for bank loans as proxied by Google search activity. The dependent variable is the Google Search Index (0–100) at the state–week level. Column (1) uses the search term "*Bank Business Loan*," which captures borrower queries explicitly referencing bank small business loans. Column (2) uses the broader Google topic "*SBA Loa*." The key independent variable is *Treated×Post*, equal to one for California in weeks after December 9, 2022. Control variables include state–time macroeconomic characteristics-home price index growth (*HPI Growth*), the natural logarithm of per capita income (*PI Capita*), and the employment rate *(%Employment*)-as well as state–time measures of banking market structure constructed by aggregating county-level data: bank concentration (*HHI*), the log number of small businesses *(#SME*), the share of small banks (*%Small Bank*), the share of national banks (*%National Bank*), total deposits (*Deposits*), and the number of bank branches (*#Bank Branch*). In addition, the Google topic "*Small Business Financing*" is included as a control to account for shifts in general small business loan demand. All regressions include state and week fixed effects. Standard errors, clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Dep. Var.	Google Search Index: *"Bank Business Loan"* (1)	Google Search Index: *"SBA Loan"* (2)
Treated×Post	3.710**	9.963***
	(1.625)	(1.963)
"Small Business Financing"	0.030**	0.037**
	(0.013)	(0.016)
HPI Growth	0.037	-0.258
	(0.086)	(0.195)
PI Capita	-22.329	-69.905
	(20.819)	(54.284)
%Employment	0.889	1.895
	(0.664)	(1.716)
HHI	-31.861	46.488
	(56.771)	(51.762)
#SME	105.700	-90.451
	(84.204)	(115.720)
%Small Bank	-5.532	-56.963*
	(20.771)	(30.044)
%National Bank	-14.366	31.730
	(36.618)	(85.608)
Deposits	-0.016	0.003
	(0.023)	(0.030)
#Bank Branch	0.491	-23.567
Mean Dep. Var.	5.144	9.204
State FE	Y	Y
Week FE	Y	Y
Adj. R^2	0.446	0.601
N	4,620	4,620

Table 6 Risk

This table reports estimates of equation (1) examining the effect of the California Financing Disclosure Law (CFDL) on the distribution of borrower risk, measured by the model-predicted ex-ante probability of default (*PD*) using SBA 7(a) loan-level data. The sample is restricted to loans between $5,000 and $500,000, consistent with the regulation threshold. The dependent variable in Column (1) is the mean PD; in Columns (2) – (11), the dependent variable is the *k*th percentile ($k \in \{5, 15, \ldots, 95\}$) of the county–quarter PD distribution. County–quarters with fewer than ten loans are dropped to ensure stable percentile estimates. All regressions include the same set of state–quarter macroeconomic and county–year market-structure controls as in the previous tables. All specifications include county and quarter fixed effects. Standard errors, clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

		Percentile									
	Mean	5th	15th	25th	35th	45th	55th	65th	75th	85th	95th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Treated×Post	-0.264*	0.005	0.006	0.010	0.009	0.013	0.030	0.044	-0.559*	-0.428	-1.340*
	(0.148)	(0.005)	(0.007)	(0.015)	(0.028)	(0.041)	(0.081)	(0.185)	(0.305)	(0.422)	(0.665)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean Dep. Var.	2.007	1.764	1.783	1.803	1.827	1.855	1.896	1.958	2.058	2.221	2.528
Adj. R^2	0.678	0.522	0.594	0.501	0.417	0.392	0.362	0.370	0.416	0.553	0.645
N	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492

Table 7 Size and Maturity

This table reports regression estimates of the effect of the California Financing Disclosure Law (CFDL) on the distribution of loan characteristics using SBA 7(a) loan-level data. The sample is restricted to loans between $5,000 and $500,000, consistent with the regulation threshold. Panel A examines loan size, and Panel B examines loan maturity. The dependent variable in Column (1) is the mean, and in Columns (2) – (11) is the *k*th percentile ($k \in \{5, 15, \ldots, 95\}$) of the distribution of *Loan Size* (Panel A) or *Loan Maturity* (Panel B), computed at the county–quarter level. County–quarters with fewer than ten loans are excluded to ensure stable percentile estimates. All regressions include the same set of state–quarter macroeconomic and county–year market-structure controls as in the previous tables. All specifications include county and quarter fixed effects. Standard errors, clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

		Percentile									
	Mean	5th	15th	25th	35th	45th	55th	65th	75th	85th	95th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Panel A: *Loan Size*					
Treated×Post	-5.857*	1.642	-0.623	-3.900	-13.177***	-10.286*	-12.032**	-15.904***	-16.329**	1.676	12.355**
	(3.219)	(1.250)	(2.266)	(2.597)	(3.819)	(5.653)	(4.831)	(4.584)	(6.057)	(5.693)	(5.419)
Mean Dep. Var.	59.352	34.489	37.923	41.77	46.251	51.389	57.365	64.388	72.687	82.629	94.953
Adj. R^2	0.511	0.212	0.247	0.341	0.427	0.453	0.466	0.467	0.455	0.430	0.340
						Panel B: *Loan Maturity*					
Treated×Post	-5.452***	-4.358**	1.383	4.609***	1.158	-1.504	-1.284**	0.604	-1.137	-7.906***	-46.040***
	(0.703)	(1.798)	(1.742)	(1.614)	(1.038)	(0.966)	(0.619)	(0.475)	(1.033)	(2.195)	(4.322)
Mean Dep. Var.	46.393	38.555	41.215	43.174	44.556	45.568	46.491	47.454	48.622	50.537	55.071
Adj. R^2	0.391	0.480	0.508	0.454	0.365	0.320	0.279	0.022	0.075	0.153	0.204
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492

Table 8 Pricing

This table reports the effect of the California Financing Disclosure Law (CFDL) on loan interest rates using SBA 7(a) loan-level data. The dependent variable is the loan interest rate, measured as the spread over the SBA base (prime) rate. The sample is restricted to loans between $5,000 and $500,000, consistent with the regulation threshold. Loan-level controls include the log of loan size (*Loan Size*), the log of loan maturity (*Loan Maturity*), the predicted probability of default (*PD*), an indicator for "Express" loans (*Express Loan*), an indicator for young businesses (*Young Business*, less than two years old), the log number of jobs supported (*#Job Supported*), and an indicator for new borrowers (*New Borrower*). Additional market-structure and macroeconomic controls are the same as in previous tables. All specifications include bank-by-quarter fixed effects; Columns (1) and (3) include county fixed effects, while Columns (2) and (4) replace these with ZIP code fixed effects. Columns (3) and (4) additionally include industry fixed effects. Standard errors, clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Panel A Interest Rate Summary Statistics

	N	mean	std	25%	50%	75%
Interest Rate	59837	2.505	1.582	1.750	2.490	3.000
Loan Maturity	59837	4.715	0.357	4.796	4.796	4.796
Loan Size	59837	11.415	1.090	10.529	11.513	12.399
PD	59837	5.025	4.175	4.066	4.085	4.187
Young Business	59837	0.389	0.487	0.000	0.000	1.000
#Job Supported	59837	1.596	1.049	0.693	1.609	2.303
Express Loan	59837	0.594	0.491	0.000	1.000	1.000
New Borrower	59837	0.804	0.397	1.000	1.000	1.000

Panel B Pricing

Dep. Var.	*Interest Rate*			
	(1)	(2)	(3)	(4)
Treated×Post	0.109**	0.045**	0.120**	0.053**
	(0.049)	(0.021)	(0.060)	(0.022)
Post	-0.009	0.001	0.004	0.006
	(0.042)	(0.040)	(0.045)	(0.040)
Loan Maturity	0.063	0.070	0.091	0.088
	(0.057)	(0.065)	(0.068)	(0.065)
Loan Size	-0.433***	-0.439***	-0.424***	-0.442***
	(0.063)	(0.069)	(0.076)	(0.068)
PD	0.023***	0.025***	0.024***	0.024***
	(0.003)	(0.003)	(0.003)	(0.003)
Young Business	0.057*	0.070**	0.040	0.081***
	(0.030)	(0.030)	(0.038)	(0.029)
#Job Supported	-0.005	-0.009	-0.016	-0.007
	(0.009)	(0.010)	(0.012)	(0.010)
Express Loan	0.158***	0.152***	0.150***	0.126***
	(0.034)	(0.035)	(0.035)	(0.035)
New Borrower	0.033	0.001	-0.008	-0.002
	(0.023)	(0.019)	(0.019)	(0.019)
Controls	Y	Y	Y	Y
County FE	Y	N	Y	N
Bank×Quarter FE	Y	Y	Y	Y
ZIP Code FE	N	Y	N	Y
Industry FE	N	N	Y	Y
Adj. R^2	0.600	0.603	0.603	0.607
N	59,837	56,908	59,694	56,753

Table 9 Bank Loan–Geography

This table examines whether the effect of the California Financing Disclosure Law (CFDL) on bank small business lending varies across counties with different socioeconomic and skill characteristics. To align with the regulation's $5,000–$500,000 coverage threshold, I use three dependent variables: (i) the log number of CRA loans ≤$1m (county–year), (ii) the log number of CRA loans ≤$250,000 (county–year, closer proxy for the treated range), and (iii) the log number of SBA loans ≤$500,000 (county–quarter, exactly within the threshold). I re-estimate equation (1), interacting Treated×Post with county-level measures from the NCES PIAAC State and County Estimates: *Numeracy*, *Literacy*, *%Poverty*, *%High Edu*, *%Minority*, and *#Bank Branch*. All regressions include the same set of state–quarter macroeconomic and county–year market-structure controls as in the previous tables. All regressions include county and quarter (or year for CRA data) fixed effects. Standard errors, clustered at the state level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Panel A: CRA Bank Loan

Dep. Var.	*#Bank Loan CRA <1m* (1)	*#Bank Loan CRA<1m* (4)	*#Bank Loan CRA<1m* (7)	*#Bank Loan CRA<1m* (10)	*#Bank Loan CRA<1m* (10)	*#Bank Loan CRA<1m* (13)
Treated×Post×Numeracy	0.001*					
	(0.000)					
Treated×Post×Literacy		0.001				
		(0.000)				
Treated×Post×%Poverty			-0.406***			
			(0.116)			
Treated×Post×%High Edu				0.080**		
				(0.040)		
Treated×Post×%Minority					0.237***	
					(0.038)	
Treated×Post×#Bank Branch						0.006
						(0.005)
Lower Interaction Effects	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.997	0.997	0.997	0.997	0.997	0.997
N	5,468	5,468	5,468	5,468	5,468	5,470

Panel B SBA Bank Loan

Dep. Var.	*#Bank Loan SBA<500* (3)	*#Bank Loan SBA<500* (6)	*#Bank Loan SBA<500* (9)	*#Bank Loan SBA<500* (12)	*#Bank Loan SBA<500* (12)	*#Bank Loan SBA<500* (15)
Treated×Post×Numeracy	-0.000					
	(0.000)					
Treated×Post×Literacy		-0.001*				
		(0.001)				
Treated×Post×%Poverty			-1.043***			
			(0.131)			
Treated×Post×%High Edu				0.270***		
				(0.073)		
Treated×Post×%Minority					1.004***	
					(0.048)	
Treated×Post×#Bank Branch						0.148***
						(0.011)
Lower Interaction Effects	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.850	0.850	0.850	0.850	0.850	0.851
N	21,194	21,194	21,194	21,194	21,194	21,194

Online Appendix

Online Appendix. T1 Sample Construction

Data Step	Remaining # of Observations
Raw UCC filing–level data from January 1, 2021 to December 31, 2023	18,427,663
Keep only initial filings; drop amended, terminated, and released filings	9,825,394
Exclude states with concurrent regulation (Utah, New York, Virginia)	9,087,471
Drop filings with missing creditor information	8,971,270
Exclude nonprofit lenders	8,960,421
Exclude other exempt lenders, including credit unions	8,784,194
Drop debtors that are not small businesses (e.g., government entities, universities, councils)	5,702,650
Exclude lenders that are individuals	5,681,491
Restrict to lenders with more than one loan	5,549,323
Aggregate to state–county–quarter level for 2022Q1–2023Q4	25,046
Keep only the 50 states and the District of Columbia	24,873
Merge in SBA loan data	24,873
Merge in additional control variables and retain only valid observations	23,104
Drop singletons based on fixed effects	21,194

Online Appendix. T2 Federal Reserve's Small Business Credit Survey (SBCS)

This table reports state-level application shares from the Federal Reserve's *Small Business Credit Survey* (SBCS) for 2022 and 2023. Firms were asked whether they applied for credit in the past 12 months and, if so, to which provider type: large bank, small bank, online lender, finance company, or credit union. The SBCS data provide a complementary measure of credit demand to Google Trends.

State	Year	Large Bank	Small Bank	Online Lender	Finance Company	Credit Union	Year	Large Bank	Small Bank	Online Lender	Finance Company	Credit Union
California	2022	44%	15%	37%	16%	4%	2023	40%	21%	34%	7%	16%
Alabama	2022	39%	35%	17%	7%	11%	2023	47%	33%	16%	10%	9%
Arizona	2022	68%	29%	20%	4%	11%	2023					
Connecticut	2022						2023	46%	17%	25%	3%	33%
Florida	2022	46%	15%	29%	15%	10%	2023	51%	15%	27%	11%	16%
Georgia	2022	43%	34%	26%	15%	2%	2023	48%	25%	24%	20%	10%
Hawaii	2022	46%	29%	30%	14%	2%	2023					
Illinois	2022	52%	39%	13%	13%	2%	2023	52%	33%	12%	16%	0%
Louisiana	2022	42%	31%	14%	9%	7%	2023					
Maryland	2022	49%	12%	22%	18%	17%	2023					
Massachusetts	2022	35%	31%	32%	9%	1%	2023	33%	23%	42%	18%	2%
Michigan	2022	37%	12%	36%	14%	27%	2023					
Minnesota	2022	17%	62%	11%	12%	2%	2023					
New Jersey	2022	53%	13%	23%	12%	3%	2023	56%	24%	14%	14%	4%
North Carolina	2022	64%	17%	29%	5%	4%	2023	52%	24%	17%	14%	4%
Ohio	2022	53%	16%	17%	16%	14%	2023	40%	21%	26%	22%	1%
Oregon	2022						2023					
Pennsylvania	2022	48%	29%	14%	11%	9%	2023	39%	36%	17%	12%	8%
Tennessee	2022						2023					
Texas	2022	36%	30%	26%	13%	12%	2023	48%	26%	19%	17%	8%
Washington	2022						2023	48%	17%	35%	14%	12%