The Shadow Cost of Collateral*

Guangqian Pan Zheyao Pan Kairong Xiao

November 17, 2021

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. The magnitude of the collateral cost depends on the type of the collateral requirements (fixed lien vs. floating lien) and firms' business sectors. Our finding suggests that a strict pecking order between secured and unsecured borrowing may not exist. Instead, the secured borrowing decision may be best characterized by a trade-off theory. We embed the collateral trade-off to the standard model of Kiyotaki and Moore (1997). We find that in the presence of collateral cost, the collateral constraint does not always bind, and the financial accelerator mechanism becomes state-dependent and highly non-linear.

JEL Classification Codes: E44, E51, G21, G23, G33
Keywords: collateral, secured and unsecured debt, financial accelerator, bunching estimation, government-subsidized loan program

*Guangqian Pan is from the University of Sydney, email: guangqian.pan@sydney.edu.au. Zheyao Pan is from Macquarie University, email: terry.pan@mq.edu.au. Kairong Xiao is from Columbia University, email: kx2139@gsb.columbia.edu. We thank Jason Donaldson, Adair Morse, Stijn Van Nieuwerburgh, Panos Mavrokonstantis, Giorgia Piacentino, Adriano Rampini, Johannes Stroebel, and participants at the various seminars for helpful comments and discussions. We thank Yiyuan Zhang for his excellent research assistance.

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, 2020). Empirically, collateralized debt usually entails substantially lower interest rates than uncollateralized one, which seems to be consistent with this view.

Pledging collateral, however, cedes important control rights from borrowers to lenders. Without the protection or consent of the lender, assets pledged as collateral cannot be sold to a third party, moved to a different location, used for another purpose, refurbished, and transformed. Such inflexibility could be costly for firms. As a CFO of a real estate company explained, "in a secured loan, you just don't have the same flexibility of dealing with your properties as if you owned them unencumbered" (Mann, 1996).

A recent strand of theoretical literature has started to study the cost of pledging collateral for firms (Mello and Ruckes, 2017; Donaldson, Gromb, and Piacentino, 2020, 2019; Rampini and Viswanathan, 2020). However, evidence on such a cost is still scant. The lack of empirical studies could be attributed to the fact that, unlike the interest cost, the collateral cost is a shadow cost. Researchers often cannot observe such a cost directly, let alone analyze it. One may attempt to infer the collateral cost from how firms trade-off between collateral requirements with other contract terms such as interest rates. However, contracts are often endogenous outcomes of lender-borrower negotiation, and it is difficult to isolate borrowers' preferences from lenders'. For instance, although the interest spread between secured and unsecured debt could be viewed as compensation for the collateral cost for borrowers, it may also reflect that lenders are protected in default by collateral and are willing to accept lower interest rates.

To address this challenge, we exploit a regulatory quirk of the disaster loan program provided

by the Small 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. This setting can help us address the existing empirical challenges along several dimensions. First, unlike private lenders, which often adjust interest rates based on collateral, the SBA holds the interest rate constant regardless of whether collateral is posted or not. Therefore, we can infer firms' collateral cost solely from the trade-off between loan size and collateral without worrying about confounding variations in interest rates. Second, unlike other government lending programs such as the SBA 7(a) loan and the Paycheck Protection Program (PPP), the disaster loan program is administered directly by the SBA instead of being intermediated by private lenders. This feature holds constant the supply-side factors, such as lender market power and racial biases, which may affect the loan terms and the program take-up (Bachas, Kim, and Yannelis, 2021; Chernenko and Scharfstein, 2021).

We observe a significant number of firms bunch exactly 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. 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 our setting, which helps us estimate the collateral cost using the bunching patterns. The intuition is essentially a revealed preference argument: a larger excess mass at the collateral threshold implies a higher collateral cost because more firms choose to bunch to avoid pledging collateral.

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 profit that the marginal firm is willing to give up to avoid pledging collateral reveals the shadow cost of collateral.

We estimate the desired loan size of the marginal firm and the implied collateral cost via a bunching estimator. 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%. The estimated collateral cost appears to be stable over time. 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 could be as low as $100.

We further explore the heterogeneity in the collateral cost across collateral types and business sectors. There are two broad categories of collateral requirements: a fixed lien or a floating lien. Under a fixed lien, a specific fixed asset, such as real estate property, is pledged to secure the repayment of a loan. Under a floating lien, assets that are continually changing in quantity and value, such as inventory and accounts receivables, can be 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. This result suggests that firms are more averse to pledging fixed assets, possibly because lenders can more easily seize fixed assets than floating assets. We also find 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.

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 choose not 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 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 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. Therefore, it is unlikely that our results are driven by firms that want to maximize the total loan amount.

Our findings have important implications for corporate capital structure decisions. Given a substantial collateral cost, a strict pecking order between secured and unsecured borrowing may not hold. Instead, the secured borrowing decision may be characterized by a trade-off theory in which firms balance the benefit of collateral against the cost. Understanding this trade-off and how

it interacts with other corporation decisions may deepen our understanding of the role of collateral for firms.

We then 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 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, which depresses 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 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 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 empirical work studies whether secured debt is costly or not relative to unsecured debt by comparing interest rates.[1] However, this line of thinking raises 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 causally reduces default rates by 35% using an instrumental variables (IV) estimation. Our paper studies the shadow cost of collateral for firms rather than consumers. This question is important because firms may face different trade-offs than consumers, as the aforementioned theoretical works show. We also document interesting heterogeneity in the collateral costs across collateral types (fixed business assets vs. floating business assets) and business sectors. Finally, we explore the implications of collateral cost for the financial acceleration mechanism and the optimal design for 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

[1] See Rampini and Viswanathan (2020) for a detailed review of this literature.

investigating the magnitude of the financial accelerator mechanism (Lian and Ma, 2021; Catherine, Chaney, Huang, Sraer, and Thesmar, 2018). A key finding of this literature is that the sensitivity of firm-level investment to collateral values is well below the magnitude predicted by the standard Kiyotaki and Moore (1997) model. While the prior literature often rationalizes this low sensitivity by arguing that only a small fraction of firm capital can be pledged as collateral,[2] 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, fluctuations in asset prices would naturally have lower impacts than those implied by models in which assets are fully collateralized.

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.

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

[2]For instance, Catherine et al. (2018) estimate that firms can only pledge about 25% of their capital stock in order to match the reduced-form sensitivity of investment to collateral prices.

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).[3]

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 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

[3]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.

cost.[4] 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.

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

[4]The application website is DisasterLoan.sba.gov.

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.[5] 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 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.[6] 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

[5]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.

[6]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.

businesses for BPDLs provide another 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. We see 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 chooses 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.

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 in this way 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. The collateral cost can be motivated by a loss of operational and financial flexibility or a loss of bargaining power. Firms' payoff function in 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 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 $B \equiv \int_{K_L}^{K}(f(K) - f_0(K))dK$, where K_L is set to $\underline{K}$.[7] 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 distribution, 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

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

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.[8] 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:

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

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

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

[8] 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.

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

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. Table 3 extends the estimation to the 2003-2007 and 2008-2013 samples. Although the collateral thresholds are quite different in the earlier samples, the estimated collateral cost is stable over time.

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 do 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 cost of pledging collateral may differ depending on the type of collateral requirement. In theory, firms may be more averse to a fixed lien than a floating lien because lenders can seize the fixed assets more easily than the current assets. 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 4 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 5, 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 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.

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.[9] Table 6 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.

The estimated collateral cost is in the same order of magnitude as the interest spread between unsecured and secured loans.[10] As a result, firms face a meaningful trade-off between paying lower interest and bearing the collateral cost when borrowing secured. 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 (Mello and Ruckes, 2017; Donaldson et al., 2020; Benmelech et al., 2020; Rampini and Viswanathan, 2020).

A conceptual issue is 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

[9] 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.

[10] 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., 2020, Figure 1).

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 to be 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.

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.[11] This alternative interpretation is unlikely to be applicable for three 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. It seems suboptimal to give up the subsidized public funding to obtain more expensive private funding. Finally, the typical loan sizes of the bunching firms are much smaller than the maximum loan size cap, $2 million. So it is unlikely that firms want to maximize the total loan amount by borrowing from both the public and private sectors.

4.3 Robustness checks

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.

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

4.3.1 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 7. 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.

4.3.2 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 a lot of noise when the sample size is small. Therefore, we check the robustness of our results using alternative bin sizes in Table 8. 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

In this section, we discuss implications of our findings for firm capital structure, financial acceleration mechanism, and the design of government lending.

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., 2020). This intuition seems consistent with the observation that collateralized debt usually entails substantially lower interest rates than uncollateralized one. 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., 2020). 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 constraint does not take into account 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), but it is worth noting that land and fruit can be interpreted as capital and consumption good, 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.

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

$$E_t\left(\sum_{s=0}^{+\infty}\beta^s x_{t+s}\right), \tag{14}$$

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:

$$y_{t+1} = F(k_t) = (a+c)\, k_t, \tag{15}$$

where k_t denotes the farmer's holding of land 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

$$E_t\left(\sum_{s=0}^{+\infty}(\beta')^s\, x'_{t+s}\right), \tag{16}$$

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

$$y'_{t+1} = G(k'_t) \tag{17}$$

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 $t+1$:

$$Rb_t \leq q_{t+1}(1-\delta)\, k_t. \tag{18}$$

Markets. There is a competitive spot market in which land is exchanged for fruits at 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

$$q_t \left(k_t - (1-\delta) k_{t-1}\right) + R b_{t-1} + x_t + \lambda b_{t-1} \mathbb{1}_{b_{t-1}>0} = (a+c) k_{t-1} + b_t \tag{19}$$

$$q_t \left(k'_t - (1-\delta) k'_{t-1}\right) + R b'_{t-1} + x'_t + \lambda b'_{t-1} \mathbb{1}_{b'_{t-1}>0} = G\left(k'_t\right) + b'_t \tag{20}$$

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

$$x_t = c k_{t-1}. \tag{21}$$

Farmers determine the borrowing amount based on whether the 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

$$b_t = \mathbb{1}_{a+c-u_t-R>\lambda q_{t+1}} (1-\delta) k_t / R. \tag{22}$$

where the net investment return equals the marginal product of the capital, $a + c$, subtracts the user cost, u_t, and the interest, R.

A farmer's land holding is given by

$$k_t = \frac{1}{q_t - \frac{1-\delta}{R} q_{t+1} \mathbb{1}_{b_t>0}} \left[(a + q_t(1-\delta)) k_{t-1} - R b_{t-1} - \lambda b_{t-1} \mathbb{1}_{b_{t-1}>0}\right] \tag{23}$$

We can aggregate across farmers and the dynamics of aggregate borrowing of farmers and

land holding of the farmer section are:

$$B_t = \mathbb{1}_{a+c-u_t-R>\lambda} q_{t+1} \left(1-\delta\right) K_t / R, \tag{24}$$

$$K_t = \frac{1}{q_t - \frac{1-\delta}{R} q_{t+1} \mathbb{1}_{B_t>0}} \left[(a + q_t(1-\delta))K_{t-1} - RB_{t-1} - \lambda B_{t-1} \mathbb{1}_{B_{t-1}>0}\right]. \tag{25}$$

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:

$$\frac{1}{R} G'\left(k_t'\right) = u_t. \tag{26}$$

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

$$u_t = q_t - \frac{1-\delta}{R} q_{t+1}. \tag{27}$$

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

$$u_t = u(K_t) \equiv \frac{1}{R} G'\left(\bar{K} - K_t\right), \tag{28}$$

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,

$$q_t = \sum_{s=0}^{+\infty} \left(\frac{1-\delta}{R}\right)^s u(K_{t+s}). \tag{29}$$

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 $a + c - u - R \geq \lambda$, we have:

$$\left(1 - \frac{1-\delta}{R}(1-\lambda)\right) q = a, \tag{30}$$

$$B = \frac{1-\delta}{R} qK. \tag{31}$$

$$\frac{1}{R} G'\left(\bar{K} - K\right) = u, \tag{32}$$

$$u = \left(1 - \frac{1-\delta}{R}\right) q. \tag{33}$$

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

$$\delta q = a, \tag{34}$$

$$B = 0, \tag{35}$$

$$\frac{1}{R} G'\left(\bar{K} - K\right) = u, \tag{36}$$

$$u = \left(1 - \frac{1-\delta}{R}\right) q. \tag{37}$$

Aggregate Dynamics. Suppose at $t-1$ the economy is in the 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. In Kiyotaki and Moore (1997), a positive shock and a negative shock are identical under log-linearization. However, with collateral cost, the effects are asymmetric, so we consider them separately. We also separately discuss the high and low productivity steady states because the impulse responses could be state-dependent.

We first consider a negative productivity shock occurs in a high productivity steady state, which reduces farmers' productivity to $a - \Delta a$ at t. Combining the market clearing condition (28),

farmers' aggregate borrowing (24), and their demand for land (25), we obtain farmers' demand for land at time t is given by

$$\left[u(K_t) + \frac{1-\delta}{R} q_{t+1}(1 - \mathbb{1}_{B_t>0})\right] K_t = \left[a - \Delta a + (q_t - q^*)(1-\delta)\right] K^*, \tag{38}$$

where $u(K_t) + \frac{1-\delta}{R} q_{t+1}(1 - \mathbb{1}_{B_t>0})$ is the down payment for a unit of land, and the right hand side is the net worth of the farmers.

Figure 6a shows the case in which the negative productivity shock is small such that the net investment return is still above the collateral cost, $a - \Delta a + c - u_t - R > \lambda$. In this case, farmers keep using their land as collateral to borrow from the gathers and the model is equivalent to Kiyotaki and Moore (1997). 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 by $(q_t - q^*)(1-\delta)$. Because the land price is forward-looking, the dynamic effect is much larger than the static effect due to the productivity shock. The feedback between asset price and collateral constraint is the core of the financial acceleration mechanism in Kiyotaki and Moore (1997).

Figure 6b shows the case in which the negative productivity shock is large enough such that the net investment return falls below the collateral cost, $a - \Delta a + c - u_t - R < \lambda$. In this case, farmers find it too costly to borrow collateralized. Instead, they will pay the full price in cash to buy lands $u(K_t) + \frac{1-\delta}{R} q_{t+1} = q_t$, which further decreases the farmers' demand and amplifies the negative shock. Therefore, the collateral cost creates another amplification mechanism because farmers endogenously decide their borrowing amount by trading-off the investment returns and collateral costs.

Now we switch to a different steady state in which the productivity is low and farmers do not borrow from gathers because the investment return does not justify the cost of posting collateral. Figure 6c shows the case in which a small negative shock hits the economy. We find that the shock has limited impacts on the economy because the collateral constraint is never binding, so the financial accelerator mechanism is muted. The same pattern applies if the negative shock is

big, as illustrated in Figure 6d.

To summarize, incorporating the collateral cost into the standard financial accelerator model leads to a new amplification mechanism in which borrowers trade-off the investment return and collateral cost and the quantity of collateralized borrowing responds endogenously to a productivity shock. This amplification mechanism is asymmetric for positive vs. negative shocks, and is non-linear for small vs. large shocks.

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 do not respond to the collateral threshold in the data. Instead, they always stick to their desired loan size Z, even if Z is just 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:

$$W(\underline{K}) = (1-\gamma)\int \left[AK^*(Z)^\alpha - \ell K^*(Z) + \mathbb{1}_{K^*>\underline{K}}(\beta K^*(Z) - \lambda Z - \phi)\right] f_0(Z)dZ \\ +\gamma \int \left[AZ^\alpha - \ell Z + \mathbb{1}_{Z>\underline{K}}(\beta Z - \lambda Z - \phi)\right] f_0(Z)dZ. \tag{39}$$

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.[12] We calibrate the 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 40%. 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 7a 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.[13]

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 7b 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

[12] See "Small Business Administration: Physical Disaster Loan Performance Before and After Changes in Statutory Collateral Requirements".

[13] 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.

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 7c. 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 reducing the charge-off rate. Specifically, we assume that the collateral requirement only reduces the charge-off rate by 4.8%. Figure 7d 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 turn to be 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 collateral in alleviating the informational and contractual frictions 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 the collateral cost depends on the collateral type and business sector. These results have important implications for understanding firms' borrowing constraints, the financial accelerator mechanism, and the design of government lending programs.

References

Adelino, M., A. Schoar, and F. Severino (2015). House prices, collateral, and self-employment. *Journal of Financial Economics 117*(2), 288–306.

Alvero, A., S. Ando, and K. Xiao (2020). Watch what they do, not what they say: Estimating regulatory costs from revealed preferences. *Available at SSRN 3735143*.

Antill, S. (2020). Are bankruptcy professional fees excessively high? *Available at SSRN 3554835*.

Bachas, N., O. S. Kim, and C. Yannelis (2021). Loan guarantees and credit supply. *Journal of Financial Economics 139*(3), 872–894.

Bartik, A. W., Z. B. Cullen, E. L. Glaeser, M. Luca, C. T. Stanton, and A. Sunderam (2020). The targeting and impact of Paycheck Protection Program loans to small businesses. Technical report, National Bureau of Economic Research.

Benmelech, E., N. Kumar, and R. Rajan (2020). The decline of secured debt. Technical report, National Bureau of Economic Research.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics 1*, 1341–1393.

Catherine, S., T. Chaney, Z. Huang, D. A. Sraer, and D. Thesmar (2018). Quantifying reduced-form evidence on collateral constraints. *Available at SSRN 2631055*.

Chaney, T., D. Sraer, and D. Thesmar (2012). The collateral channel: How real estate shocks affect corporate investment. *The American Economic Review 102*(6), 2381–2409.

Chernenko, S. and D. S. Scharfstein (2021). Racial disparities in the Paycheck Protection Program. *Available at SSRN 3907575*.

Chetty, R., J. N. Friedman, T. Olsen, and L. Pistaferri (2011). Adjustment costs, firm responses, and micro vs. macro labor supply elasticities: Evidence from Danish tax records. *The Quarterly Journal of Economics 126*(2), 749–804.

Collier, B., C. Ellis, and B. Keys (2021). The cost of consumer collateral: Evidence from bunching. *Unpublished working paper*.

Dagostino, R. (2018). The impact of bank financing on municipalities' bond issuance and the real economy. *Unpublished working paper*.

DeFusco, A. A., S. Johnson, and J. Mondragon (2020). Regulating household leverage. *The Review of Economic Studies 87*(2), 914–958.

DeFusco, A. A. and A. Paciorek (2017). The interest rate elasticity of mortgage demand: Evidence from bunching at the conforming loan limit. *American Economic Journal: Economic Policy 9*(1), 210–40.

DeMarzo, P. M. (2019). Presidential address: Collateral and commitment. *The Journal of Finance 74*(4), 1587–1619.

DeMarzo, P. M. and Z. He (2021). Leverage dynamics without commitment. *The Journal of Finance 76*(3), 1195–1250.

Donaldson, J. R., D. Gromb, and G. Piacentino (2019). Conflicting priorities: A theory of covenants and collateral. *Unpublished working paper*.

Donaldson, J. R., D. Gromb, and G. Piacentino (2020). The paradox of pledgeability. *Journal of Financial Economics 137*(3), 591–605.

Dubey, P., J. Geanakoplos, and M. Shubik (2005). Default and punishment in general equilibrium. *Econometrica 73*(1), 1–37.

Ewens, M., K. Xiao, and T. Xu (2020). Regulatory costs of being public: Evidence from bunching estimation. *Available at SSRN*.

Fairlie, R. W. and F. Fossen (2021). Did the $660 billion Paycheck Protection Program and $220 billion Economic Injury Disaster Loan Program get disbursed to minority communities in the early stages of covid-19? Technical report, National Bureau of Economic Research.

Gale, W. G. (1991). Economic effects of federal credit programs. *The American Economic Review 81*(1), 133–152.

Gan, J. (2007). Collateral, debt capacity, and corporate investment: Evidence from a natural experiment. *Journal of Financial Economics 85*(3), 709–734.

Granja, J., C. Makridis, C. Yannelis, and E. Zwick (2020). Did the Paycheck Protection Program hit the target? Technical report, National Bureau of Economic Research.

Humphries, J. E., C. A. Neilson, and G. Ulyssea (2020). Information frictions and access to the Paycheck Protection Program. *Journal of Public Economics 190*, 104244.

Kiyotaki, N. and J. Moore (1997). Credit cycles. *Journal of Political Economy 105*(2), 211–248.

Kleven, H. J. (2016). Bunching. *Annual Review of Economics 8*, 435–464.

Kleven, H. J. and M. Waseem (2013). Using notches to uncover optimization frictions and structural elasticities: Theory and evidence from Pakistan. *The Quarterly Journal of Economics 128*(2), 669–723.

Lian, C. and Y. Ma (2021). Anatomy of corporate borrowing constraints. *The Quarterly Journal of Economics 136*(1), 229–291.

Lucas, D. (2016). Credit policy as fiscal policy. *Brookings Papers on Economic Activity 2016*(1), 1–57.

Mann, R. J. (1996). Explaining the pattern of secured credit. *Harvard Law Review 110*(3), 625–683.

Mello, A. S. and M. Ruckes (2017). Collateral in corporate financing. *Unpublished working paper*.

Mendoza, E. G. (2010). Sudden stops, financial crises, and leverage. *The American Economic Review 100*(5), 1941–66.

Myers, S. C. and N. S. Majluf (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics 13*(2), 187–221.

Rampini, A. A. and S. Viswanathan (2010). Collateral, risk management, and the distribution of debt capacity. *The Journal of Finance 65*(6), 2293–2322.

Rampini, A. A. and S. Viswanathan (2020). Collateral and secured debt. *Unpublished working paper*.

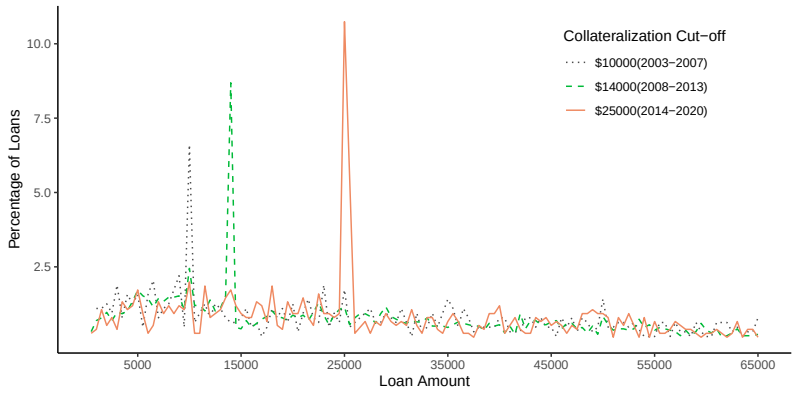
Saez, E. (2010). Do taxpayers bunch at kink points? *American Economic Journal: Economic Policy 2*(3), 180–212.

Smith, B. (1983). Limited information, credit rationing, and optimal government lending policy. *The American Economic Review 73*(3), 305–318.

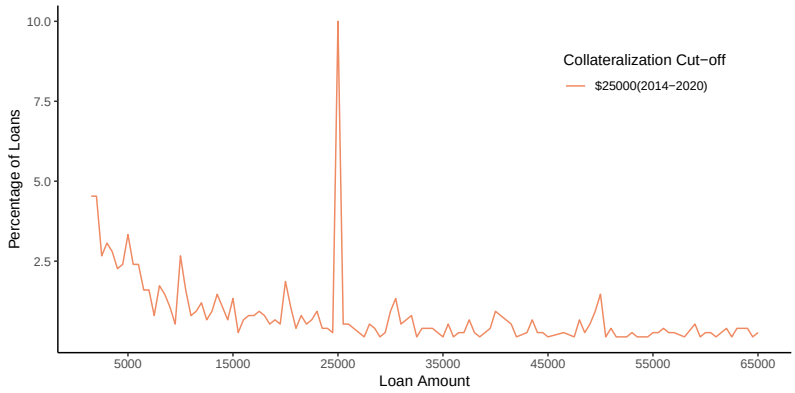
Tirole, J. (2010). *The theory of corporate finance*. Princeton University Press.

Figure 1: Loan size distribution

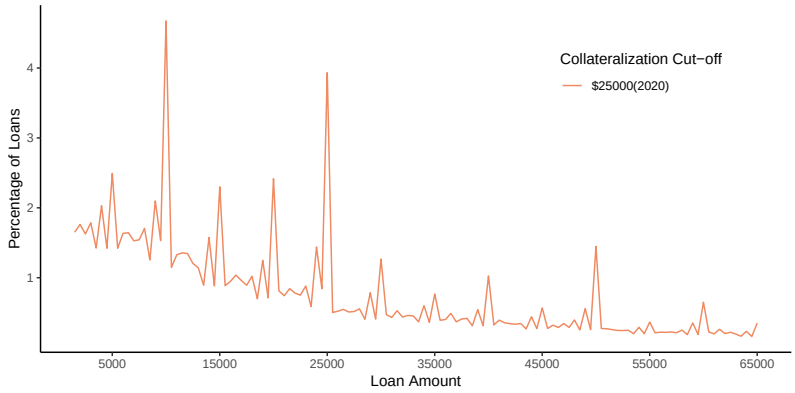
(a) BPDL



(b) Regular EIDL



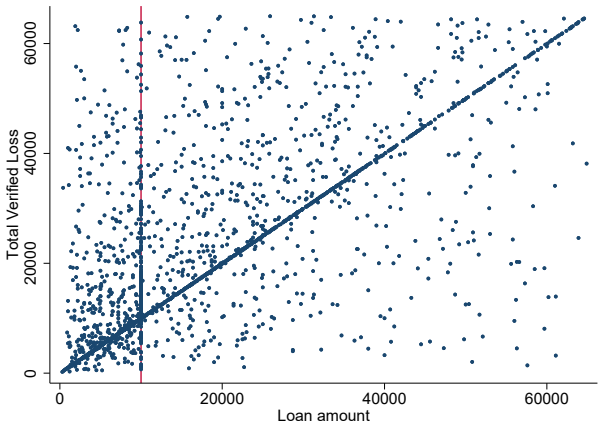
(c) COVID EIDL



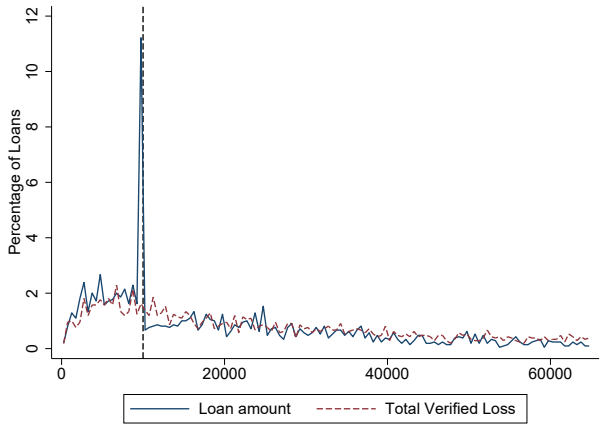
Note: The figure shows the loan size distribution of BPDLs, regular EIDLs, and COVID EIDLs, respectively. Data source: SBA.

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

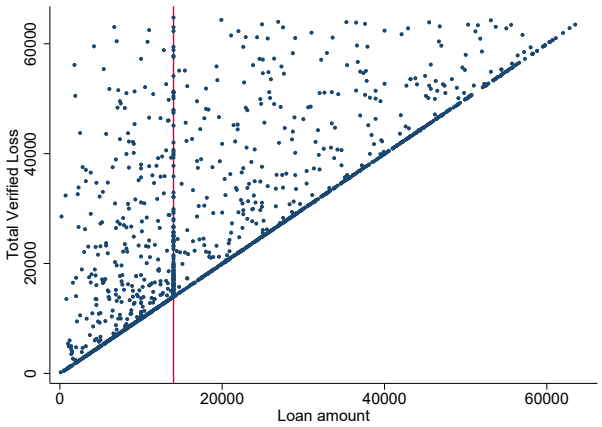
(a) 2003 to 2007



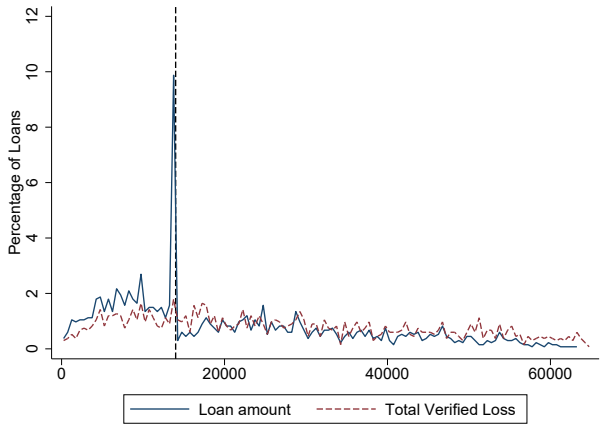
(b) 2003 to 2007



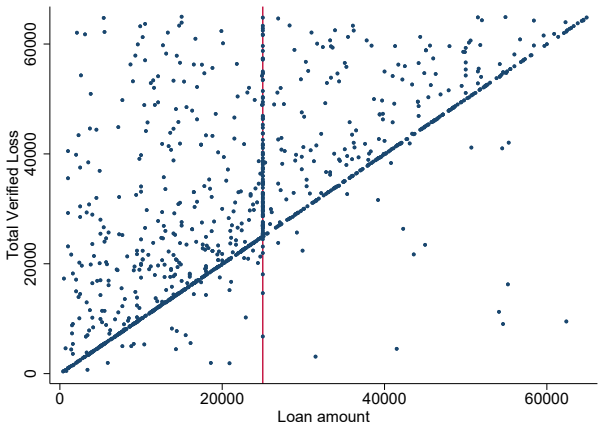
(c) 2008 to 2013



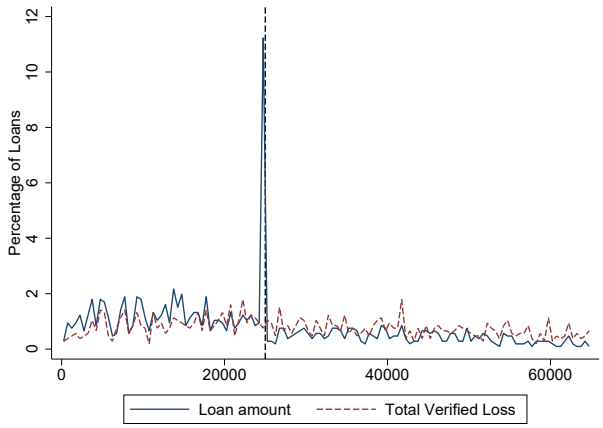
(d) 2008 to 2013



(e) 2014 to 2020



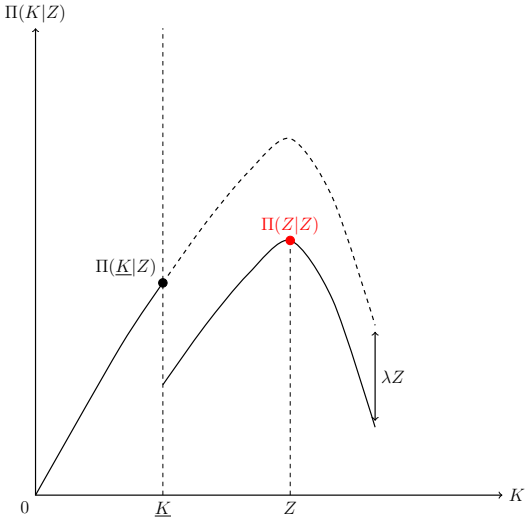
(f) 2014 to 2020



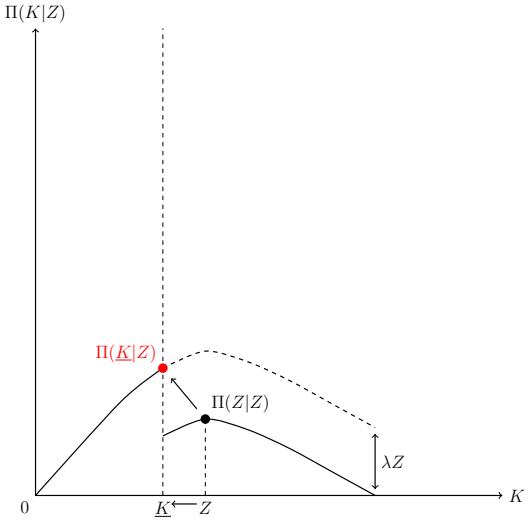
Note: The figure shows the verified loss and loan size distribution for BPDLs. The vertical lines indicate the collateral thresholds. Data source: SBA.

Figure 3: Bunching condition with collateral costs

(a) No bunching



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



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

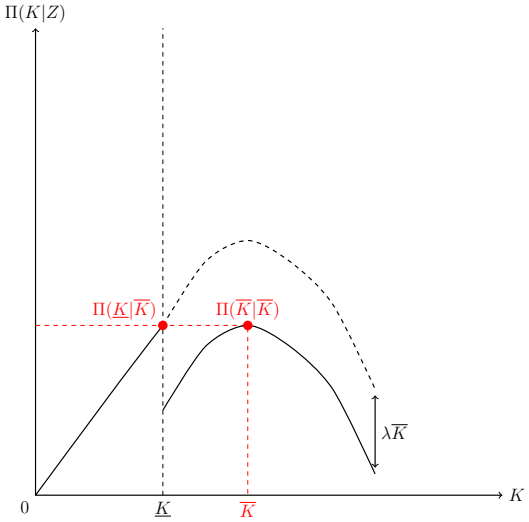
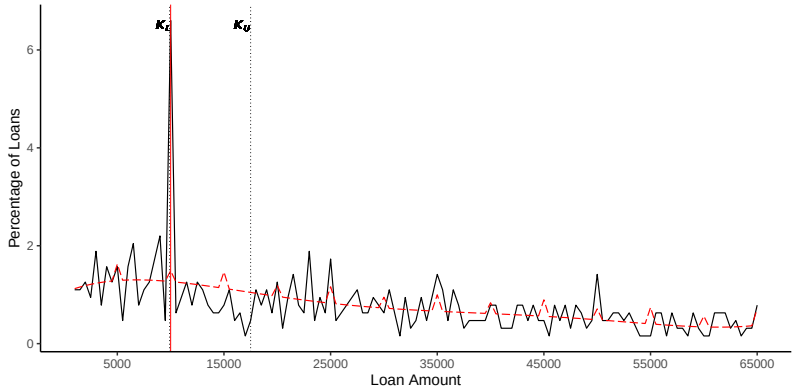
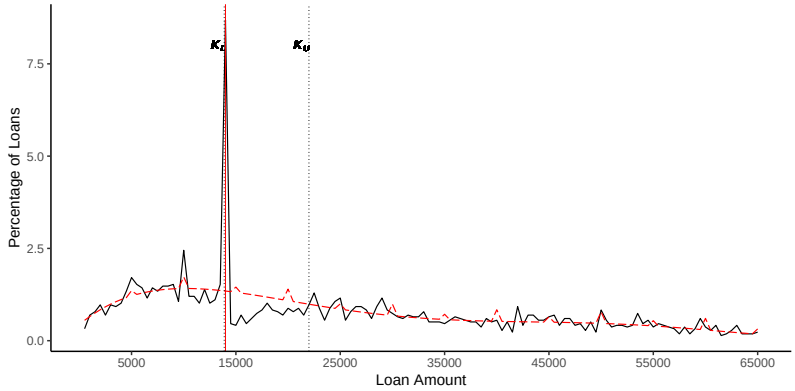


Figure 4: Counterfactual distribution and marginal buncher of BPDLs

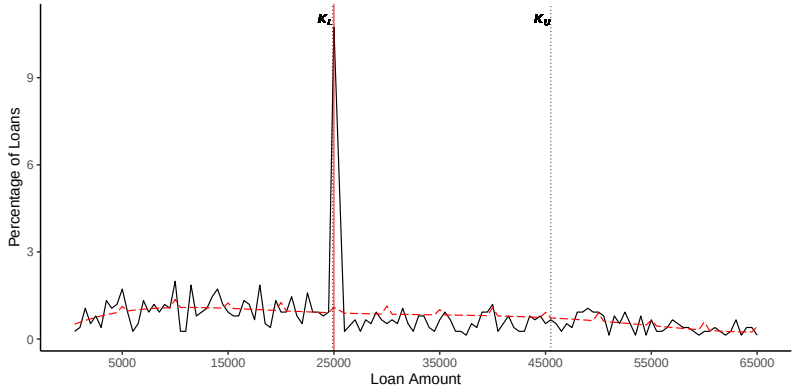
(a) 2003 to 2007



(b) 2008 to 2013



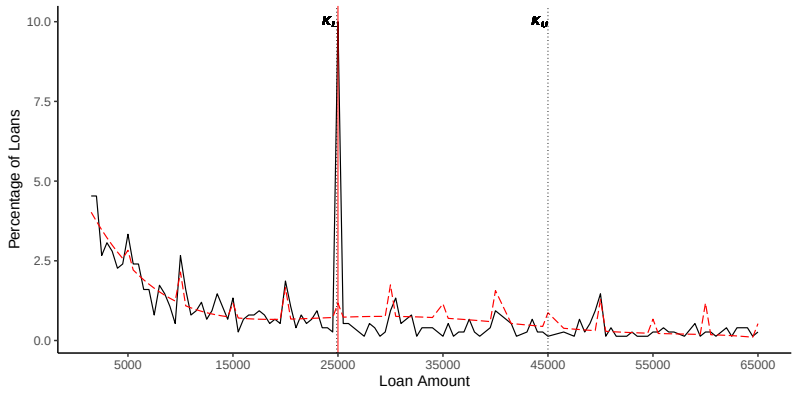
(c) 2014 to 2020



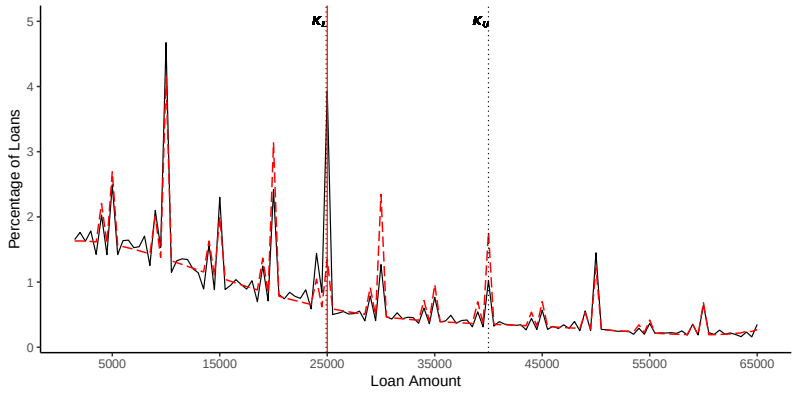
Note: This figure shows the observed (black) and counterfactual (red) percentage of loans in each bin. The counterfactual is estimated for each sample separately by fitting a fifth-order polynomial with round number dummies to the observed distribution using a bin size of $500 excluding data in the bunching 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



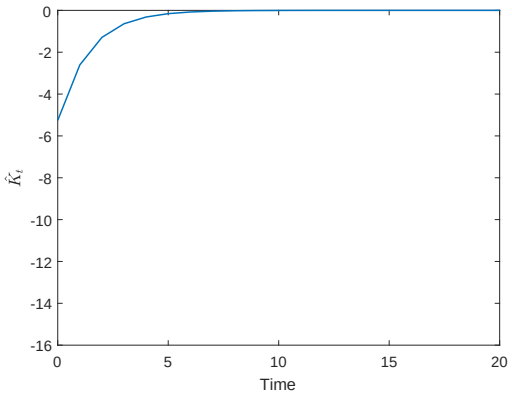
(b) COVID EIDL



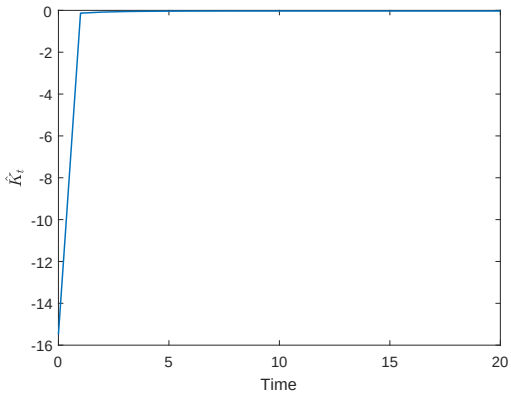
Note: This figure shows the observed (black) and counterfactual (red) percentage of loans in each bin. The counterfactual is estimated for each sample separately by fitting a fifth-order polynomial with round number dummies to the observed distribution using a bin size of $500 excluding data in the bunching 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

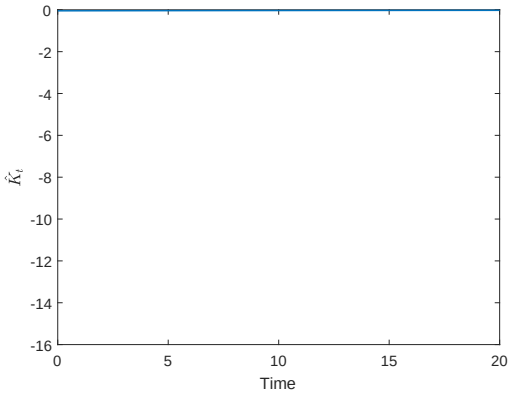
(a) High-productivity state, small shock



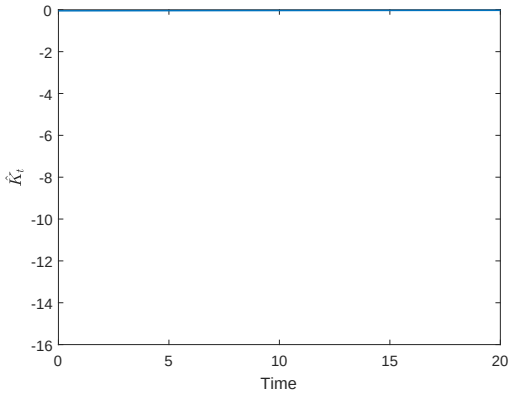
(b) High-productivity state, big shock



(c) Low-productivity state, small shock



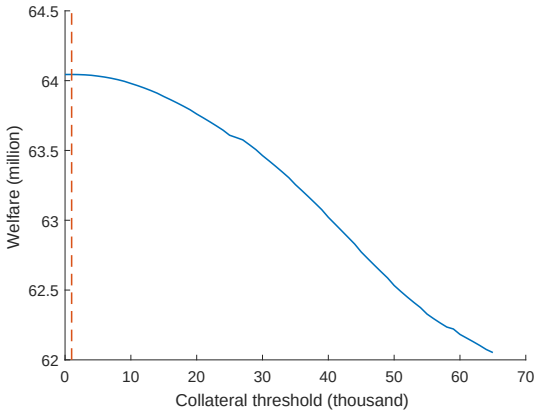
(d) Low-productivity state, big shock



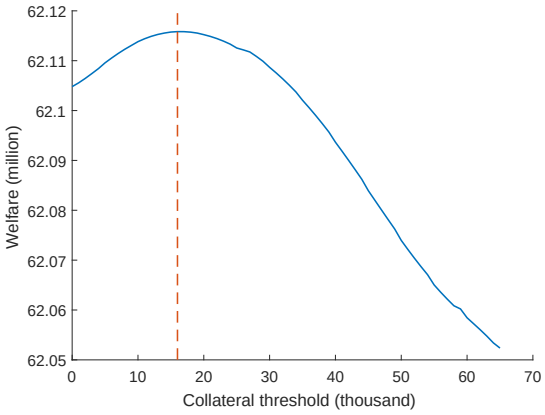
Note: This figure shows the impulse response functions in a Kiyotaki and Moore (1997) model with collateral cost. The gross interest rate R is set to 1.01. The depreciation rate δ is set to 0.05. The elasticity of the residual supply of land to the farmers with respect to the user cost at the steady state η is set to 1. The impulse response is normalized by the size of the shock.

Figure 7: Counterfactual policy simulation

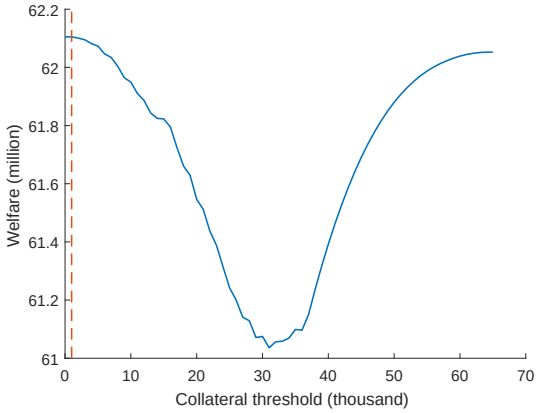
(a) Without collateral cost and manipulation



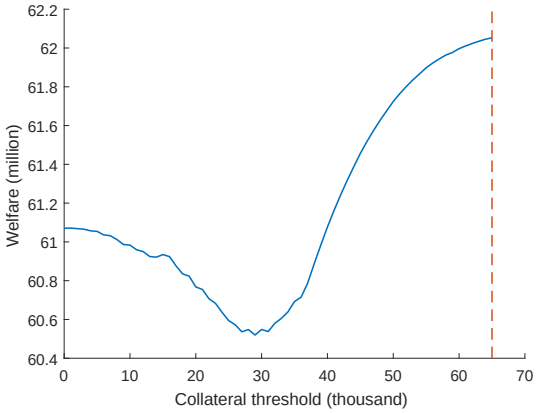
(b) With collateral cost, without manipulation



(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.

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 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). 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	$\underline{K} = 25000$	$\underline{K} = 25000$	$\underline{K} = 25,000$
Collateral requirement	Fixed lien	Fixed lien	Fixed lien
	$P = 4$	$P = 5$	$P = 6$
	(1) 2014-2020	(2) 2014-2020	(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 BPDL: alternative sample periods

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	$\underline{K} = 10,000$	$\underline{K} = 14,000$	$\underline{K} = 25,000$
Collateral requirement	Fixed lien	Fixed lien	Fixed lien
	$P = 5$	$P = 5$	$P = 5$
	(1) 2003-2007	(2) 2008-2013	(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%)
Collateral cost (λ)	8.52%	5.82%	9.60%
	(1.79%)	(1.65%)	(1.39%)

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

Table 5: 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 6: 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 7: 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 8: 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%)