The Shadow Cost of Collateral*

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Abstract

Collateral is often viewed as a low-cost mechanism to mitigate external financing frictions. However, we find that firms face a substantial cost to pledge collateral. Exploiting a regulatory quirk of the disaster loan program of the Small Business Administration (SBA), we estimate that the cost of collateral is equivalent to 6%-9% of the loan value for small businesses. The magnitude of the collateral cost depends on the type of the collateral requirements (fixed lien vs. floating lien), business sectors, and collateral laws. Our finding suggests that a pecking order between secured and unsecured borrowing may not hold. Instead, the secured borrowing decision may be best characterized by a trade-off theory. The collateral trade-off has important implications for firms' financing decisions, the financial accelerator mechanism, and the design of government lending programs.

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Keywords: collateral, secured and unsecured debt, financial accelerator, bunching estimation, government-subsidized loan program

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1 Introduction

Collateral is often viewed as a low-cost mechanism to mitigate conflicts of interest and enforcement frictions in lending (DeMarzo, 2019). Since the seminal work of Myers and Majluf (1984), it is long believed that there exists a pecking order between collateralized and uncollateralized borrowing: firms should first issue collateralized debt, and then, after exhausting such claims, issue uncollateralized debt (Benmelech, Kumar, and Rajan, 2020a). Empirically, collateralized debt usually entails substantially lower interest rates than uncollateralized one, which seems to be consistent with this view.

Pledging collateral, however, could impose hidden costs for firms. First, firms may lose operational flexibility because encumbered assets cannot be sold to a third party, moved to a different location, used for another purpose, refurbished, and transformed without the protection or consent of the lender (Mello and Ruckes, 2017).[1] Firms could also lose financial flexibility because high asset encumbrance makes it harder to obtain unsecured financing (Donaldson, Gromb, and Piacentino, 2020) or access liquidity through an asset sale (Donaldson, Gromb, and Piacentino, 2019).[2] Finally, firms may lose bargaining power in financial distress as secured creditors may not be interested in restructuring the debt payment (Benmelech, Kumar, and Rajan, 2020a). Although the aforementioned theoretical literature has advanced our understanding of the role of collateral, there is still a lack of evidence on whether the collateral cost is empirically relevant for firms' financing decisions.

The lack of empirical evidence could be partly attributed to the fact that, unlike the interest cost, the cost of pledging collateral is largely a shadow cost. To address this challenge, we use a revealed preference approach to infer the collateral cost from firms' choice of loan contracts. Specifically, we exploit a regulatory quirk of the disaster loan program provided by the Small

[1] In a series of interviews with practitioners conducted by Mann (1996), a CFO attributes his company's aversion to secured debt to "a question of flexibility and having to deal with it". He further explains that "in a secured loan, you just don't have the same flexibility of dealing with your properties as if you owned them unencumbered."

[2] For instance, according to S&P RatingsDirect, "In the real estate industry, where companies have substantial unencumbered assets, this can be a critical source of financial flexibility, given the very large and liquid market for property-specific mortgages."

Business Administration (SBA). This program provides secured loans to firms affected by natural disasters, but collateral is exempted if the loan size is below a certain threshold. We observe a significant number of firms bunch at the collateral threshold, as shown in Figure 1. This bunching pattern provides *prima facie* evidence that firms are averse to pledging collateral and would rather accept a smaller loan amount than they would naturally desire. The extent of bunching could reveal the collateral cost. If many firms avoid pledging collateral by bunching at the threshold, the collateral cost is likely to be high. On the contrary, if only a few firms bunch, the collateral cost is likely to be low.

We use a simple model to formalize the intuition and guide the estimation. In the model, firms have different desired loan sizes, which follows a smooth distribution in the absence of regulatory distortion. The collateral requirement creates a discontinuity in firms' payoff. Firms respond to the collateral threshold differently based on how far away their desired loan size is above the threshold. Firms just above the threshold choose to bunch at the threshold to avoid pledging collateral. Firms far away from the threshold choose not to bunch because they would have to forgo too much funding, which reduces their profits. Finally, there exists a marginal firm that is indifferent between bunching and no bunching. The funding that the marginal firm is willing to give up to avoid pledging collateral reveals the shadow cost of collateral.

We adapt the bunching estimation technique developed in the public finance and labor literature (Saez, 2010; Kleven and Waseem, 2013; Chetty, Friedman, Olsen, and Pistaferri, 2011) to estimate the collateral cost. Firms' bunching creates an excess mass at the threshold and a missing mass above it. The desired loan size of a marginal firm is identified when the missing mass equals the excess mass. Applying the bunching estimator to the Business Physical Disaster Loan (BPDL) program, we find that the collateral cost is equivalent to an interest of 9% for the sample firms. In terms of the dollar value, the shadow cost of collateral amounts to $2,300 for a loan of $25,000. The estimated collateral cost is an order of magnitude larger than the direct cost associated with pledging collateral, such as the appraisal fee or filing fee, which is only $100 as of 2020. The estimated collateral cost is in the same order of magnitude as the secured-unsecured interest spreads faced by small firms. This result suggests that a pecking order between secured and unsecured borrowing may not hold. Instead, the secured borrowing decision may be best characterized by a trade-off theory in which firms balance the benefit of collateral against the cost. This new perspective has important implications for corporate capital structure.

We further explore how the collateral cost depends on collateral types, business sectors, and collateral laws. There are two broad categories of collateral requirements: a fixed lien or a floating lien. Under a fixed lien, fixed assets, such as real estate property, machinery, or fixtures, are pledged to secure the repayment of a loan. Under a floating lien, current assets such as inventory and accounts receivables are pledged. We exploit a unique change in collateral requirement from a fixed lien to a floating lien in the COVID-19 pandemic to study the relationship between collateral type and collateral cost. We find that the estimated collateral cost decreases by around 30% after changing to a floating lien, suggesting that firms are more averse to pledging fixed assets. We also find that the collateral cost varies significantly across business sectors. For example, agriculture, accommodation, and food sectors have higher collateral costs, while retail trade and real estate sectors have lower collateral costs. Finally, we find that the collateral cost depends on collateral laws. Exploiting the staggered adoption of the Uniform Voidable Transactions Act (UTVA), which weakens secured creditor rights, we find that the take-up of secured loans increases significantly after the law change. The estimated collateral cost appears to be lower in states with weaker secured creditor rights.

We conduct various robustness checks for our results. The validity of the bunching estimator relies on a key assumption that the counterfactual distribution is smooth in the absence of the discontinuity of collateral requirement. Consistent with the identification assumption, we find no excess mass around the thresholds in the sample periods before these thresholds are introduced. Furthermore, placebo tests correctly indicate null results on factitious thresholds. We also show that our results are robust to alternative specifications of the bunching estimator, such as the degree of polynomials and the bin size to estimate the counterfactual distribution.

One may worry that the estimated collateral cost could reflect the scarcity of the collateral rather than the cost of pledging it. In other words, if some firms do not have collateral in the first place, they will not have the option to pledge it. However, a careful examination of the institutional setting suggests that collateral scarcity is unlikely to be an issue for our estimation. For the BPDL program, the loans are used to repair or replace damaged property, which typically serves as collateral. For the COVID EIDL program, general business assets which are broadly available can be used as collateral. In addition, the SBA does not require the collateral value to cover the loan amount fully. Instead, it only requires firms to pledge what is available. Therefore, the estimated collateral cost is more likely to reflect the aversion to pledge collateral rather than the scarcity of the collateral.

Another alternative explanation is that firms may want to use the collateral to secure another loan from the private sector when the disaster hits them. In this case, the collateral cost may reflect their desire to maximize the total external financing rather than the aversion to losing flexibility and bargaining power. This alternative explanation is unlikely to be applicable in our setting for two reasons. First, firms that participate in the SBA disaster lending programs generally lack access to private financing. Second, even if they have access to private funding, the rates that they can get are much higher than those offered by the SBA. Given that the loans taken by the bunching firms are far below the maximum loan size cap of the SBA, firms could have got more funding from the SBA at a below-market rate if they wanted to do so. It seems suboptimal to give up subsidized public financing to get more expensive private financing.

Although our setting sheds light on the shadow cost of collateral, which is otherwise difficult to observe, there are a few caveats to these results. First, the estimated collateral costs are pertinent to small businesses. These firms play an important role in the process of creative destruction and aggregate employment so it is crucial to understand their financing frictions (Krishnan, Nandy, and Puri, 2015). However, small firms could differ from large firms in many aspects, so the specific estimate may not be transportable. Nevertheless, the general economic lesson—the collateral cost is crucial for secured borrowing decisions—is likely to remain valid. Second, the lender of our setting is a government agency, which may not pursue the collateral with the same vigor as private lenders. If that is the case, the estimates may be a lower bound of the true collateral cost. Nevertheless, unlike the Paycheck Protection Program (PPP), the SBA disaster loan program is not a grant. The SBA tries to use collateral to increase recovery upon defaults, and the liquidation procedure is similar to those of private lenders, alleviating such concerns.[3] Despite these caveats, our setting offers many advantages over typical datasets on corporate borrowings. First, in typical settings, only the equilibrium outcome of borrower-lender negotiation is observed by econometricians, making it difficult to separate lenders' preferences from borrowers'. In contrast, in our setting, the potential choice set of borrowers can be observed, allowing us to analyze the trade-off faced by borrowers. Second, the secured and unsecured markets are usually segmented, with different lenders being active in different markets. In contrast, the same lender provides both the unsecured and secured loans in our setting, which provides a clean setting to study firms' choices.

We explore the implications of a substantial collateral cost for macro-finance analyses. An implicit assumption in standard financial acceleration models is that firms do not incur any cost to post collateral. Therefore, firms always borrow up the limit allowed by the collateral constraint. We relax this assumption by introducing the collateral cost to the standard model of Kiyotaki and Moore (1997). Instead of borrowing up the collateral limit, firms now face a trade-off between the investment return and collateral cost. We find that this collateral trade-off introduces a new amplification mechanism. When a large negative productivity shock drives investment returns below the collateral cost, firms may endogenously reduce collateralized borrowing, depressing collateral prices. The falling asset prices further decrease borrowers' net worth, amplifying the negative shock. The effect is highly non-linear: a small shock may not necessarily change the relative magnitude of investment return, and collateral costs thus may have a substantially weaker effect. We also find that the collateral trade-off can make the financial amplification mechanism state-dependent. The aggregate investment is more sensitive to asset price fluctuations in a high productivity state as more firms borrow up to the collateral limit. In contrast, the opposite is true when the productivity is low as few firms borrow up to the collateral limit.

Finally, we study the implications of collateral cost for designing government lending programs

[3]See 13 CFR § 120.545. for SBA's policies concerning the liquidation of collateral.

in counterfactual policy experiments. While collateral is often viewed as an essential tool to protect taxpayers' money in government lending programs, our findings suggest two potential downsides associated with such requirements. First, requiring collateral would impose substantial costs on participating firms as they lose operational and financial flexibility. Second, because firms may strategically respond to the collateral threshold, such requirements may significantly reduce the program's take-up and social welfare. We show that the optimal program could be quite different depending on whether these costs are considered.

This article contributes to a vast literature in economics and law on collateral. Collateral can mitigate enforcement frictions between borrowers and creditors (Tirole, 2010), complete the contract space (Dubey, Geanakoplos, and Shubik, 2005), and prevent debt dilution (DeMarzo, 2019; Donaldson, Gromb, and Piacentino, 2020). Collateral has important implications for corporate decisions, such as investments, production, and dynamic optimal capital structure (Gan, 2007; Chaney, Sraer, and Thesmar, 2012; Adelino, Schoar, and Severino, 2015; DeMarzo, 2019; DeMarzo and He, 2021). A large body of work shows that collateralized borrowing reduces the interest cost for borrowers (Berger and Udell, 1990; Rauh and Sufi, 2010; Benmelech and Bergman, 2009; Benmelech et al., 2020b). However, the existing literature leaves the puzzle of why firms do not always borrow secured debt given the low interest rates (Rampini and Viswanathan, 2020). A contribution of this paper is to show that recognizing the sizable collateral cost is the key to resolving this puzzle. Our work complements Collier, Ellis, and Keys (2021), which is the first study to examine how housing collateral impacts consumers' borrowing behavior and default rates. They similarly exploit the SBA program's collateral thresholds in a bunching estimation and find that the median consumer in their sample is willing to give up 40% of the loan amount to avoid placing a lien on their home. They also find that collateral reduces default rates by 35% using an instrumental variables (IV) estimation. Our paper studies the shadow cost of collateral for firms rather than consumers. Given the crucial role of collateral in firms' operations, investments, and financing, it is important to understand the collateral cost for firms. We also document interesting heterogeneity in the collateral costs across collateral types, business sectors, and collateral laws. We also show that the collateral cost has important implications for the financial acceleration mechanism and the design of government-subsidized business lending programs.

This article also contributes to a large body of literature on the financial accelerator mechanism, which shows that collateral is an important reason why financial frictions affect macroeconomic dynamics (Kiyotaki and Moore, 1997; Bernanke, Gertler, and Gilchrist, 1999; Mendoza, 2010). This literature assumes that firms incur no cost to pledge collateral, so the collateral constraint is always binding. We introduce the collateral trade-off to the standard model of Kiyotaki and Moore (1997) and show that it can generate rich implications for the financial accelerator mechanism. This article also speaks to the extensive empirical research that has been devoted to investigating the magnitude of the financial accelerator mechanism (Lian and Ma, 2021; Catherine, Chaney, Huang, Sraer, and Thesmar, 2018). This literature often finds that the sensitivity of firm-level investment to collateral values is well below the magnitude predicted by the standard Kiyotaki and Moore (1997) model.[4] While the low sensitivity is typically rationalized by low asset pledgability, we suggest that the substantial collateral cost could be another reason why the asset price-investment sensitivity is low. Because firms may choose not to pledge collateral to avoid the collateral cost, fluctuations in asset prices would naturally have lower impacts than those implied by models without collateral cost.

This article also adds to the literature on the efficiency of the government-supported lending program (Smith, 1983; Gale, 1991; Lucas, 2016; Bachas et al., 2021). This literature has grown rapidly since the COVID-19 pandemic as numerous government lending programs are installed. Recent studies show that the pre-crisis banking relationship, bank market power, and racial biases of loan officers could significantly affect the access to government lending programs (Fairlie and Fossen, 2021; Bartik, Cullen, Glaeser, Luca, Stanton, and Sunderam, 2020; Humphries, Neilson, and Ulyssea, 2020; Granja, Makridis, Yannelis, and Zwick, 2020; Chernenko and Scharfstein, 2021). This paper shows that collateral requirements intended to protect taxpayers' money could inadvertently reduce the take-up of the program. The optimal collateral requirement should trade off these costs against the benefits of reducing the expected default loss.

[4]In Kiyotaki and Moore (1997), the sensitivity of investment to collateral prices is 1. In contrast, Catherine et al. (2018) estimate this sensitivity to be 0.06.

Finally, this article adds to a growing literature that applies the bunching estimation to finance topics, including mortgage (DeFusco and Paciorek, 2017; DeFusco, Johnson, and Mondragon, 2020), small business lending (Bachas, Kim, and Yannelis, 2021), municipal bond issuance (Dagostino, 2018), bankruptcy fees (Antill, 2020), banks (Alvero, Ando, and Xiao, 2020), and public firms (Ewens, Xiao, and Xu, 2020). Our paper is related to Bachas, Kim, and Yannelis (2021), who study the SBA 7(a) loan program in which banks' credit supply strategically responds to government loan guarantee thresholds. We study a different lending program by the SBA, the disaster loan program, in which the government agency directly dispenses the loans without the involvement of private banks. This feature allows us to hold the supply side constant when analyzing the demand.

2 Institutional Background and Data

2.1 SBA Disaster Loans

The U.S. Small Business Administration (SBA) provides low-interest, long-term loans to businesses and private nonprofits after a disaster. There are two major loan programs: Business Physical Disaster Loans (BPDL) and Economic Injury Disaster Loan (EIDL).[5]

Business Physical Disaster Loans (BPDL)

The first main category is the Business Physical Disaster Loans (BPDL), which assists businesses that experienced physical damages in declared disaster areas to cover the verifiable and uninsured portion of damages to their real estate property, machinery, equipment, and fixture. Firms are required to provide available collateral such as a lien on the damaged or replacement property, a security interest in business property, or both unless the loan amount is below a certain threshold ($25,000 as of 2020). It is worth noting that the SBA does not require the collateral value

[5]More details about the rules of the disaster loan programs can be found in Code of Federal Regulations, Title 13 - Business Credit and Assistance Chapter I - Small Business Administration, Part 123 - Disaster Loan Program.

to cover the loan amount fully. Neither will the SBA deny a loan solely for insufficient collateral. Instead, the SBA only requires the business to pledge what is available. Furthermore, the SBA holds the interest rate fixed regardless of the loan amount and whether a firm pledges collateral or not. This feature provides a clean setting to isolate how the collateral requirement affects firms' borrowing behavior.

Many government lending programs for small businesses, such as the SBA 7(a) program and the Paycheck Protection Program, are dispensed by private lending institutions. In contrast, the disaster loan program is dispensed by the SBA itself. Firms can apply directly to SBA at no cost.[6] This feature allows us to avoid the concern that market power or racial biases of private lending institutions may affect firms' access to government lending programs (Bachas et al., 2021; Chernenko and Scharfstein, 2021).

Economic Injury Disaster Loan (EIDL)

The second main category of the SBA disaster loans is the Economic Injury Disaster Loans (EIDL) program. Unlike the BPDL program, the EIDL program assists businesses broadly affected by declared disasters to meet their necessary working capitals like the continuation of health care benefits, rent, utilities, and fixed debt payments. However, the regular EIDL program has similar features as the BPDL program: (1) it also uses a fixed lien with real estate assets being the preferred collateral; (2) firms are exempted from the collateral requirement if the loan size is below a threshold ($25,000 as of 2020); (3) the interest rate is fixed regardless of the loan size and collateral; (4) the loans are distributed directly by the SBA.

In addition to the regular EIDL program, we also study the COVID-19 EIDL program, introduced by the Coronavirus Aid, Relief, and Economic Security (CARES) Act in 2020. Unlike the previous disaster loan programs (BPDL and regular EIDL), which use a fixed lien, the COVID EIDL program allows a floating lien: firms can post floating assets, such as inventory and accounts receivables, as collateral.

[6] The application website is `DisasterLoan.sba.gov`.

2.2 Data

We obtain the disaster loan data from the SBA. The data contain firm location, loan amount, disaster information, verified losses (BPDL), and firm names (COVID EIDL). The geographic coverage of our data is quite broad. 88% of the ZIP codes are covered by at least one of the programs. Table 1 provides the summary statistics of our sample. The median loan amounts are $66,300, $30,200, and $26,000 for BPDL, regular EIDLs, and COVID EIDLs, respectively. The total number of loans is around 14,000 for the BPDLs, 11,000 for regular EIDLs, and 3,617,000 for COVID EIDLs. The total number of loans is much larger in the COVID EIDL sample because of its broader geographical coverage. We exclude loans for nonprofit businesses, which represent 0.4 percent of total loans. The whole sample covers 3,681,475 loans with a total value of $188.70 billion. The empirical analysis focuses on loan amounts ranging between $0 to $65,000 because there are insufficient observations to estimate density for loan size beyond $65,000.

We further collect interest rate information from the US Federal Register. The SBA announces a single fixed interest rate to all the businesses in one disaster. The majority of the regular disaster loans (58.54% for BPDLs and 62.36% for regular EIDLs) are offered an interest rate of 4%. Consequently, we will use loans with 4% interest rates as our baseline sample for regular disaster loans. All of the COVID EIDLs have a fixed interest rate of 3.75%.

The solid red line of Figure 1a shows the loan size distribution of BPDLs in 2014-2020.[7] We observe a sharp spike at the $25,000 collateral threshold. The spike at the $25,000 is not present in earlier sample periods such as 2008-2013 or 2003-2007, in which different collateral thresholds are in place. Instead, the spikes of the earlier samples are located at $14,000 or $10,000, which correspond to the collateral thresholds in earlier samples. A similar bunching pattern is observed for regular EIDL and COVID EIDL, as shown in Figures 1b and 1c. It is worth noting that the loan size distribution of the COVID EIDL program displays additional mass points at round

[7] Note that a small fraction of the BPDLs (general disaster BPDLs) changes the threshold from $14,000 to $25,000 in 2016 rather than in 2014. In the following analysis, we remove the observations affected by the delayed change (general disaster BPDLs in 2014-2015) from the 2014-2020 sample so that all observations have $25,000 as the threshold.

numbers that are not collateral thresholds, such as $15,000 and $20,000. Such round-number bunching is often a consequence of people using salient round numbers as the behavioral reference point.[8] Nevertheless, the excess mass at the $25,000 collateral threshold is larger than other similar round numbers such as $15,000 and $20,000, suggesting firms are still strategically avoiding the collateral requirements.

In addition to the spikes in the loan size distribution, the verified losses incurred by the businesses for BPDLs provide further evidence for borrowing amount bunching. Unlike the loan amount chosen by the firms, the verified losses are exogenously determined by the severity of the disaster and the value of the properties. The left panels of Figure 2 plot the verified losses against the BPDL amount. Many observations are at the 45-degree line, suggesting that many firms simply choose a loan amount to cover the losses in the disaster. However, a substantial fraction of firms choose a loan amount exactly at the collateral thresholds even if their losses are substantially greater, suggesting some firms avoid pledging collateral deliberately. The right panels of Figure 2 plot the distribution of the verified losses due to the disaster, together with the loan amount of BPDLs. Indeed, we do not see any bunching in the distribution of the verified loss at the collateral thresholds.

These bunching patterns provide visual evidence that firms are averse to pledge collateral so that they would reduce their loan amount instead. Intuitively, more firms bunching at the collateral threshold implies that the collateral cost perceived by firms is higher. In the following analysis, we will formalize this intuition to estimate the collateral costs from the extent of bunching at the collateral threshold using a simple theoretical framework.

[8] A possible explanation for the round-number bunching in COVID EIDLs is that large uncertainty during the pandemic makes it difficult to determine a precise loan amount. As a result, firms use behavioral reference points to calibrate a rough loan amount.

3 Theoretical Model

This section proposes a theoretical framework to guide our estimation. Suppose there is a set of firms with Cobb-Douglas production function. Firms borrow K unit of capital to produce AK^{α} unit of output, where A is the productivity, and α is the curvature of the production function. A is heterogeneous across firms. We can broadly interpret A as any non-regulatory factor that affects firms' desired loan size. Firms are offered a menu of loans with different sizes but a constant interest rate, R. In the absence of collateral requirement, firms' payoff function is given by:

$$AK^{\alpha} - RK. \tag{1}$$

The optimal loan size without collateral requirement, Z, is given by the first-order condition:

$$Z = \left(\frac{\alpha A}{R}\right)^{\frac{1}{1-\alpha}}. \tag{2}$$

One can interpret Z as the desired loan amount in the absence of the collateral requirement. Z is heterogeneous across firms, which follows a distribution f_0. In the following discussion, we use Z to index the firms.

Suppose firms now face a collateral requirement if their loan size K exceeds a threshold $\underline{K}$. Firms incur a cost of λZ when pledging collateral. We define the collateral cost as proportional to the loan size because λ can be intuitively interpreted as a shadow interest rate. We scale the collateral cost with the undistorted loan size to capture the idea that the dollar value of collateral cost should be different for firms with different sizes.[9] The collateral cost can be motivated by a loss of operational and financial flexibility or a loss of bargaining power. Firms' payoff function in

[9]If we assume the collateral cost is a fixed dollar value, then the collateral cost becomes trivial mechanically when the loan size becomes bigger. We discuss the robustness of our results to this assumption in Section 4.3.3. It is worth noting that the collateral threshold remains a notch point even if it is a proportional cost because firms incur the cost for the entire loan amount rather than the incremental value above the threshold.

the presence of the collateral requirement is given by

$$\Pi(K|Z) = A(Z)K^{\alpha} - RK - \lambda Z \mathbb{1}_{K>\underline{K}}, \tag{3}$$

where $A(Z)$ is the productivity of firm Z. $A(Z)$ can be solved from equation (2).

Firms with undistorted loan sizes above the threshold face the following trade-off. Firms could either: (1) borrow Z, and bear collateral cost, or (2) reduce their borrowing amount to $\underline{K}$ and avoid any collateral commitment, which reduces the output. Firms' optimal choice depends on how far away their undistorted loan size is above the threshold, as illustrated in Figure 3. We plot firms' payoff $\Pi(K|Z)$ as a function of the loan size K. Firms whose undistorted loan size is just above the threshold will find it optimal to bunch at the threshold because they only need to shrink their loan size by a small amount, as shown by Figure 3b. Firms that are far above the threshold will find it too costly to bunch at the threshold, as shown by Figure 3a. There exists a marginal buncher that is indifferent between bunching and no bunching, as shown by Figure 3c. Denote the undistorted loan size of the marginal buncher as $Z = \overline{K}$. The indifference condition of the marginal buncher is given by

$$\Pi(\overline{K}|\overline{K}) = \Pi(\underline{K}|\overline{K}), \tag{4}$$

Firms' optimal choices are given by

$$K^* = \begin{cases} \underline{K} & \text{if } Z \in [\underline{K}, \overline{K}] \\ Z & \text{if } Z \notin [\underline{K}, \overline{K}]. \end{cases} \tag{5}$$

Define the distortion ratio, θ, as the percentage changes in loan size for the marginal firm to bunch at the threshold,

$$\theta = (\overline{K} - \underline{K})/\overline{K}. \tag{6}$$

Using the indifference condition (4), we can derive the collateral aversion as:

$$\lambda = \left(\frac{1}{\alpha}(1-(1-\theta)^{\alpha}) - \theta\right) R. \tag{7}$$

In the next section, we will use the distribution of the loan size to estimate the marginal buncher, which further allows us to calculate the implied collateral aversion, λ, using equation (7).

4 Empirical Analysis

4.1 Bunching estimation

As discussed in Section 3, the critical parameter to estimate a borrower's implied collateral cost is the loan size of the marginal buncher ($\overline{K}$). For this purpose, we use the bunching estimation approach developed by Kleven and Waseem (2013). Specifically, the collateral threshold induces firms whose preferred loan size in $[\underline{K}, \overline{K}]$ to bunch at the threshold, $\underline{K}$. Therefore, the actual probability density function, $f(K)$, should display some excess mass at the threshold relative to the smooth counterfactual density function, $f_0(K)$. We define the excess mass as $B \equiv \int_{K_L}^{\underline{K}} (f(K) - f_0(K))dK$, where K_L is set to $\underline{K}$.[10] Since firms whose preferred loan size in $[\underline{K}, \overline{K}]$ choose to bunch at $\underline{K}$, there is also some missing mass above the threshold, which is defined as $M(\overline{K}) \equiv \int_{\underline{K}}^{\overline{K}} (f_0(K) - f(K))dK$. The bunching mass should equal to the missing mass:

$$B = M(\overline{K}). \tag{8}$$

Note that the missing mass M is a function of the marginal buncher, $\overline{K}$. So we can solve the marginal buncher using the above equation.

To measure the excess mass and missing mass, we estimate the counterfactual loan size dis-

[10] K_L can be set to a value slightly below $\underline{K}$ if there is a diffusion of the bunching mass.

tribution, f_0, i.e., the distribution in the absence of the collateral requirement. We estimate the counterfactual distribution by fitting a polynomial function to the observed distribution, excluding observations in the collateral requirement affected range $[K_L, K_U]$ around the collateral threshold $\underline{K}$. The lower bound of the excluded region, K_L, equals the collateral threshold, $\underline{K}$, which is known. The upper bound of the excluded region, K_U, equals the marginal buncher, $\overline{K}$, which is unknown ex-ante. We will use an iterative procedure introduced by Kleven and Waseem (2013) to determine this bound, which we will describe later.

We group our data sample into \$500 bins and fit the binned data by the following regression model:

$$N_j = \sum_{p=0}^{P} \beta_p (K_j)^p + \sum_{i=K_L}^{K_U} \gamma_i \cdot \mathbb{1}(K_j = i) + \sum_{r \in \{5000, 10000\}} \delta_r \mathbb{1}(K_j / r \in \mathbb{N}) + \epsilon_j. \tag{9}$$

where N_j denotes the number of observations in bin j. K_j is the loan amount within bin j using the midpoint of the bin. P is the degree of the polynomial, which we set as five in our baseline. $[K_L, K_U]$ is the excluded region. In our data, loan sizes corresponding to round numbers such as \$5,000 and \$10,000 tend to appear more frequently than other values. Since the collateral thresholds are themselves located at salient round numbers, using the total excess mass at the collateral threshold would overstate the strategic response to the collateral requirements. We follow Kleven and Waseem (2013) to include a set of dummies, δ_r, for multiples of the round numbers to absorb the round-number bunching.[11] Intuitively, this approach controls for round-number bunching at the collateral thresholds by using excess bunching at "similar round numbers" that are not regulatory thresholds as counterfactuals.

The counterfactual number of observations in bin j, $\hat{N}_j$, is estimated as the predicted values from equation (9) subtracting the contribution of the exclusion region dummies:

$$\hat{N}_j = \sum_{p=0}^{P} \hat{\beta}_p (K_j)^p + \sum_{i \in \{5000, 10000\}} \hat{\delta}_r \mathbb{1}(K_j / r \in \mathbb{N}). \tag{10}$$

[11] In the COVID EIDL data, the extent of round-number bunching appears to vary across the loan size. To reflect this pattern, we add an interaction term between round number dummies and the loan size, $K_j \mathbb{1}(K_j / r \in \mathbb{N})$ following Antill (2020). In addition, there is also bunching at numbers that are \$1,000 below multiples of \$5,000. For instance, the number of observations tends to be higher at \$14,000 than other values. We include "pre-round-number dummies" to absorb the excess mass \$1,000 below round numbers.

We estimate the excess mass $\hat{B}$ and the missing mass $\hat{M}$ respectively, the differences between the observed and counterfactual bin count in regions before and after the collateral requirement. More specifically, we calculate excess mass and missing mass as following:

$$\hat{B} = \frac{1}{N}\sum_{j=K_L}^{\underline{K}}(N_j - \hat{N}_j), \tag{11}$$

$$\hat{M} = \frac{1}{N}\sum_{j>\underline{K}}^{K_U}(\hat{N}_j - N_j), \tag{12}$$

where N is the total number of observations in the sample.

To identify the upper limit K_U, we follow the iterative procedure introduced by Kleven and Waseem (2013). Specifically, we start the estimation by setting K_U to be one bin right above $\underline{K}$, and we calculate $\hat{B} - \hat{M}(K_U)$. We repeat such process by keeping adding one bin size further as long as $\hat{B} - \hat{M}(K_U) > 0$. We derive K_U to be the bin satisfies that

$$\hat{B} = \hat{M}(K_U). \tag{13}$$

The value of K_U that satisfies the above convergence condition is the marginal buncher, $\overline{K}$. We then plug the marginal buncher into equations (6) and (7) to solve the collateral cost. The interest rate, R, is set to the observed gross interest rates of the loans. The curvature of the production function, α, is set to the standard value $\frac{1}{3}$.

To calculate the standard errors of our variables of interest, we use a bootstrap procedure in which we generate 1,000 samples by random resampling observed residuals and replacing the residuals in equation (9). For each generated data sample, we estimate its marginal buncher $\overline{K}$, distortion ratio θ, and collateral cost λ with the same approach as above. The standard error is measured as the standard deviation of the 1000 estimates.

4.2 Estimation results

4.2.1 Baseline estimates

Table 2 presents the bunching estimates in the BPDL 2014-2020 sample, which has a collateral threshold of \$25,000. Columns 1, 2, and 3 show the results with polynomial degrees 4, 5, and 6, respectively. We find around 10% of firms bunch at the collateral threshold. The marginal firm's undistorted loan amount, $\overline{K}$, is around \$45,000, which implies a distortion ratio of around 45%. The estimated shadow cost of collateral is around 9%. The estimates are robust to the polynomial degree of the counterfactual distribution.

Figure 4 provides the visualization of the bunching estimates in the BPDL data. Each panel plots the loan size distribution for each sub-sample, which features a different collateral threshold. The solid black line demonstrates the observed distribution of loans, while the red dashed line presents the counterfactual distribution of loans as determined according to equation (10). We highlight K_L and K_U with dashed vertical lines. There is a visible bunch at the collateral thresholds in the corresponding sample period. The counterfactual densities are higher than the actual density of loans between the affected range $[K_L, K_U]$, which implies missing mass to the right of the collateral thresholds. K_U is the point at which the missing mass equals the bunching mass. The region between K_L and K_U is excluded when estimating the counterfactual distribution because the bins inside this range are affected by the collateral requirement. It is worth noting that the region between K_L and K_U should have zero mass according to the simple model in Section 3 because all firms in this region should strictly prefer bunching over not bunching. However, this dominated region has a positive mass in our data. This pattern is common in many bunching settings and is typically a result of optimization frictions (Kleven, 2016). In other words, a fraction of firms does not respond to the discontinuity in the incentive due to frictions such as inattention and inertia. The bunching estimator that we use is robust to optimization frictions, as shown by Kleven and Waseem (2013).

The estimated collateral cost is in the same order of magnitude as the interest spread between unsecured and secured loans.[12] As a result, firms face a meaningful trade-off between paying lower interest and bearing the collateral cost when borrowing secured debt. Explicit transaction costs associated with pledging collateral are unlikely to explain the collateral cost. For instance, the estimated shadow cost of a fixed lien for a $25,000 loan is around $2,300, while firms only need to pay a one-time $100 fee for filing a lien on business assets as of 2020. The majority of the estimated collateral cost is more likely to reflect the concern on operational and financial flexibility and bargaining power with creditors.

4.2.2 Collateral type

The cost of pledging collateral may differ depending on the type of collateral requirement. We compare two broad types of collateral: fixed assets vs. floating assets. In theory, firms may be more averse to pledging fixed assets than floating assets because fixed assets are typically less fungible and are indispensable to firms' operation. For instance, it could be detrimental for a firm if its lender seizes its machinery used for production. To test this hypothesis, we exploit a unique change in collateral requirement in the EIDL program during the COVID pandemic when the SBA changed the collateral requirement from a fixed lien to a floating lien. Table 3 presents the estimates in the COVID EIDL sample. We find that the implied shadow cost of collateral is only around 6%, which is significantly lower than the estimates for the BPDLs. The estimates are robust to the degree of polynomials for the counterfactual distribution.

One may worry that the difference in the estimated collateral cost may be driven by some differences between the BPDL and EIDL programs. To address this concern, we compare the COVID EIDLs with the regular EIDLs. Similar to the BPDLs, the regular EIDLs also use a fixed lien. As shown in column 1 of Table 4, we find the shadow cost of collateral is around 9% for the regular EIDLs, which is consistent with the BPDL estimates in Table 2. This result suggests

[12] The average interest rate of secured small business loans is around 7% from 2001 to 2020 based on RateWatch data. The interest rate of unsecured small business loans for an average credit score borrower is around 14% based on the quote from American Express (`https://www.americanexpress.com/us/business/business-funding/`). For large syndicated loans, the difference between secured and unsecured loans is around 2% (Benmelech et al., 2020a, Figure 1).

that the difference in the estimated collateral cost is more likely to be driven by the differences in collateral type rather than other differences in the loan programs.

Figures 5a and 5b provide the visualization of the bunching estimates in the regular and COVID EIDL data, respectively. COVID EIDLs exhibit stronger round-number bunching, as noted earlier. The flexible round-number dummies included in our estimation successfully capture the strong round number bunching in this sample, as shown by the spikes at round numbers in the counterfactual distribution. The excess mass at the $25,000 collateral threshold in the actual distribution is significantly larger than the predicted value due to round-number bunching, suggesting that the collateral threshold creates additional bunching mass. The estimated marginal buncher in the COVID EIDL sample is much smaller than that in the BPDL and regular EIDL samples, suggesting that the floating lien entails a lower collateral cost than the fixed lien.

4.2.3 Cross-industry heterogeneity

We also explore the heterogeneity of collateral cost across industries. Note that we can only do this exercise in a subsample of COVID EIDLs for which the industry information is available.[13] Table 5 shows that there are considerable variations in collateral cost across industries. Agriculture, accommodation, and food sectors have higher collateral costs, while retail trade and real estate sectors have lower collateral costs.

4.2.4 Secured creditor rights

The collateral cost may also depend on the rights of the secured creditors. If the statutes give stronger rights to secured creditors, firms are likely to lose more flexibility and bargaining power when pledging assets as collateral. Consequently, firms may be more averse to borrowing secured debt.

[13]We obtain industry classification by matching the COVID EIDLs with PPP loans by firm names and zip codes. The matched sample contains around 10% of the COVID EIDLs.

To assess the relationship between secured creditor rights and the collateral cost, we explore the staggered adoption of the Uniform Voidable Transactions Act (UVTA) across different states in the U.S. The UVTA was proposed in 2014 as an amendment of the Uniform Fraudulent Transfer Act (UFTA). Under the UVTA, strict foreclosure of UCC Article 9 security interests will no longer be exempted from being treated as voidable transactions (UVTA § 8(e)(2)). Forster and Boughman (2015) suggest that under the UVTA, "creditors with an Article 9 security interest can no longer foreclose on the property and retain it without risking the transfer being avoided." In other words, secured creditors' rights would be weakened as the collateral transfer becomes voidable under the UVTA. It is worth noting that UVTA also contains other changes that affect both secured and unsecured creditors.[14] We isolate the effect of secured creditor rights by comparing firms with verified losses above and below the collateral threshold. The idea is that firms with verified losses above the collateral threshold are more likely to face the trade-off of borrowing secured versus unsecured. In contrast, firms with verified losses below the threshold do not face this trade-off. Because this test requires information on the verified losses, we restrict our sample to the BPDLs.

Table 7 shows the adoption year of UVTA of each state. Note that six states—Alaska, South Carolina, Kentucky, Maryland, New York, and Virginia—used state-specific laws different from the UFTA. We exclude these states to ensure that the adoption of the UVTA captures the same change in the secured creditor rights. The sample period is from 2014, when the UVTA is first introduced, to 2020, when the BPDL sample ends.

We examine whether borrowers become more willing to borrow secured loans after the law change by estimating the following regression model in the sample of BPDLs:

$$\text{Take-up}_{i,t} = \beta_1 \text{Adoption}_{i,t} \times \text{Loss} > 25\text{k}_{i,t} + \beta_2 \text{Adoption}_{i,t} + \beta_3 \text{Loss}{>}25\text{k}_{i,t} + \tau_t + \tau_s + \varepsilon_{i,t}. \quad (14)$$

The dependent variable, $\text{Take-up}_{i,t}$, is defined as the ratio of the loan amount over the verified

[14]For instance, Ersahin et al. (2021) suggest that the UVTA could allow creditors to have "the power to undo a much broader set of transactions than those that fall within the scope of fraud." However, the Uniform Law Commission, the commission which wrote this law, argues that the general purpose of the UTVA introduction is to "address a few narrowly defined issues, ... not a comprehensive revision". See "Uniform Voidable Transactions Act: a Summary" by the Uniform Law Commission.

losses. $\text{Adoption}_{i,t}$ is a dummy variable that equals one if the state in which firm i locates has adopted UVTA. This dummy captures the law changes that affect both secured and unsecured debt. β_1, the coefficient of the interaction of $\text{Adoption}_{i,t}$ and the $\text{Loss}{>}25\text{k}_{i,t}$ dummy captures the impact of the law change on firms that are more likely to borrow secured. Table 6 presents the results. Before the law change, the take-up ratio of firms with losses above \$25,000 is around 30% lower than those with losses below \$25,000, consistent with our earlier evidence that firms bunch to avoid pledging collateral. The take-up increases by around 10% after the law change, consistent with the idea that weakened secured creditor rights reduce collateral costs. The increase in take-up ratio accounts for a third of the take-up ratio gap between firms above and below the \$25,000 threshold.

We further verify our results by estimating the implied collateral cost in UVTA and UFTA states using the bunching estimator. We can only do this exercise in the COVID EIDLs because the BPDL sample does not have enough observations to construct densities for the bunching estimator. Figure 9 illustrates each state's collateral law as of 2021. Table 8 presents the estimated collateral costs in the UVTA and UFTA states, respectively. Consistent with the results in Table 6, the collateral cost is significantly lower in the UVTA states in which secured creditor rights are weaker.

4.3 Alternative interpretations and robustness checks

This section discusses alternative interpretations and robustness checks on our baseline results.

4.3.1 Collateral scarcity

A conceptual issue is that the high collateral cost may reflect the scarcity of collateral for the sample firms rather than firms' aversion to pledge it. To elaborate, our estimation assumes that firms can choose whether to pledge collateral or not. One may worry that some firms may not have any collateral, so they have to bunch at the threshold. So the high collateral cost may partly reflect the scarcity of collateral, rather than firms' aversion to pledge it. We do not think collateral scarcity is likely an issue in our setting. For the BPDL program, the loans are used to repair or replace damaged property, which typically serves as collateral. For the COVID EIDL program, general business assets, which are broadly available, can be used as collateral. Furthermore, the SBA does not require the collateral value to cover the loan amount fully. Instead, it only requires firms to pledge what is available. Therefore, the estimated collateral cost is more likely to reflect the aversion to pledge collateral rather than the scarcity of the collateral.

4.3.2 Preserve collateral for loans from private lenders

One may also worry that firms may not have an intrinsic aversion to pledge collateral. Instead, they need the collateral to secure another loan from a private lender to maximize the total external financing.[15] This alternative interpretation is unlikely to be applicable for two reasons. First, firms that participated in the SBA disaster lending programs generally lack access to private financing. Second, even if they have access to private funding, the rates that they can get are much higher than those offered by the SBA. Since the typical loan sizes of the bunching firms are much smaller than the maximum loan size cap, $2 million, it would be suboptimal to give up the subsidized public funding to obtain expensive private funding.

4.3.3 Fixed vs proportional costs

Our baseline estimation assumes that the collateral cost is proportional to loan size. This assumption is natural because larger loans typically involve more collateral, and the economic costs associated with the loss of control rights are likely to be greater. Nevertheless, we now examine this assumption by exploiting the changes in the collateral thresholds. Specifically, the SBA has changed the collateral threshold several times during our sample period, from $10,000 to $14,000 and $25,000. These changes allow us to identify the collateral costs for different marginal bunchers. If the collateral cost is a fixed cost, we expect the dollar values estimated from different thresholds

[15]Note that this interpretation is different from the one that firms would like to keep assets unencumbered to preserve financial flexibility for future contingencies.

to be similar. If the collateral cost scales with the loan size, we expect the proportional cost to be similar. Table 9 presents the results. We find the dollar collateral cost is considerably larger for bigger marginal bunchers. It increases from $1,491 to $4,368 when the marginal buncher increases from $17,500 to $45,500. However, if we express the collateral costs as a percentage of the loan value, the magnitude is more similar across thresholds. This result suggests that the collateral cost is unlikely to be fixed. Instead, it appears to scale proportionally with the loan size.

4.3.4 Placebo tests

We conduct a set of placebo tests by repeating the same estimation procedure on factitious thresholds. Specifically, we use $25,000 as a factitious threshold in the 2008-2013 sample before the $25,000 threshold was introduced. The results are reported in Table 10. The estimation correctly indicates no excess mass in this sample at the $25,000 threshold. These placebo tests reaffirm our confidence that our results are not driven by the $25,000 threshold being special for reasons that are unrelated to the collateral requirement.

4.3.5 Sensitivity to bin size

In our baseline estimation, we set the bin size to $500. A smaller bin size pins down the density at a more local level, but it could introduce noise when the sample size is small. Therefore, we check the robustness of our results using alternative bin sizes in Table 11. We change the bin size from 500 to 100 and 250 for both the BPDL and the COVID EIDL samples. The point estimates stay mostly the same, while the standard errors vary modestly when the bin size varies.

5 Implications of Collateral Costs

This section discusses a set of robustness checks on our baseline results. We first conduct placebo tests on the samples in which the thresholds have not been introduced. We then evaluate the sensitivity of our results to alternative specifications of the bunching estimator.

5.1 Capital structure decisions

Our results have important implications on the role of collateral in capital structure decisions. Since the influential work by Myers and Majluf (1984), it is long believed that there exists a pecking order between secured and unsecured borrowing: firms should first issue collateralized debt, and then, after exhausting such claims, issue more junior claims like unsecured debt (Benmelech et al., 2020a). This intuition seems consistent with the observation that collateralized debt usually entails lower interest rates than uncollateralized debt. However, our results show that pledging collateral imposes a considerable shadow cost on firms. Our result supports a more recent theoretical literature that shows that pledging collateral could be costly because it limits firms' operational and financial flexibility and bargaining power (Mello and Ruckes, 2017; Rampini and Viswanathan, 2010; Donaldson et al., 2020; Benmelech et al., 2020a). Our estimates suggest these potential costs are first-order and have important implications on firms' capital structure decisions.

5.2 Financial acceleration

The estimated collateral cost has important macroeconomic implications. A large body of literature following the seminal work of Kiyotaki and Moore (1997) shows that collateral constraint can amplify macroeconomic fluctuation via the feedback loop between collateral value and debt capacity. Specifically, a negative shock to collateral value can tighten firms' collateral constraints, leading to a further decline in collateral value. The standard macro-finance model with collateral constraints does not consider the collateral cost. Since firms incur no cost when pledging collateral, they always borrow up to the collateral limit. We now examine the implications of our findings by incorporating the collateral cost into the standard Kiyotaki and Moore (1997) model.

We consider a discrete-time, infinite-horizon economy with two goods: a durable land and a nondurable fruit, and two groups of agents: farmers and gatherers. We maintain the terminology in Kiyotaki and Moore (1997). Still, it is worth noting that land and fruit can be interpreted as capital and consumption goods, while farmers and gathers can be interpreted as firms and lenders. There is no aggregate uncertainty in the model aside from an initial unanticipated shock, and so given rational expectations, agents have perfect foresight. Following Kiyotaki and Moore (1997), we assume that agents can only borrow secured debt. This can be viewed as a limiting case of Rampini and Viswanathan (2020) that the implicit collateralizability of firms' residual value is zero. Our results still hold if agents can borrow unsecured as long as unsecured debt capacity is lower than secured debt.

Farmers. We have a measure one of infinitely lived, risk-neutral farmers, and they maximize the expected utility:

$$E_t\left(\sum_{s=0}^{+\infty}\beta^s x_{t+s}\right), \tag{15}$$

where x_{t+s} is the consumption of fruits at time $t+s$, and β is the discount rate. Each farmer spends one period to produce the fruits with the following production function:

$$y_{t+1} = F\left(k_t\right) = \left(a+c\right)k_t, \tag{16}$$

where k_t denotes the farmer's landholding at the end of time t, ak_t is the tradable output, while the c is non-tradable and can only be consumed by the farmer.

Gatherers. There is a measure one of infinitely lived, risk neutral gatherers. Their expected utility at time t is

$$E_t\left(\sum_{s=0}^{+\infty}\left(\beta'\right)^s x'_{t+s}\right), \tag{17}$$

where x'_{t+s} is the consumption of fruits at time $t+s$, and β' is the discount rate. We assume $\beta' > \beta$ so that farmers are relatively impatient and do not want to postpone production.

Each gatherer has an identical production function to use land k'_t to produce y'_{t+1} tradable fruits at $t+1$ that exhibits decreasing returns to scale

$$y'_{t+1} = G\left(k'_t\right) \tag{18}$$

where $G' > 0$, $G'' < 0$ and $G'(0) > aR > G'\left(\bar{K}\right)$ to ensure that both farmers and gatherers are producing in the neighborhood of a steady-state equilibrium.

Collateral Constraints. In period t, if the farmer has land k_t then she can borrow b_t in total, as long as the repayment does not exceed the market value of land (net of depreciation) at $t+1$:

$$Rb_t \leq q_{t+1}\left(1-\delta\right)k_t. \tag{19}$$

Markets. There is a competitive spot market in which land is exchanged for fruits at a price q_t at each time t. The only other market is a one-period credit market in which one unit of fruit at time t can be exchanged for a claim to R_t units of fruits at date $t+1$. In equilibrium, as farmers are more impatient, they borrow from gatherers, and thus the rate of interest is always determined by gatherers' time preferences $R_t = \frac{1}{\beta'} = R$.

We introduce the collateral cost to the model. Agents incur the collateral cost, $\lambda b_t \mathbb{1}_{b_t>0}$, if they borrow a positive amount of debt. Each farmer and each gatherer's budget constraint in each period t can then be summarized as

$$q_t\left(k_t - \left(1-\delta\right)k_{t-1}\right) + Rb_{t-1} + x_t + \lambda b_{t-1}\mathbb{1}_{b_{t-1}>0} = (a+c)k_{t-1} + b_t \tag{20}$$

$$q_t\left(k'_t - \left(1-\delta\right)k'_{t-1}\right) + Rb'_{t-1} + x'_t + \lambda b'_{t-1}\mathbb{1}_{b'_{t-1}>0} = G\left(k'_{t-1}\right) + b'_t \tag{21}$$

Farmers' Behavior. Farmers prefer to invest in land and consuming no more than their current output of non-tradable fruits,

$$x_t = ck_{t-1}. \tag{22}$$

Define the net investment return as tradable and non-tradable fruits subtracting the user cost,

$$\mu_t \equiv a + c - u_t, \tag{23}$$

where the user cost equals the change in the depreciation-adjusted land value:

$$u_t = q_t - \frac{1-\delta}{R} q_{t+1}. \tag{24}$$

Farmers determine the borrowing amount based on whether the net investment return exceeds the collateral cost. When the investment return exceeds the collateral cost, farmers borrow to the collateral limit. When the investment return falls below the collateral cost, farmers do not borrow. Formally, farmers' borrowing amount is given by

$$b_t = \frac{1-\delta}{R} q_{t+1} k_t \mathbb{1}_{\mu_t > \lambda}. \tag{25}$$

Substituting in equation (25) into equation (20), a farmer's land holding is given by

$$k_t = \frac{1}{u_t} \left[(a + q_t(1-\delta))k_{t-1} - Rb_{t-1} - \lambda b_{t-1} \mathbb{1}_{\mu_t > \lambda} + \frac{1-\delta}{R} q_{t+1} k_t (\mathbb{1}_{\mu_t > \lambda} - 1). \right] \tag{26}$$

We can aggregate across farmers, and the dynamics of aggregate borrowing of farmers and landholding of the farmer section are:

$$B_t = \frac{1-\delta}{R} q_{t+1} K_t \mathbb{1}_{\mu_t > \lambda}, \tag{27}$$

$$K_t = \frac{1}{u_t} \left[(a + q_t(1-\delta))K_{t-1} - RB_{t-1} - \lambda B_{t-1} \mathbb{1}_{\mu_t > \lambda} + \frac{1-\delta}{R} q_{t+1} K_t (\mathbb{1}_{\mu_t > \lambda} - 1) \right]. \tag{28}$$

Gatherers' Behavior. As the gatherer is not credit constrained, her demand for land is determined so the present value of the marginal product of land is equal to the user cost of holding land, u_t:

$$\frac{1}{R}G'\left(k_t'\right) = u_t. \tag{29}$$

Market clearing. Since all the gatherers have identical production functions, their aggregate demand for land is given by K_t'. The sum of the aggregate demands for land by the farmers and gatherers is equal to the total supply; that is, $K_t + K_t' = \overline{K}$. Thus, the land market equilibrium condition is

$$u_t = u(K_t) \equiv \frac{1}{R}G'\left(\bar{K} - K_t\right), \tag{30}$$

where $u(K)$ expresses the user cost in each period as an increasing function of farmers' aggregate land holding.

We can express the land price as the present value of user costs,

$$q_t = \sum_{s=0}^{+\infty} \left(\frac{1-\delta}{R}\right)^s u(K_{t+s}). \tag{31}$$

Steady State. The nature of the steady state depends on the relative magnitude of the investment return and the collateral cost. In a high productivity steady state where the net investment return exceeds the collateral cost at the steady state $\mu \geq \lambda$, we have:

$$\left(1 - \frac{1-\delta}{R}(1-\lambda)\right) q = a, \tag{32}$$

$$B = \frac{1-\delta}{R} qK, \tag{33}$$

$$\frac{1}{R}G'\left(\bar{K} - K\right) = u, \tag{34}$$

$$u = \left(1 - \frac{1-\delta}{R}\right) q. \tag{35}$$

In a low productivity steady state where the net investment return is below the collateral cost in the steady state $\mu < \lambda$, we can characterize the steady state as the following:

$$\delta q = a, \tag{36}$$

$$B = 0, \tag{37}$$

$$\frac{1}{R} G' \left(\bar{K} - K\right) = u, \tag{38}$$

$$u = \left(1 - \frac{1-\delta}{R}\right) q. \tag{39}$$

State-dependency. Suppose at $t-1$ the economy is in a steady state. We consider the impulse response to an unexpected aggregate shock to farmers' productivity at t, which changes the productivity of the tradable goods by Δa. The production technologies then revert to the steady-state level a.

We first show that the collateral trade-off makes the impulse responses state-dependent. The solid line in Figure 6 shows the impulse responses of farmers' landholding to the productivity shock when the economy was originally in a high productivity state. We assume that the negative productivity shock is small such that the net investment return is still above the collateral cost, $\mu_t > \lambda$. Because the collateral constraint is binding before and after the shock hits the economy, a temporary productivity shock leads to a large and persistent drop in landholding and asset prices. The financial amplification comes from the fact that, on top of the direct productivity shock, Δa, the depreciation in land prices further reduces farmers' net worth. Because the land price is forward-looking, the dynamic effect is much larger than the static effect due to the productivity shock. Note that this case is equivalent to Kiyotaki and Moore (1997).

The solid line in Figure 6 shows the impulse responses of farmers' landholding to the productivity shock when the economy is originally in a low productivity state. The shock has a limited impact on the economy because the collateral constraint is not binding. In other words, the financial accelerator mechanism is muted when the economy is originally at a low productivity state.

This result speaks to the extensive empirical studies on the magnitude of the financial accelerator mechanism (Lian and Ma, 2021; Catherine et al., 2018), which often finds that the sensitivity of firm-level investment to collateral values is well below the magnitude predicted by the standard Kiyotaki and Moore (1997) model. For instance, Catherine et al. (2018) find the sensitivity of investment to asset prices is 0.06 while the standard Kiyotaki and Moore (1997) model implies a sensitivity of 1. The existing literature often uses low asset plegibility to rationalize this discrepancy. While asset plegibility is certainly a crucial factor, we suggest that the collateral cost can also contribute to the low sensitivity. If the collateral cost is substantial, firms may choose not to pledge their assets even if lenders are willing to accept them as collateral. Therefore, the fluctuations in asset prices would have a smaller impact on firms' investments.

Amplification due to collateral trade-off. Next, we show that embedding the collateral trade-off into the standard financial accelerator model of Kiyotaki and Moore (1997) generates a new amplification mechanism in which borrowers endogenously reduce the borrowing amount below the debt capacity. We compare the impulse response of farmers' capital in models with and without the collateral trade-off. We assume that the economy is at a high productivity steady state, and then a negative shock hits at time t.

Figure 7 compares the impulse responses of farmers' capital at time t when the productivity shock hits with and without the collateral trade-off for different shock sizes. When the shock size is small, the impulse responses are almost identical. However, when the shock size is large, the model with the collateral trade-off generates greater amplification. The intuition is that when the net investment return falls below the collateral cost, $\mu_t < \lambda$, farmers find it too costly to borrow collateralized. Instead, they will pay the full price in cash to buy lands without borrowing. As a result, the farmers' demand for capital falls more than that in Kiyotaki and Moore (1997).

5.3 Design of government lending program

The estimated collateral cost also has important implications for designing the government lending program. To illustrate this point, we use our estimated model to conduct a set of counterfactual policy experiments. We start by deriving the social welfare created by the lending program, which is given by the output enabled by the loans, $AK^*(Z)^\alpha$, subtracting the expected default loss, $\ell K^*(Z)$, and the costs associated with pledging collateral. The optimal loan size chosen by firms, $K^*(Z)$, can be solved by equation (5). ℓ is the charge-off rate for uncollateralized loans. The collateral requirement can lower the charge-off rate by β. However, it imposes a shadow cost λZ on firms. Furthermore, the collateral requirement may distort the loan size choice from the desired level, $K^*(Z) \leq Z$. Finally, a fixed transaction cost is associated with the collateral requirement, ϕ.

A fraction of firms does not respond to the collateral threshold in the data. Instead, they always stick to their desired loan size Z, even if Z is in the dominated region above the threshold. We refer to them as the non-optimizing firms following the terminology of Kleven and Waseem (2013). We denote the fraction of non-optimizing firms as γ.

The total social welfare created by the lending program with a collateral threshold $\underline{K}$ is given by:

$$\begin{aligned} W(\underline{K}) = (1-\gamma) \int \left[AK^*(Z)^\alpha - \ell K^*(Z) + \mathbb{1}_{K^*>\underline{K}}(\beta K^*(Z) - \lambda Z - \phi)\right] f_0(Z)dZ \\ +\gamma \int \left[AZ^\alpha - \ell Z + \mathbb{1}_{Z>\underline{K}}(\beta Z - \lambda Z - \phi)\right] f_0(Z)dZ. \end{aligned} \tag{40}$$

The first and second terms are the welfare for optimizing and non-optimizing firms, respectively.

We first calibrate the model parameters to the corresponding moments in the data. First, the collateral cost λ is set to 9% based on the estimates in Table 2. Second, the distribution of firms' desired loan size f_0 is calibrated using the estimated counterfactual distribution in equation (10) in the 2014-2020 BPDL sample. Third, the charge-off rates of uncollateralized loans are calibrated to 24% according to the Government Accountability Office (GAO) statistics.[16] We calibrate the

[16]See "Small Business Administration: Physical Disaster Loan Performance Before and After Changes in Statu-

reduction in the charge-off rate, β, to 9.6%, which is consistent with Collier et al. (2021) who find collateral requirements reduce mortgage default rates by around 35%. Fourth, the fraction of the non-optimizing firms γ is calibrated to the fraction of firms in the bunching range $[\underline{K}, \overline{K}]$, which is 0.63. Finally, the fixed transaction cost of pledging collateral ϕ is calibrated to \$100.

We calculate the aggregate welfare for different values of collateral threshold, $\underline{K}$. Figure 8a shows the simplest case in which the shadow cost of collateral is set to zero, $\lambda = 0$. In this scenario, the benefits of the collateral requirements—reducing the expected default loss βZ—dominate the explicit transaction cost of collateral requirement ϕ. Therefore, the welfare is maximized when most of the loans, except those tiny ones below \$1,000, are subject to the collateral requirements.[17]

We then introduce the collateral costs into the welfare calculation. We assume that none of the firms manipulate their loan size strategically in response to the collateral requirement, $\gamma = 1$. Figure 8b shows that the optimal collateral threshold becomes a much larger value, \$16,000, which suggests that more loans should be exempted from the collateral requirements if the shadow cost of collateral is taken into account.

Next, we allow a fraction of firms to respond strategically to the collateral threshold. We calibrate the fraction of non-optimizing firms to the data, $\gamma = 0.63$. In other words, 37% of the firms will manipulate their loan size in response to the collateral threshold. Introducing manipulation significantly changes the trade-off, as shown in Figure 8c. The relation between welfare and collateral threshold becomes a "V" shape—the social welfare is lower when the collateral threshold is at intermediate values but is higher at the extreme values. The intuition for this result is that an intermediate threshold value induces more manipulation, which is socially costly. In contrast, an extremely low threshold makes manipulation very costly so that not many firms do it, and an extremely high threshold makes manipulation unnecessary for most firms. In this case, the optimal collateral threshold is at \$1,000.

Finally, we consider a scenario in which the collateral requirement becomes less effective in

tory Collateral Requirements".

[17]The tiny loans are exempted because the fixed transaction cost is large relative to the benefits of the collateral, which is proportional to the loan size.

reducing the charge-off rate. Specifically, we assume that the collateral requirement only reduces the charge-off rate by 4.8%. Figure 8d shows that the optimal collateral threshold is at the maximum loan size, which means that all loans should be exempted from the collateral requirement. The intuition for this result is that the social benefits of collateral requirements become lower than the shadow cost of collateral, so all firms should be exempted from the collateral requirements.

In summary, the counterfactual policy experiments show that the collateral cost has important implications for the design of government lending programs. If one ignores the shadow cost of collateral, the benefits of collateral requirements—reducing the expected default loss for taxpayers—can easily dominate the explicit transaction costs associated with collateral requirements, which are usually quite small in practice. However, if one incorporates the collateral cost, it becomes unclear whether the collateral requirement is welfare improving or not. The counterfactual policy experiments also show that firms' strategic response to the collateral threshold is important for policy design. As firms bunch below the threshold to avoid the collateral cost, the take-up of the program will be significantly reduced. The strategic responses by firms limit policymakers' ability to use threshold-based policies to fine-tune the collateral requirements.

6 Conclusion

Collateral plays a crucial role in the economy. While the benefit of pledging collateral has received extensive studies, the cost of pledging collateral is less well understood. This article empirically estimates the shadow cost of collateral by exploiting a unique setting in which firms can be exempted from collateral requirements if the loan amount is below a threshold. We find that the implied shadow cost of collateral is equivalent to 6%-9% of the loan value.

Our results cast doubt on the conventional wisdom that the choice of collateralized and uncollateralized debt follows a strict pecking order. Instead, firms face a trade-off between the shadow cost to pledge collateral and the low-interest rate. This result is consistent with the recent theoretical literature that shows that pledging collateral could limit firms' operational and financial flexibility and reduce their bargaining power if they enter financial distress. Moreover, we show that the collateral cost depends on collateral types, business sectors, and collateral laws. These results have important implications for understanding firms' borrowing constraints, the financial accelerator mechanism, and the design of government lending programs.

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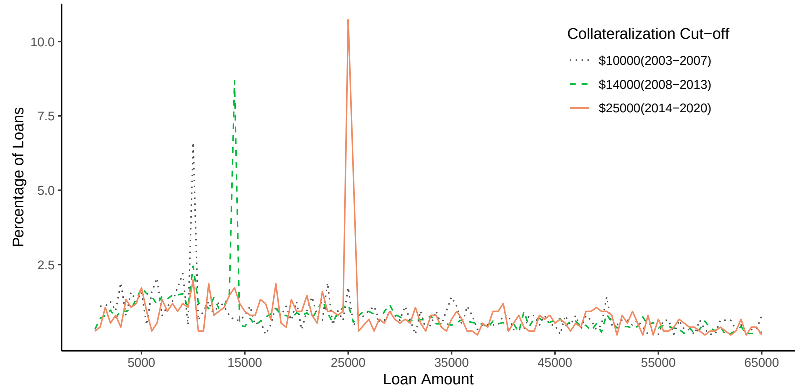
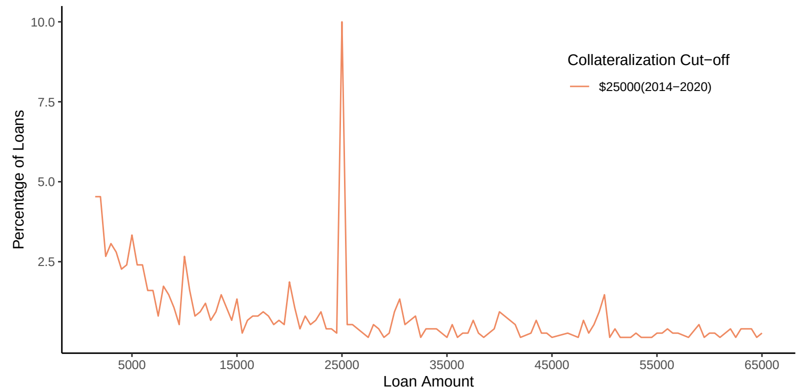
Figure 1: Loan size distribution

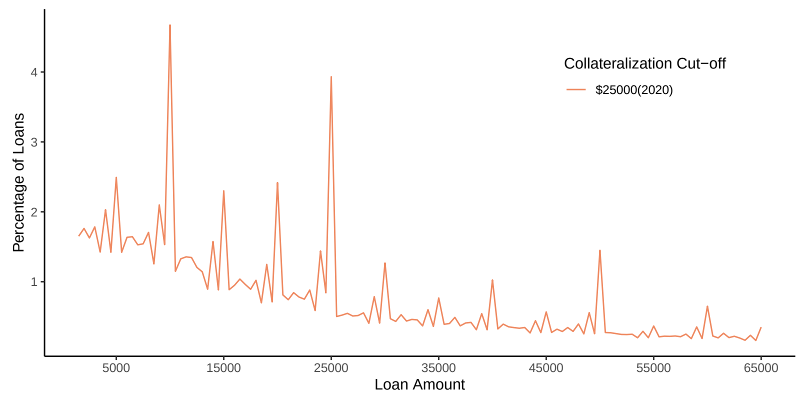
(a) BPDL



(b) Regular EIDL



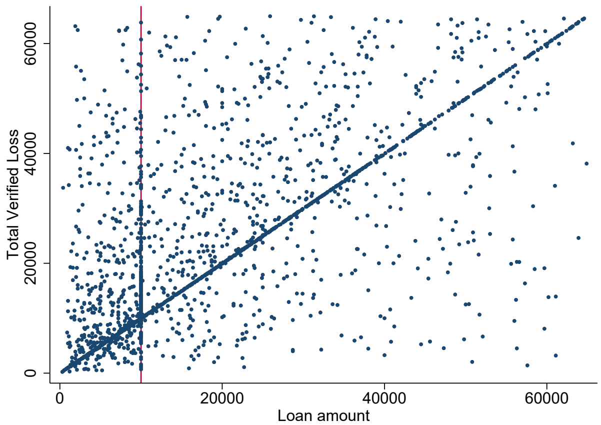
(c) COVID EIDL



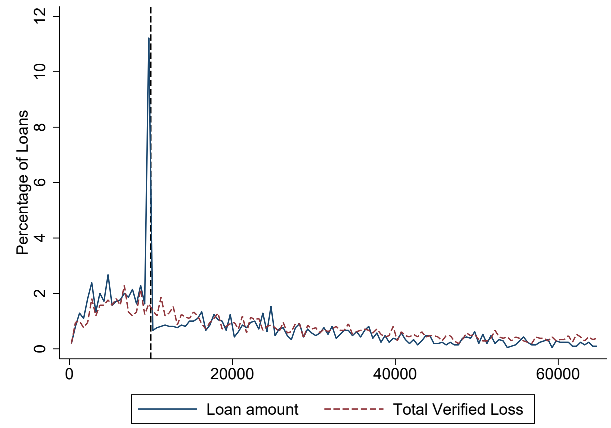
Note: The figure shows the loan size distribution of BPDLs, regular EIDLs, and COVID EIDLs, respectively. Data source: SBA.

Figure 2: Distributions for BPDLs: loan amounts vs. verified losses

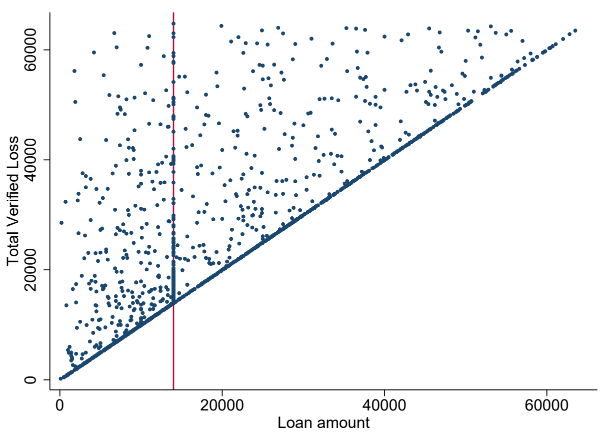
(a) 2003 to 2007



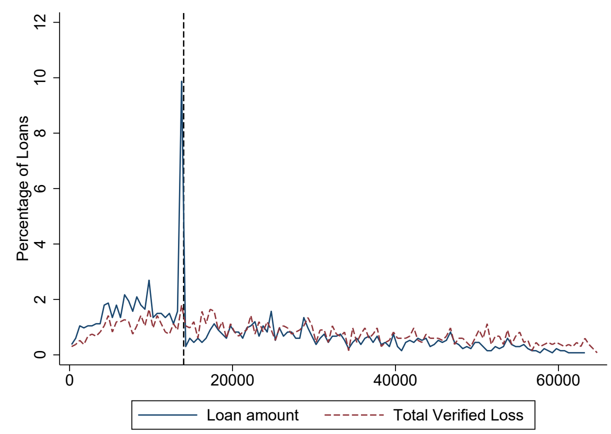
(b) 2003 to 2007



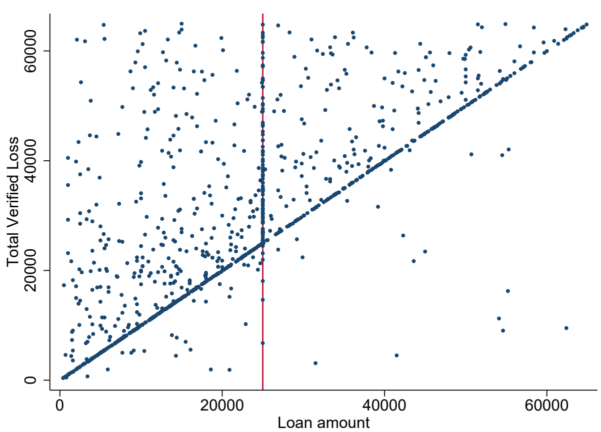
(c) 2008 to 2013



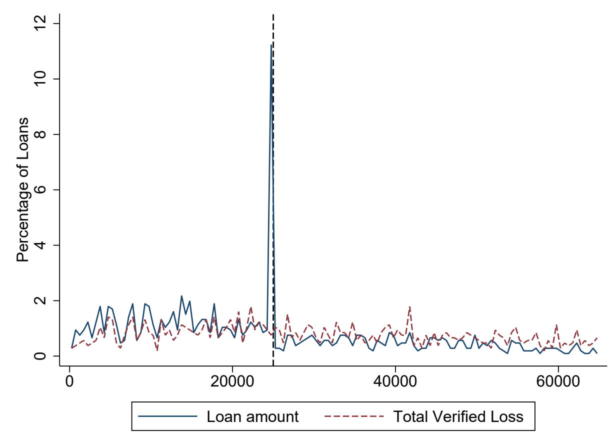
(d) 2008 to 2013



(e) 2014 to 2020



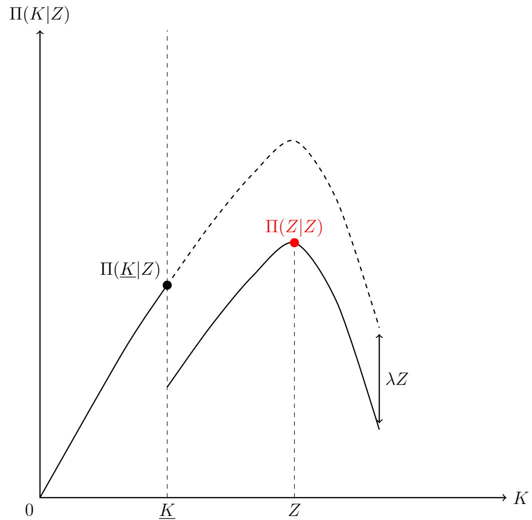
(f) 2014 to 2020



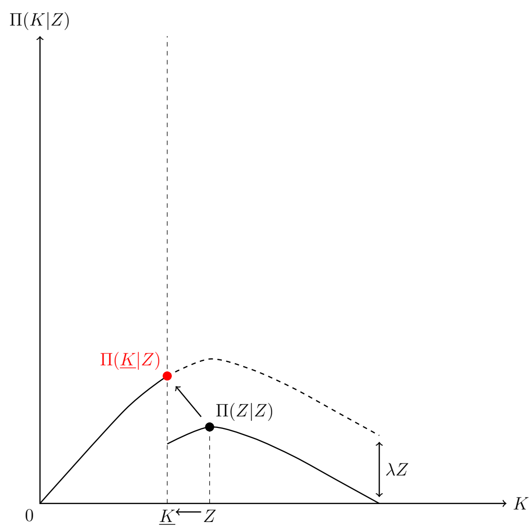
Note: The figure shows the verified loss and loan size distribution for BPDLs. The vertical lines indicate the collateral thresholds. Data source: SBA.

Figure 3: Bunching condition with collateral costs

(a) No bunching



(b) Bunches at $\underline{K}$



(c) Marginal buncher $\overline{K}$

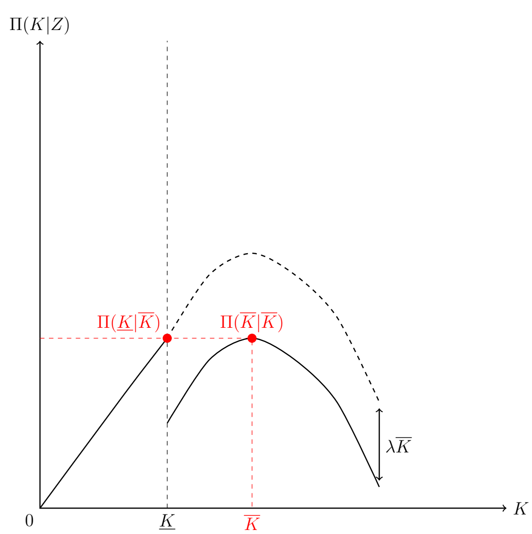
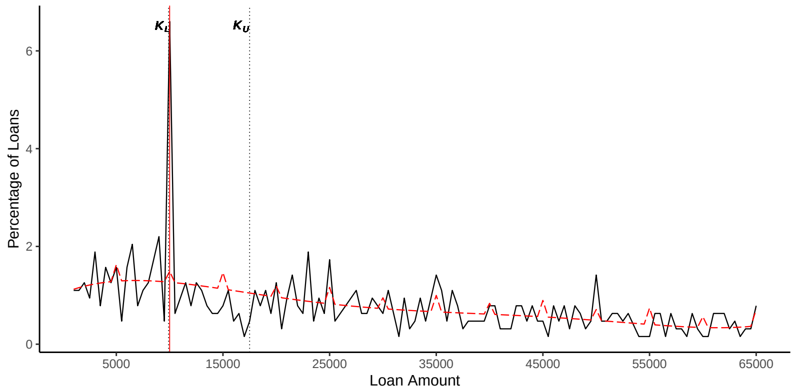
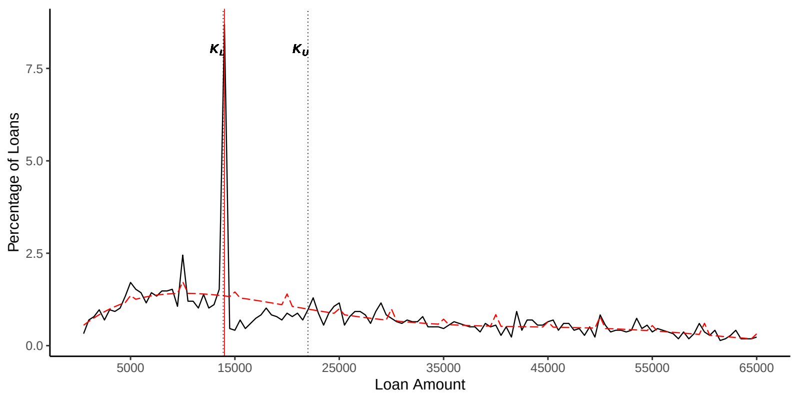


Figure 4: Counterfactual distribution and marginal buncher of BPDLs

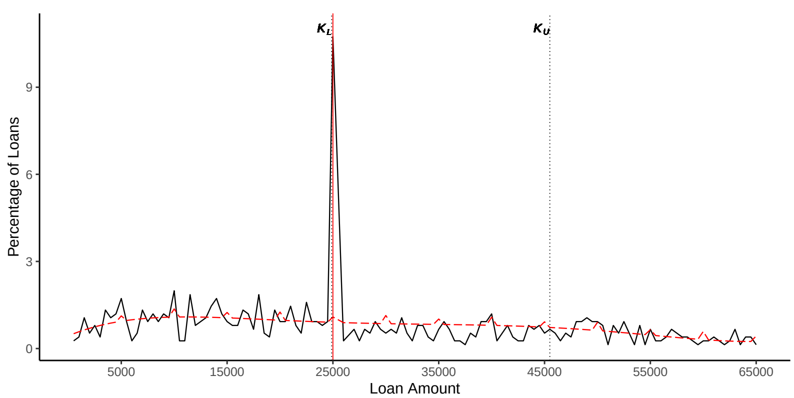
(a) 2003 to 2007



(b) 2008 to 2013



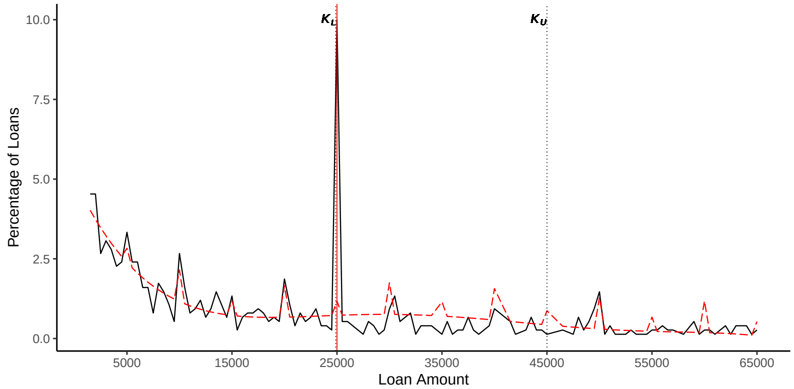
(c) 2014 to 2020



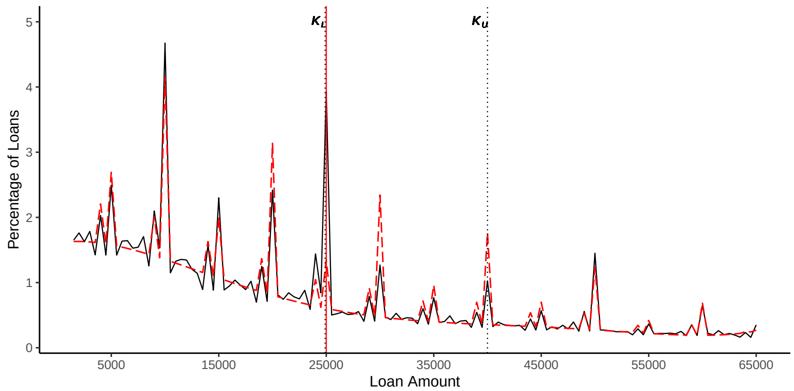
Note: This figure shows the observed (black) and counterfactual (red) percentage of loans in each bin. The counterfactual is estimated for each sample separately by fitting a fifth-order polynomial with round number dummies to the observed distribution using a bin size of $500 excluding data in the bunching region. We set all estimation ranges to be from $0 to $65,000.

Figure 5: Loan size distribution and marginal buncher of EIDLs

(a) Regular EIDL

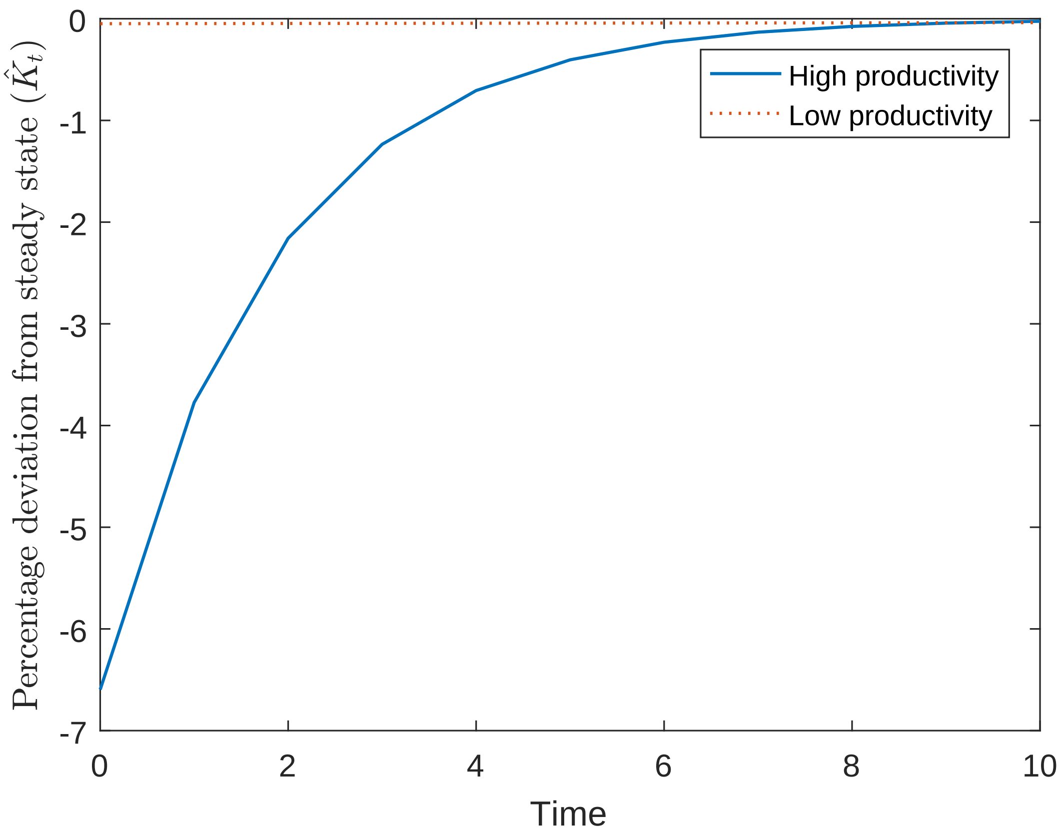


(b) COVID EIDL



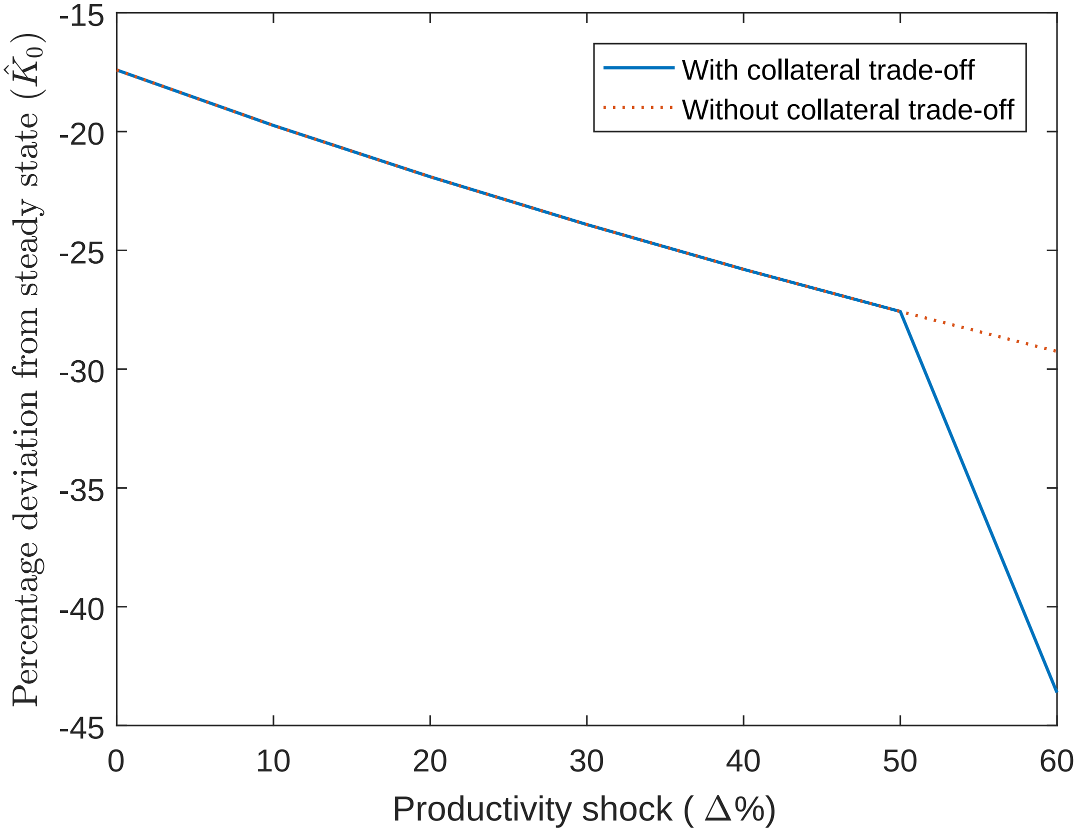
Note: This figure shows the observed (black) and counterfactual (red) percentage of loans in each bin. The counterfactual is estimated for each sample separately by fitting a fifth-order polynomial with round number dummies to the observed distribution using a bin size of \$500 excluding data in the bunching region. We set estimation ranges to be from \$1000 to \$65,000 for both regular EIDL and COVID EIDL.

Figure 6: Impulse response functions in a Kiyotaki and Moore (1997) model with collateral cost



Note: This figure shows the impulse response functions in a Kiyotaki and Moore (1997) model with collateral cost. The vertical axis is the percentage deviation of farmers' land from the steady state, $\hat{K}_t$. The horizontal axis is time. Productivity of tradable goods a is set to 1. Productivity of non-tradable goods c is set to 0.01. The collateral cost is set to 6%. The gross interest rate R is set to 1.01. The depreciation rate δ is set to 0.05. The elasticity of the residual supply of land to the farmers to the user cost at the steady state η is set to 1.5.

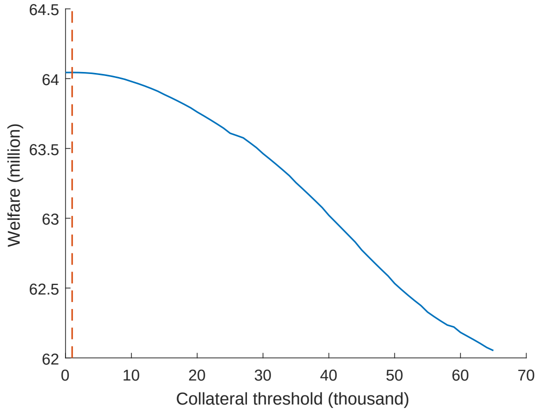
Figure 7: Time-0 impulse responses in a Kiyotaki and Moore (1997) model with vs. without collateral cost



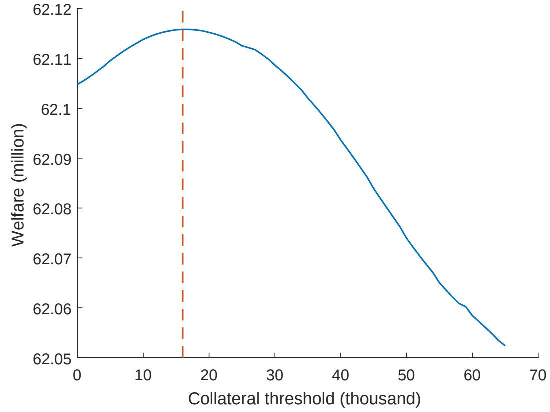
Note: This figure shows time-0 impulse response for shocks of different sizes in Kiyotaki and Moore (1997) model with collateral cost. The vertical axis is the percentage deviation of farmers' land at time 0 from the steady state, $\hat{K}_0$. The horizontal axis is the size of the productivity shock. Productivity of tradable goods a is set to 1. Productivity of non-tradable goods c is set to 0.01. The collateral cost is set to 6%. The gross interest rate R is set to 1.01. The depreciation rate δ is set to 0.05. The elasticity of the residual supply of land to the farmers to the user cost at the steady state η is set to 1.5.

Figure 8: Counterfactual policy simulation

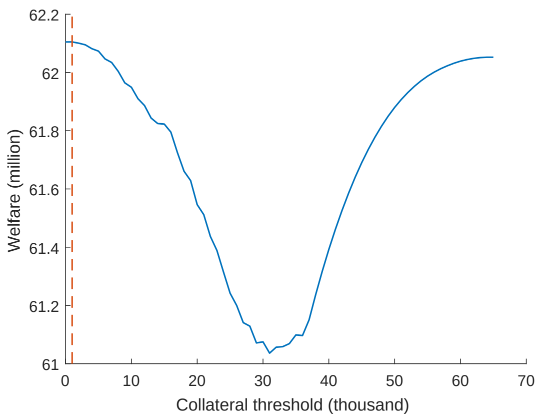
(a) Without collateral cost and manipulation



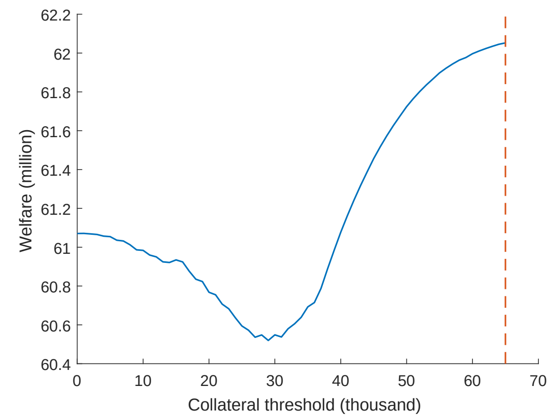
(b) With collateral cost, without manipulation



(c) With collateral cost and manipulation

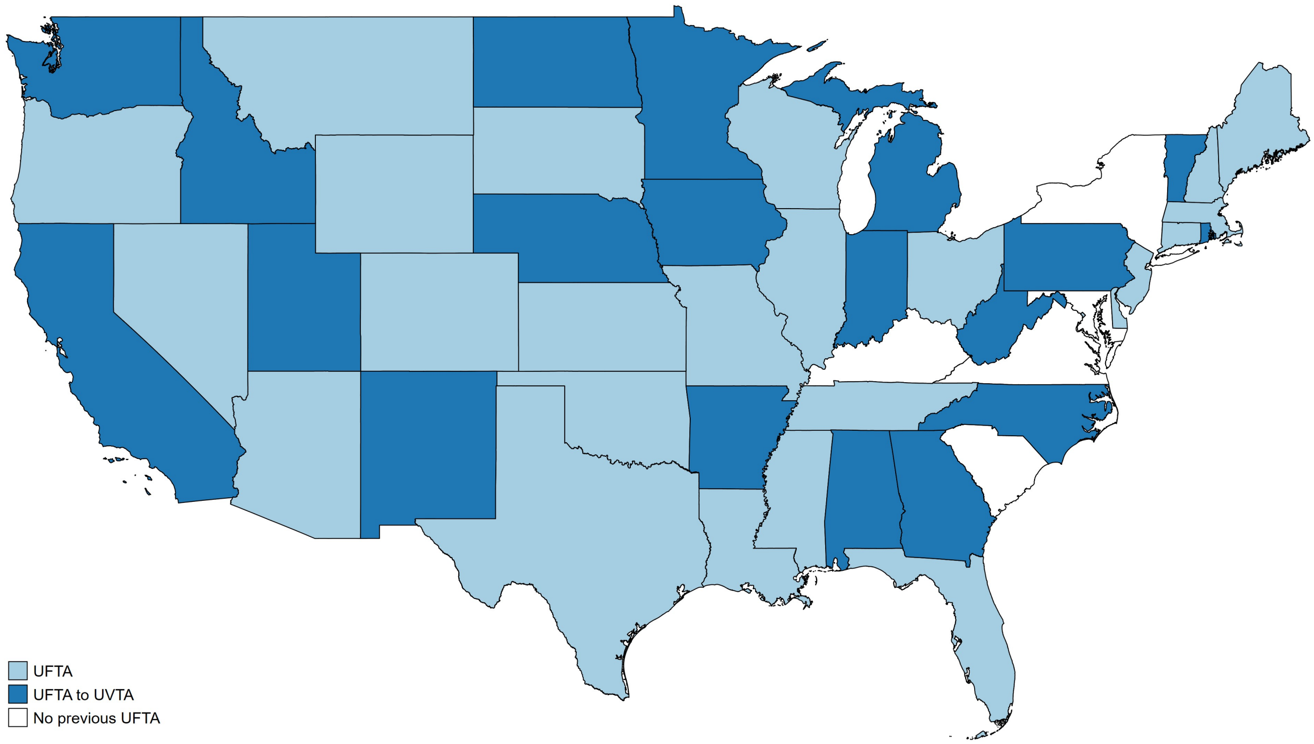


(d) Lower benefit of collateral



Note: This figure shows the social welfare for different values of the collateral threshold ($\underline{K}$). The red dashed lines indicate the optimal collateral threshold in each scenario.

Figure 9: UVTA and UFTA status by state as of 2021



Note: This figure shows each state's status for UVTA and UFTA as of 2021.

Table 1: Summary statistics

This table reports summary statistics for the main variables. The first two columns report the mean and the standard deviation, and the The third to fifth columns report the minimum, median, and maximum, respectively. Panel A reports summary statistics for the full sample of the Business Physical Disaster Loan (BPDL), panel B reports statistics for the full sample of the Economic Inquiry Disaster Loan (EIDL), and panel C reports statistics for the full sample of the COVID Economic Inquiry Disaster Loan (COVID EIDL). The loan amount is the approved loan amount of a given loan in the sample. Interest rate is the SBA assigned interest rate for a particular disaster. Verified loss is the total disaster physical damage losses associated with BPDLs. Loans per disaster is the total number of disaster loans approved for a particular disaster. Loans per zip code is the total number of disaster loans approved for a particular zip code region.

Panel A: BPDL (2003-2020)

Outcome	Mean	Std.Dev.	Min	Median	Max	Observations
Loan amount ($)	469,771	2,534,953	100	66,300	141,125,104	14,055
Interest rate (%)	3.59	0.46	2.75	4.00	4.00	14,125
Verified losses ($)	2,128,843	14,447,101	0	144,571	531,025,562	14,056
Loans per disaster	325.62	419.89	1	139	1,566	14,383
Loans per zip code	5.54	10.62	1	3	137	14,383

Panel B: EIDL (2003-2020)

Outcome	Mean	Std.Dev.	Min	Median	Max	Observations
Loan amount ($)	126,676	384,592	100	30,200	13,971,500	11,202
Interest rate (%)	3.55	0.46	2.75	3.67	4.00	11,185
Loans per disaster	364.72	441.21	1	173	1,566	11,600
Loans per zip code	5.80	9.97	1	4	137	11,600

Panel C: COVID EIDL (2020)

Outcome	Mean	Std.Dev.	Min	Median	Max	Observations
Loan amount ($)	53,255	58,315	100	26,000	713,900	3,616,791
Interest rate (%)	3.75	0.00	3.75	3.75	3.75	3,616,791
Loans per zip code	625.39	627.78	1	435	4,705	3,616,791

Table 2: Bunching estimates for BPDLs: baseline

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for BPDLs between 2014 and 2020 at $25,000 collateral threshold. The sample contains loans with loan amount between $0 and $65,000. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral cost λ is calculated as in equation (7). The bin size is set to $500 and the degree of the polynomial is set to 4 in column 1, 5 in column 2 and 6 in column 3. Bootstrapped standard errors are presented in parentheses.

	BPDL		
	Bin Size = 500		
Estimates Collateral requirement	$\underline{K} = 25000$ Fixed lien $P = 4$ (1) 2014-2020	$\underline{K} = 25000$ Fixed lien $P = 5$ (2) 2014-2020	$\underline{K} = 25,000$ Fixed lien $P = 6$ (3) 2014-2020
Bunching mass (B)	9.57%	9.65%	9.64%
	(0.13%)	(0.15%)	(0.15%)
Marginal buncher ($\overline{K}$)	47,500	45,500	45,000
	(2857.88)	(2277.11)	(2493.37)
Distortion ratio (θ)	46.81%	45.05%	44.44%
	(3.34%)	(2.73%)	(3.07%)
Collateral cost (λ)	10.83%	9.60%	9.29%
	(1.74%)	(1.39%)	(1.52%)

Table 3: Bunching estimates for COVID EIDLs: baseline

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for COVID EIDLs at \$25,000 collateral threshold. The sample contains loans with loan amount between \$1,000 and \$65,000. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral cost λ is calculated as in equation (7). The bin size is set to \$500 and the degree of the polynomial is set to 4 in column 1, 5 in column 2 and 6 in column 3. Bootstrapped standard errors are presented in parentheses.

COVID EIDL			
	Bin Size = 500		
Estimates	$\underline{K} = 25000$	$\underline{K} = 25000$	$\underline{K} = 25,000$
Collateral requirement	Floating lien	Floating lien	Floating lien
	$P = 4$	$P = 5$	$P = 6$
	(1) COVID EIDL	(2) COVID EIDL	(3) COVID EIDL
Bunching mass (B)	2.52%	2.58%	2.55%
	(0.07%)	(0.08%)	(0.08%)
Marginal buncher ($\overline{K}$)	40,000	40,000	40,000
	(4432.43)	(3635.17)	(2868.36)
Distortion ratio (θ)	37.50%	37.50%	37.50%
	(6.67%)	(5.03%)	(4.74%)
Collateral cost (λ)	6.23%	6.23%	6.23%
	(2.60%)	(2.18%)	(1.67%)

Table 4: Bunching estimates: regular vs. COVID EIDLs

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for EIDLs. Columns 1 and 2 report the regular and COVID EIDL sample respectively. The collateral threshold are \$25,000 for both samples. The sample contains loans with loan amount between \$1,000 and \$65,000. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral cost λ is calculated as in equation (7). The bin size is set to \$500 and the degree of the polynomial is set to 5. Bootstrapped standard errors are presented in parentheses.

	EIDL	
	Bin Size = 500	
Estimates	$\underline{K} = 25,000$	$\underline{K} = 25,000$
Collateral requirement	Fixed lien	Floating lien
	$P = 5$	$P = 5$
	(1) Regular EIDL	(2) COVID EIDL
Bunching mass (B)	8.74%	2.58%
	(0.13%)	(0.08%)
Marginal buncher ($\overline{K}$)	45,000	40,000
	(1673.92)	(3635.17)
Distortion ratio (θ)	44.44%	37.50%
	(2.18%)	(5.03%)
Collateral cost (λ)	9.29%	6.23%
	(1.02%)	(2.18%)

Table 5: Estimates by industry

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for different industry's COVID-19 EIDLs at \$25,000 collateral threshold. The sample contains loans with loan amount between \$1,000 and \$65,000. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral cost λ is calculated as in equation (7). The degree of the polynomial is set to 5 and the bin size is set to \$500. Bootstrapped standard errors are presented in parentheses.

Sector	NAICS	B	$\overline{K}$	Distortion ratio θ	Collateral cost λ
Agriculture	11	6.38%	44,000	43.18%	8.66%
		(0.23%)	(2355.47)	(3.40%)	(1.42%)
Construction	23	5.40%	40,000	37.5%	6.23%
		(0.15%)	(2087.54)	(3.04%)	(1.26%)
Manufacturing	31-33	6.56%	40,000	37.5%	6.23%
		(0.24%)	(2345.25)	(3.29%)	(1.41%)
Wholesale Trade	42	6.00%	40,000	37.5%	6.23 %
		(0.22%)	(3151.03)	(4.49%)	(1.89%)
Retail Trade	44-45	4.23%	37,500	33.33%	4.76 %
		(0.09%)	(1813.46)	(3.12%)	(1.05%)
Transportation	48-49	4.23%	40,000	37.5%	6.23%
		(0.07%)	(1802.55)	(2.71%)	(1.08%)
Information	51	4.56%	40,000	37.5%	6.23%
		(0.11%)	3871.54	(7.55%)	(2.10%)
Finance and Insurance	52	6.02%	40,500	38.27%	6.53%
		(0.17%)	(2956.14)	(3.92%)	(1.80%)
Real Estate	53	2.98%	35,000	28.57%	3.38%
		(0.10%)	(2594.37)	(4.93%)	(1.43%)
Professional Services	54	5.69%	40,000	37.5%	6.23%
		(0.11%)	(1996.08)	(2.93%)	(1.20%)
Waste Management	56	4.80%	44,000	43.18%	8.66%
		(0.10%)	(3067.32)	(4.88%)	(1.81%)
Educational Services	61	6.17%	46,000	45.65%	9.88%
		(0.79%)	(5086.99%)	(5.49%)	(3.09%)
Health Care	62	5.02%	43,500	42.53%	8.35%
		(0.16%)	(2398.66)	(3.28%)	(1.46%)
Recreation	71	4.73%	40,000	37.5%	6.23%
		(0.34%)	(3978.92)	(5.83%)	(2.37%)
Accommodation and Food	72	5.11%	44,500	43.82%	8.96%
		(0.18%)	(2493.73)	(3.27%)	(1.52%)
Other Services	81	4.69%	40,000	37.5%	6.23%
		(0.10%)	(2036.33)	(2.87%)	(1.23%)

Table 6: The effects of secured creditor rights on loan take-up

This table presents estimates of the loan level effects of the Uniform Voidable Transfer Act (UVTA) state adoption on the BPDL loan take-up ratio between 2014 and 2020. The loan take-up ratio is calculated as following: Take-up $= \frac{\text{Loan amount}}{\text{Loss}}$. "Adoption" is the dummy variable that indicates whether the state had adopted UVTA when the loan was issued: 1 is after the adoption, and 0 is before the adoption. "Loss $>$ 25k" is the dummy variable that indicates whether the disaster loan's associated verified losses exceed $25,000: 1 is verified losses above $25,000, and 0 is verified losses below or equal to $25,000. Column (1) reports the results without fixed effects. Column (2) reports results with year-fixed effects. Column (3) reports results with state-fixed effects. Column (4) reports results with both year and state fixed effects. All standard errors are clustered both at the year level and the state level.

	BPDL 2014-2020			
Dependent variable:	Take-up ratio			
	(1)	(2)	(3)	(4)
Adoption × Loss>25k	0.100**	0.094**	0.085***	0.084***
	(0.029)	(0.035)	(0.015)	(0.012)
Loss>25k	-0.375***	-0.366***	-0.345***	-0.339***
	(0.033)	(0.031)	(0.016)	(0.008)
Adoption	-0.019	-0.029	0.111	-0.013
	(0.046)	(0.082)	(0.066)	(0.046)
Constant	0.902***	0.898***	0.862***	0.876***
	(0.025)	(0.013)	(0.016)	(0.001)
State fixed effects	No	No	Yes	Yes
Year fixed effects	No	Yes	No	Yes
Observations	581	581	575	575
Adjusted R^2	0.203	0.233	0.238	0.251

Table 7: UVTA Adoption status by state

State	Acting adopted Uniform Act as of 2021	UFTA	UVTA	UVTA bill
Alabama	Uniform Voidable Transaction Act	1990	2018	SB152
Alaska	Non-Uniform			
Arizona	Uniform Fraudulent Transfer Act	1990		
Arkansas	Uniform Voidable Transactions Act	1987	2017	HB2139
California	Uniform Voidable Transactions Act	1986	2015	SB161
Colorado	Uniform Fraudulent Transfer Act	1991		
Connecticut	Uniform Fraudulent Transfer Act	1991		
Delaware	Uniform Fraudulent Transfer Act	1996		
District of Columbia	Uniform Fraudulent Transfer Act	1996		
Florida	Uniform Fraudulent Transfer Act	1988		
Georgia	Uniform Voidable Transactions Act	2002	2015	SB65
Hawaii	Uniform Fraudulent Transfer Act	1985		
Idaho	Uniform Voidable Transactions Act	1987	2015	HB92
Illinois	Uniform Fraudulent Transfer Act	1990		
Indiana	Uniform Voidable Transactions Act	1994	2017	SB316
Iowa	Uniform Voidable Transactions Act	1995	2016	HF2400
Kansas	Uniform Fraudulent Transfer Act	1999		
Kentucky	Uniform Voidable Transactions Act		2015	SB204
Louisiana	Uniform Fraudulent Transfer Act	1985		
Maine	Uniform Fraudulent Transfer Act	1986		
Maryland	Uniform Fraudulent Conveyance Act			
Massachusetts	Uniform Fraudulent Transfer Act	1996		
Michigan	Uniform Voidable Transactions Act	1998	2017	SB982
Minnesota	Uniform Voidable Transactions Act	1987	2015	HF1342 & SF1816
Mississippi	Uniform Fraudulent Transfer Act	2006		
Missouri	Uniform Fraudulent Transfer Act	1992		
Montana	Uniform Fraudulent Transfer Act	1991		
Nebraska	Uniform Voidable Transactions Act	1980	2019	LB70
Nevada	Uniform Fraudulent Transfer Act	1987		
New Hampshire	Uniform Fraudulent Transfer Act	1988		
New Jersey	Uniform Voidable Transactions Act	1989	2021	AB3384 & SB3171
New Mexico	Uniform Voidable Transactions Act	1989	2015	HB85
New York	Uniform Voidable Transactions Act		2019	AB5622
North Carolina	Uniform Voidable Transactions Act	1997	2015	SB123
North Dakota	Uniform Voidable Transactions Act	1985	2015	HB1135
Ohio	Uniform Fraudulent Transfer Act	1990		
Oklahoma	Uniform Fraudulent Transfer Act	1986		
Oregon	Uniform Fraudulent Transfer Act	1986		
Pennsylvania	Uniform Voidable Transactions Act	1994	2017	SB629
Rhode Island	Uniform Voidable Transactions Act	1986	2018	HB7334
South Carolina	Non-Uniform			
South Dakota	Uniform Fraudulent Transfer Act	1987		
Tennessee	Uniform Fraudulent Transfer Act	2003		
Texas	Uniform Fraudulent Transfer Act	1987		
Utah	Uniform Voidable Transactions Act	1988	2017	SB58
Vermont	Uniform Voidable Transactions Act	1996	2017	HB35
Virginia	Non-Uniform			
Washington	Uniform Voidable Transactions Act	1988	2017	SB5085
West Virginia	Uniform Voidable Transactions Act	1986	2018	HB4233
Wisconsin	Uniform Fraudulent Transfer Act	1988		
Wyoming	Uniform Fraudulent Transfer Act	2006		

Table 8: Impact of secured creditor rights on collateral costs

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for sub-samples of COVID-19 EIDLs at \$25,000 collateral threshold. The sample contains loans between \$1,000 and \$65,000. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral cost λ is calculated as in equation (7). The degree of the polynomial is set to 5, and the bin size is set to \$500. Bootstrapped standard errors are presented in parentheses.

COVID EIDL		
	Bin Size = 500	
Estimates	$\underline{K} = 25000$ $P = 5$ (1) UVTA	$\underline{K} = 25,000$ $P = 5$ (2) UFTA
Bunching mass (B)	2.66%	2.51%
	(0.12%)	(0.06%)
Marginal buncher ($\overline{K}$)	40,000	44,500
	(3639.38)	(3461.23)
Distortion ratio (θ)	37.50%	43.82%
	(5.10%)	(4.45%)
Collateral cost (λ)	6.23%	8.96%
	(2.19%)	(2.10%)

Table 9: Bunching estimates for BPDL: alternative thresholds

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for BPDLs in multiple sample periods at different collateral thresholds. The sample contains loans with loan amount between \$0 and \$65,000. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral cost λ is calculated as in equation (7). The bin size is set to \$500 and the degree of the polynomial is set to 5. Bootstrapped standard errors are presented in parentheses.

BPDL			
	Bin Size = 500		
Estimates Collateral requirement	$\underline{K} = 10,000$ Fixed lien $P = 5$ (1) 2003-2007	$\underline{K} = 14,000$ Fixed lien $P = 5$ (2) 2008-2013	$\underline{K} = 25,000$ Fixed lien $P = 5$ (3) 2014-2020
Bunching mass (B)	5.11%	7.34%	9.65%
	(0.15%)	(0.03%)	(0.15%)
Marginal buncher ($\overline{K}$)	17,500	22,000	45,500
	(1169.03)	(1536.63)	(2277.11)
Distortion ratio (θ)	42.86%	36.36%	45.05%
	(3.40%)	(4.04%)	(2.73%)
Proportional collateral cost (λ)	8.52%	5.82%	9.60%
	(1.79%)	(1.65%)	(1.39%)
Dollar collateral cost ($\lambda\overline{K}$)	1,491	1,280	4,368

Table 10: Placebo tests

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for BPDLs between 2008 and 2013 at a placebo \$25,000 collateral threshold. The sample contains loans with loan amount between \$0 and \$65,000. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral cost λ is calculated as in equation (7). The bin size is set to \$500 and the degree of the polynomial is set to 4 in column 1, 5 in column 2 and 6 in column 3. Bootstrapped standard errors are presented in parentheses.

	BPDL		
	Bin Size = 500		
Estimates Collateral requirement	$\underline{K} = 25000$ Fixed lien $P = 4$ (1) 2008-2013	$\underline{K} = 25000$ Fixed lien $P = 5$ (2) 2008-2013	$\underline{K} = 25,000$ Fixed lien $P = 6$ (3) 2008-2013
Bunching mass (B)	0.07% (0.08%)	0.19% (0.06%)	0.20% (0.07%)
Marginal buncher ($\overline{K}$)	25,000 (0.00)	25,000 (199.25)	25,000 (235.01)
Distortion ratio (θ)	0.00% (0.00%)	0.00% (0.76%)	0.00% (0.90%)
Collateral cost (λ)	0.00% (0.00%)	0.00% (0.01%)	0.00% (0.07%)

Table 11: Robustness: alternative bin sizes

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for BPDLs between 2014 and 2020 at \$25,000 collateral threshold. The sample contains loans with loan amount between \$0 and \$65,000. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral cost λ is calculated as in equation (7). The degree of the polynomial is set to 5 and the bin size is set to \$100 in column 1, \$250 in column 2 and \$500 in column 3. Bootstrapped standard errors are presented in parentheses.

BPDL			
	Bin Size = 100	Bin Size = 250	Bin Size = 500
Estimates	$\underline{K} = 25000$	$\underline{K} = 25000$	$\underline{K} = 25,000$
Collateral requirement	Fixed lien	Fixed lien	Fixed lien
	$P = 5$	$P = 5$	$P = 5$
	(1) 2014-2020	(2) 2014-2020	(3) 2014-2020
Bunching mass (B)	9.58%	9.59%	9.65%
	(0.07%)	(0.11%)	(0.15%)
Marginal buncher ($\overline{K}$)	47,300	46,750	45,500
	(2683.97)	(1871.51)	(2277.11)
Distortion ratio (θ)	47.14%	46.52%	45.05%
	(2.83%)	(1.88%)	(2.73%)
Collateral cost (λ)	10.71%	10.37%	9.60%
	(1.64%)	(1.13%)	(1.39%)

COVID EIDL			
	Bin Size = 100	Bin Size = 250	Bin Size = 500
Estimates	$\underline{K} = 25000$	$\underline{K} = 25000$	$\underline{K} = 25,000$
Collateral requirement	Fixed lien	Fixed lien	Fixed lien
	$P = 5$	$P = 5$	$P = 5$
	(1) COVID EIDL	(2) COVID EIDL	(3) COVID EIDL
Bunching mass (B)	2.08%	2.41%	2.58%
	(0.05%)	(0.09%)	(0.08%)
Marginal buncher ($\overline{K}$)	40,000	40,000	40,000
	(5307.12)	(5343.94)	(3635.17)
Distortion ratio (θ)	37.50%	37.50%	37.50%
	(8.87%)	(8.36%)	(5.03%)
Collateral cost (λ)	6.23%	6.23%	6.23%
	(3.04%)	(3.12%)	(2.18%)