# The Shadow Cost of Collateral\*

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#### Abstract

We quantify the cost of pledging collateral for small businesses using a revealed preference approach. We exploit a regulatory quirk where firms are exempt from posting collateral if their loan size is below a threshold. Firms bunch their loans below the threshold, and the resulting distortion in the loan size distribution reveals the magnitude of the collateral cost. The collateral cost is substantial and varies across collateral types, business sectors, and collateral laws in ways consistent with flexibility-based theories. Finally, we introduce the collateral cost into a standard macro-finance model and show that it has important implications for macroeconomic fluctuations.

JEL Classification Codes: E44, E51, G21, G23, G33

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## 1 Introduction

Collateral is a fundamental building block of financial markets and affects economic growth and financial stability. Voluminous research has been devoted to study the benefit of collateral, such as how collateral mitigates conflicts of interest and enforcement frictions in lending (DeMarzo, 2019). Nevertheless, the cost of pledging collateral has received much less attention. In fact, the conventional wisdom is that the cost of pledging collateral is quite low relative to the large benefit of protecting lenders and allowing borrowers to receive cheaper credit. For instance, in many prominent macro-finance models, such as Kiyotaki and Moore (1997), firms incur no cost to pledge collateral and consequently, would always borrow up to the collateral constraint.

Pledging collateral, however, could impose hidden costs for firms. Collateral agreements typically restrict encumbered assets from being sold to a third party, moved to a different location, used for another purpose, refurbished, and transformed without the protection or consent of the lender (Mello and Ruckes, 2017). These restrictions could limit firms' operational flexibility as firms need to obtain lenders' consent to deal with the encumbered assets. Firms could also lose financial flexibility because high asset encumbrance makes it harder to obtain unsecured financing (Donaldson, Gromb, and Piacentino, 2020) or access liquidity through an asset sale (Donaldson, Gromb, and Piacentino, 2019). Finally, firms may lose flexibility in financial distress as secured creditors may not be interested in restructuring the debt payment (Benmelech, Kumar, and Rajan, 2020). Although the aforementioned theoretical literature has advanced our understanding of the role of collateral, there is still a lack of empirical estimates of the economic magnitude of collateral cost for firms and whether such cost is economically relevant for firms' financing decisions.

The lack of empirical evidence could be partly attributed to the fact that the cost of pledging collateral is largely a shadow cost—it may implicitly affect firms' behavior but is not explicitly

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

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

recorded in the financial statements. To address this challenge, we use a revealed preference approach to infer the collateral cost from firms' choice of loan contracts. Specifically, we exploit a regulatory quirk of the disaster loan program provided by the Small Business Administration (SBA). This program provides secured loans to firms affected by natural disasters, but collateral is exempted if the loan size is below a certain threshold. We observe a significant number of firms bunch at the collateral threshold, as shown in Figure 1. This bunching pattern provides *prima facie* evidence that firms are averse to pledging collateral and would rather accept a smaller loan than they would naturally desire. Moreover, the extent of bunching could reveal the collateral cost. If many firms avoid pledging collateral by bunching at the threshold, the collateral cost is likely to be high. On the contrary, if only a few firms bunch, the collateral cost is likely to be low.

We build 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 not bunching. The loan amount that the marginal firm is willing to give up to avoid pledging collateral reveals the shadow cost of collateral.

We adapt the bunching estimation technique developed in the public finance and labor literature (Saez, 2010; Kleven and Waseem, 2013; Chetty, Friedman, Olsen, and Pistaferri, 2011) to estimate the degree of bunching. Firms' bunching creates an excess mass at the threshold and a missing mass above it. The desired loan size of the 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 rate of 9% for the sample firms. In terms of the dollar value, the shadow cost of collateral amounts to \$2,300 per year 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 fee to file a lien. The estimated collateral cost is in the same order of magnitude as the secured-unsecured interest spreads faced by small firms.

This result provides a new perspective for corporate capital structure. Since the seminal work of Myers and Majluf (1984), it is often believed that there exists a pecking order between collateralized and uncollateralized borrowing. Because collateral mitigates the external financial frictions, the interest rate of secured debt is lower than that of unsecured debt. Therefore, firms should first issue collateralized debt and then, after exhausting such claims, issue uncollateralized debt. Our result suggests a pecking order between secured and unsecured borrowing may not hold because of the substantial cost of pledging collateral. Instead, the secured borrowing decision may be best characterized by a trade-off theory in which firms balance the benefit of collateral against the cost.

We further explore how the collateral cost depends on collateral types and business sectors. There are two broad categories of collateral: (1) fixed assets, such as real estate property, machinery, and fixtures, and (2) floating assets, such as inventory and accounts receivables. We exploit a unique change in collateral requirement in the COVID-19 pandemic, which allows floating assets to be pledged as collateral. We find that the estimated collateral cost decreases by around 30% after the change.

Next, we explore the sources of the collateral costs. It is challenging to pin down the exact channel because we do not have detailed information on firms' balance sheets. Nevertheless, we provide some suggestive evidence for flexibility-based theories by exploring the variations in secured creditor rights across states and over time. We hypothesize that firms are less likely to lose flexibility in a secured transaction if the state collateral laws give weaker rights to secured creditors. Consequently, firms may be less averse to borrowing secured debt. Exploiting the staggered adoption of the Uniform Voidable Transactions Act (UVTA), which weakens secured creditor rights, we find that the take-up of secured loans increases significantly after the law change. The estimated collateral cost appears to be lower in states with weaker secured creditor

rights.

Firms could incur transaction costs when they pledge collateral, such as the fee to file a lien, the cost to conduct an appraisal, and the delay in processing time. While these transaction costs contribute to the total costs of pledging collateral, they are unlikely to explain most of the estimated collateral costs. First, the fee for filing a lien is an order of magnitude smaller than the total collateral cost for a typical bunching loan. Furthermore, appraisals are rare because the SBA provides free inspections in most cases. Finally, there is no significant difference in processing time between secured and unsecured loans. Overall, the explicit and implicit transaction costs are likely to be small in our setting.

The estimated collateral cost could reflect the scarcity of the collateral rather than the cost of pledging it. If some firms do not have collateral in the first place, they have to bunch at the collateral threshold, which leads to high collateral cost estimates. However, a careful examination of the institutional setting suggests that collateral scarcity is unlikely to drive our estimated costs. For the BPDL program, the loans are used to repair or replace damaged property. The repaired or replaced property typically serves as collateral. For the COVID EIDL program, general business assets such as inventories and account receivables can be used as collateral. These assets are generally available. 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. In other words, the borrowing amount is not limited by the available collateral. Instead, it is benchmarked to the verified loss incurred by the firm. Therefore, the estimated collateral cost is more likely to reflect the aversion to pledge collateral rather than the scarcity of the collateral. Finally, we also find significant collateral costs in industries in which collateral is widely available, such as agriculture and manufacture, suggesting the scarcity-based explanation is unlikely to drive our results.

Another explanation is that firms may want to use the collateral to secure another loan from the private sector. In this case, the collateral cost may reflect their desire to maximize the total external financing rather than the aversion to losing flexibility. This alternative explanation is unlikely to be applicable in our setting for two reasons. First, firms that participate in the SBA disaster lending programs generally lack access to private financing. In the data, we do not observe significant cost differences across regions with different financial accesses. Second, even if firms have access to private financing, the rates that they can get are much higher than those offered by the SBA. Given that the loans taken by the bunching firms are far below the maximum loan size cap of the SBA, firms could have gotten more funding from the SBA at a below-market rate if they wanted to do so. It is suboptimal to give up subsidized public financing to get more expensive private financing.

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 sizes. Finally, we examine the robustness of our results to alternative production functions and substitution margins. Although the specific estimates could differ across the specifications, the order magnitude of the collateral costs remains the same.

Although our study sheds light on the shadow cost of collateral, which is otherwise difficult to observe, these results have a few caveats. First, the estimated collateral costs are pertinent to small businesses. These firms play an important role in creative destruction and aggregate employment, so it is crucial to understand their financing frictions (Krishnan, Nandy, and Puri, 2015). However, small firms could differ from large firms in many aspects, so the specific estimate may not be transportable. Nevertheless, the general economic lesson—the collateral cost is crucial for secured borrowing decisions—is likely to remain valid.

Second, one may worry that the lender of our setting is a government agency, which may not pursue the collateral with the same vigor as private lenders. If that is the case, the estimates may be a lower bound of the true collateral cost. Nevertheless, unlike the Paycheck Protection Program (PPP), the SBA disaster loan program is not a grant. The terms in the SBA's security agreement

are similar to those of private lenders. The SBA tries to use collateral to increase recovery, and the liquidation procedure is similar to private lenders, alleviating such concerns.<sup>3</sup>

Despite these caveats, our setting offers many advantages over typical datasets on corporate borrowings. First, in typical settings, only the equilibrium outcome is observed by econometricians, making it difficult to separate lenders' preferences from borrowers'. In contrast, in our setting, the potential choice set of borrowers can be observed, allowing us to isolate borrowers' preferences. Second, the secured and unsecured markets are usually segmented, with different lenders being active in different markets. In contrast, the same lender provides both the unsecured and secured loans in our setting, which keeps the supply side constant when we analyze the demand.

We explore the implications of a substantial collateral cost for macro-finance models. An implicit assumption in standard financial acceleration models is that firms do not incur any cost to post collateral. Therefore, firms always borrow up to 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 to the collateral limit, firms now face a trade-off between the investment return and collateral cost. We find that this collateral trade-off introduces a new amplification mechanism. When a large negative productivity shock drives investment returns below the collateral cost, firms may endogenously reduce collateralized borrowing, depressing collateral prices. The falling prices further decrease borrowers' net worth, amplifying the negative shock. We also find that the collateral trade-off can make the financial amplification mechanism state-dependent. The aggregate investment is highly sensitive to asset price fluctuations in a high productivity state as many 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 government lending programs. 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

 $<sup>^3</sup>$ See 13 CFR  $\S120.545$ . for SBA's policies concerning the liquidation of collateral.

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 in counterfactual policy experiments depending on whether these costs are considered.

This article contributes to a vast literature in economics and law on collateral. Collateral can mitigate enforcement frictions between borrowers and creditors (Tirole, 2010), complete the contract space (Dubey, Geanakoplos, and Shubik, 2005), and prevent debt dilution (DeMarzo, 2019; Donaldson, Gromb, and Piacentino, 2020). Collateral has important implications for corporate decisions, such as investments, production, and dynamic optimal capital structure (Gan, 2007; Chaney, Sraer, and Thesmar, 2012; Adelino, Schoar, and Severino, 2015; DeMarzo, 2019; DeMarzo and He, 2021). A large body of work shows that collateralized borrowing reduces the interest cost for borrowers (Berger and Udell, 1990; Rauh and Sufi, 2010; Benmelech and Bergman, 2009; Luck and Santos, 2019; Benmelech, Kumar, and Rajan, 2022). However, the existing literature leaves the puzzle of why firms do not always borrow secured debt given the low interest rates (Rampini and Viswanathan, 2020). A contribution of this paper is to show that recognizing the sizable collateral cost is the key to resolving this puzzle.

Our work is closely related to Benmelech, Kumar, and Rajan (2022), who study the relationship between the pricing and issuance of secured debt. They find that secured debt issuance of investment grade firms is uncorrelated with the spread between secured and unsecured debt, which is puzzling given this spreads indicates the benefit of posting collateral. Their finding can be rationalized by the fact that firms face a substantial collateral cost and would only pledge collateral if they have few alternative sources of financing. Our work also complements Collier, Ellis, and Keys (2021), which is the first study to examine how housing collateral impacts consumers' borrowing behavior. They similarly exploit the SBA program's collateral thresholds in a bunching estimation and find that the median consumer in their sample is willing to give up 40% of the loan amount to avoid placing a lien on their home. They also find that collateral reduces default rates by 35% using an instrumental variables (IV) estimation. Our paper studies firms rather than

consumers. Given the crucial role of collateral in firms' operations, investments, and financing, it is important to understand the collateral cost for firms. Methodologically, we show how to use a revealed preference approach to translate the observed bunching to an interest-equivalent collateral cost. We also document interesting heterogeneity in the collateral costs across collateral types, business sectors, and collateral laws.

This article also adds to the law and finance literature on creditor rights. The seminal paper by La Porta et al. (1998) and the subsequent literature, such as Levine (1998), Qian and Strahan (2007), Campello and Larrain (2016), Calomiris et al. (2017), suggest that protecting creditor rights can foster financial development and improve financial assess. Vig (2013) provides a more nuanced view by documenting that a secularization reform in India that enhanced creditor rights surprisingly led to a reduction in secured debt. Our results are consistent with this more nuanced view. Because that the collateral cost is substantial and matters for firms' financing decisions, a strengthening in secured creditor rights can increase the cost of pledging collateral and reduce firms' demand for secured debt. Furthermore, we provide corroborative evidence using the introduction of UVTA in the U.S. and show that a weakening in secured creditor rights can in fact increase firms' willingness to take up secured debt.

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 macroe-conomic dynamics (Kiyotaki and Moore, 1997; Bernanke, Gertler, and Gilchrist, 1999; Mendoza, 2010). This literature assumes that firms incur no cost to pledge collateral, so the collateral constraint is always binding. We introduce the collateral trade-off to the standard model of Kiyotaki and Moore (1997) and show that it can generate rich implications for the financial accelerator mechanism. This article also speaks to the extensive empirical research that has been devoted to investigating the magnitude of the financial accelerator mechanism (Lian and Ma, 2021; Catherine, Chaney, Huang, Sraer, and Thesmar, 2018). This literature often finds that the sensitivity of firm-level investment to collateral values is well below the magnitude predicted by the standard Kiyotaki and Moore (1997) model.<sup>4</sup> While the low sensitivity is typically rationalized by low asset

<sup>&</sup>lt;sup>4</sup>In Kiyotaki and Moore (1997), the sensitivity of investment to collateral prices is 1. In contrast, Catherine

pledgeability, we suggest that the substantial collateral cost could be another reason why the sensitivity is low. Because firms may choose not to use pledgeable collateral to avoid the collateral cost, fluctuations in asset prices would naturally have lower impacts on firm investment.

This article also adds to the literature on the efficiency of the government-supported lending programs (Smith, 1983; Gale, 1991; Lucas, 2016; Bachas, Kim, and Yannelis, 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.

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

et al. (2018) estimate this sensitivity to be 0.06.

# 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).<sup>5</sup>

### 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). Furthermore, the SBA holds the interest rate fixed regardless of the loan amount and whether a firm pledges collateral or not. This feature provides a clean setting to isolate how the collateral requirement affects firms' borrowing behavior.

Many government lending programs for small businesses, such as the SBA 7(a) program and the Paycheck Protection Program, are dispensed by private lending institutions. In contrast, the disaster loan program is dispensed by the SBA itself. Firms can apply directly to SBA at no cost.<sup>6</sup> 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

<sup>&</sup>lt;sup>5</sup>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. 
<sup>6</sup>The application website is <code>DisasterLoan.sba.gov</code>.

(EIDL) program. Unlike the BPDL program, the EIDL program assists businesses broadly affected by declared disasters to meet their necessary working capital 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 firms to post floating assets, such as inventory and accounts receivables, as collateral.

## 2.2 Collateral requirements

When firms' loan size exceeds the collateral threshold, firms need to sign a security agreement, which is a document that provides a lender a security interest in a specified asset or property that is pledged as collateral.<sup>7</sup> The security agreement also determines the terms and conditions regarding the collateral. The terms and conditions specified in the SBA security agreement appear similar to those used by private lenders, as discussed in Mello and Ruckes (2017).<sup>8</sup>

The security agreement may restrict firms' operational flexibility. Consider an agricultural business that has taken a secured loan with a blanket lien on its assets. If the firm wants to trade in its old equipment for a new one with an equipment dealer, the firm has to contact its secured creditor to release the security interest. If the firm fails to do so, the creditor's security interest will

<sup>&</sup>lt;sup>7</sup>See https://www.sba.gov/sites/default/files/2017-11/tools\_sbf\_finasst1059\_0.pdf.

<sup>&</sup>lt;sup>8</sup>The UCC financing statements filed by the SBA are also quite similar to those filed by private lenders, as shown in Internet Appendix Figures IA1, IA2, and IA3.

<sup>&</sup>lt;sup>9</sup>More discussion on the implications of the security agreement for agriculture businesses can be found in McEowen (2021).

continue in the equipment, which could create issues for the equipment dealer, the counterparty of the trade-in transaction. Furthermore, because the security agreement is in the firm's public credit record, equipment dealers may become less willing to deal with the firm in the first place.

The security agreement may also restrict firms' financial flexibility. Support the agricultural business is having troubles to pay its suppliers. The firm cannot sell its equipment to raise cash unless it obtain a release of the security interest from the secured creditor. Furthermore, if the firm becomes delinquent on the payment to the secured creditor, the firm's commodity market transactions account would be subject to secured creditor's discretion to withdraw. Such a withdrawal would eliminate the firm's risk management protection via commodity market positions taken in commodities on the Board of Trade.

#### 2.3 Data

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

We further collect interest rate information from the US Federal Register. The SBA announces a single fixed interest rate for 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.<sup>10</sup> 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. Nevertheless, the excess mass at the \$25,000 collateral threshold is larger than other similar round numbers such as \$15,000 and \$20,000, suggesting firms are still strategically avoiding the collateral requirements.

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

 $<sup>^{10}</sup>$ 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.

<sup>&</sup>lt;sup>11</sup>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.

thresholds.

These bunching patterns provide visual evidence that firms are averse to pledging 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 understand the trade-off facing firms in the disaster loan program and guide our estimation. Suppose there is a set of firms with a Cobb-Douglas production function. Firms borrow K unit of capital to produce  $AK^{\alpha}$  unit of output, where A is the productivity, and  $\alpha$  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:

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

Z as the desired loan amount in the absence of the collateral requirement. In our context, Z can be interpreted as the verified loss incurred in a disaster because firms typically borrow at this amount when the loan size is not distorted by the collateral threshold.<sup>12</sup> Z is heterogeneous across firms, which follows a distribution  $f_0$ . In the following discussion, we use Z to index the firms.

<sup>&</sup>lt;sup>12</sup>As shown in Figure 2, most points are at the 45-degree line.

Suppose firms now face a collateral requirement if their loan size K exceeds a threshold  $\underline{K}$ . Firms incur a cost of  $\lambda Z$  when pledging collateral. We define the collateral cost as proportional to the loan size so that  $\lambda$  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.<sup>13</sup> 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

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

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

Firms with undistorted loan sizes above the threshold face the following trade-off. Firms could either: (1) borrow Z, and bear collateral cost, or (2) reduce their borrowing amount to  $\underline{K}$  and avoid any collateral commitment, which reduces the output. Firms' optimal choice depends on how far away their undistorted loan size is above the threshold, as illustrated in Figure 3. We plot firms' payoff  $\Pi(K|Z)$  as a function of the loan size K. Firms whose undistorted loan size is far above the threshold will find it too costly to bunch at the threshold, as shown by Figure 3a. Firms 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. There exists a marginal buncher that is indifferent between bunching and not 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

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

<sup>&</sup>lt;sup>13</sup>If we assume the collateral cost is a fixed dollar value, the collateral cost becomes trivial mechanically when the loan size becomes bigger. We discuss the robustness of our results to this assumption in Section 4.4.3. It is worth noting that the collateral threshold remains a notch point even if it is a proportional cost because firms incur the cost for the entire loan amount rather than the incremental value above the threshold.

Firms' optimal choices are given by

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

Define the distortion ratio,  $\theta$ , 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 cost as:

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

The above equation translates the extent of bunching measured by  $\theta$  to a measure of collateral cost,  $\lambda$ . It is worth noting that this equation is derived with several assumptions: (1) the production function is Cobb-Douglas with a constant return to scale; (2) the collateral cost is proportional to the natural loan size; and (3) firms do not have access to private financing. These assumptions simplify the model and make the estimation more transparent. We will discuss these assumptions' plausibility and the estimates' robustness in Section 4.4.

## 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,  $\underline{K}$ .<sup>14</sup> Therefore, the actual probability density function, f(K), should display some excess mass at the threshold relative to the smooth counterfactual density function,  $f_0(K)$ . We define the excess mass as  $B \equiv \int_{K_L}^{\underline{K}} (f(K) - f_0(K)) dK$ , where  $K_L$  is set to  $\underline{K}$ .<sup>15</sup> 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  $M(\overline{K}) \equiv \int_{K}^{\overline{K}} (f_0(K) - f(K)) dK$ . The bunching mass should equal the missing mass:

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

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 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:

$$N_{j} = \sum_{p=0}^{P} \beta_{p}(K_{j})^{p} + \sum_{i=K_{L}} \left( \gamma_{i} \cdot \mathbb{1}(K_{j} = i) + \sum_{r \in \{5000, 10000\}} \delta_{r} \mathbb{1}(K_{j}/r \in \mathbb{N}) + \epsilon_{j}. \right)$$
(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

 $<sup>^{-14}</sup>$ Note that the bunching mass cannot come from the left of the threshold because these firms can choose a loan size of  $\underline{K}$  if they want to without affecting their collateral requirement.

 $<sup>^{15}</sup>K_L$  can be set to a value slightly below  $\underline{K}$  if there is a diffusion of the bunching mass.

as \$5,000 and \$10,000 tend to appear more frequently than other values. Since the collateral thresholds are located at salient round numbers, using the total excess mass at the collateral threshold would overstate the strategic response to the collateral requirements. We follow Kleven and Waseem (2013) to include a set of dummies,  $\delta_r$ , for multiples of the round numbers to absorb the round-number bunching.<sup>16</sup> 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:

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

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

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

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 a process by keeping adding one bin size further as

 $<sup>^{16}</sup>$ 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,  $K_j \mathbbm{1}(K_j/r \in \mathbb{N})$  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.

long as  $\hat{B} - \hat{M}(K_U) > 0$ . We derive  $K_U$  to be the bin satisfies that

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

The value of  $K_U$  that satisfies the above convergence condition is the marginal buncher,  $\overline{K}$ . We then plug the marginal buncher into equations (6) and (7) to solve the collateral cost. The interest rate, R, is set to the observed gross interest rates of the loans. The curvature of the production function,  $\alpha$ , 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). Then, for each generated data sample, we estimate its marginal buncher  $\overline{K}$ , distortion ratio  $\theta$ , and collateral cost  $\lambda$  with the same approach as above. Finally, the standard error is measured as the standard deviation of the 1,000 estimates.

### 4.2 Estimation results

#### 4.2.1 Baseline estimates

Column 1 of Table 2 presents the bunching estimates in the BPDL 2014-2020 sample, with a collateral threshold of \$25,000. 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% of the loan value annually. Table IA2 extends the analysis to earlier samples when the collateral threshold was set at different values (\$10,000 for 2003–2007, \$14,000 for 2008–2013). The estimates are of a similar magnitude, ranging from 6% to 9%.

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 is robust to optimization frictions, as shown by Kleven and Waseem (2013).

The estimated collateral cost is economically significant. Consider a loan of \$25,000, the baseline estimate of 9% translates to a dollar cost of \$2,300 per year, which is an economically significant cost for the small businesses in our sample. How does the estimated collateral cost compare to the benefit of pledging collateral for these firms? We approximate the the benefit of collateral by the interest savings from borrowing secured loans relative to unsecured loans. Note that the average interest rate of secured small business loans is around 7% while the interest rate of unsecured small business loans for an average credit score borrower is around 14%.<sup>17</sup> This implies that the benefit of pledging collateral is around 7% of the loan value, which is in the same order of magnitude of our estimated collateral cost, ranging from 6% to 9%. As a result, firms face a meaningful trade-off between paying lower interest and bearing the collateral cost when borrowing secured debt.

It is worth noting that our estimates are pertinent to small businesses. These firms face greater external financing frictions so pledging collateral and losing flexibility could be particularly costly

<sup>&</sup>lt;sup>17</sup>The secured loan rates are computed using the RateWatch data from 2001 to 2020. The unsecured loan rates are based on the quote from American Express as of Oct 28, 2021 (https://www.americanexpress.com/us/business/business-funding/).

for them. For larger corporations, the cost of pledging collateral could be much lower. However, this does not mean that the collateral cost is irrelevant for large corporations because the benefit of pledging collateral could also be smaller for them. For instance, Benmelech et al. (2022) estimate that the average yield difference between secured and unsecured loans for large syndicated loans is around 2%. Therefore, it is possible that large corporations also face a meaningful trade-off between collateralized and uncollateralized borrowing even if their collateral cost is smaller.

## 4.2.2 Heterogeneity across collateral type and industry

The cost of pledging collateral may differ depending on the type of collateral requirement. We compare two broad types of collateral: fixed assets vs. floating assets. In theory, firms may be more averse to pledging fixed assets than floating assets because fixed assets are typically less fungible and are indispensable to firms' operations. For instance, it could be detrimental for a firm if its lender seizes its machinery used for production. To test this hypothesis, we exploit a unique change in collateral requirement in the EIDL program during the COVID pandemic when the SBA changed the collateral requirement to allow firms to post floating assets as collateral. Column 2 of Table 2 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 3 of Table 2, we find the shadow cost of collateral is around 9% for the regular EIDLs, which is consistent with the BPDL estimates in column 1 of 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.

#### 4.3 Sources of collateral costs

The high degree of bunching implies that the cost of pledging collateral is surprisingly high, equivalent to 6-9% of the loan value annually. What are the underlying sources of the collateral costs? Pinpointing the exact channel is challenging because we do not have much information on firms' operational and financial decisions. Nevertheless, we provide some suggestive evidence for flexibility-based theories using the variations in secured creditor rights. We also discuss some alternative mechanisms that could contribute to the collateral costs.

#### 4.3.1 Evidence from changes in secured creditor rights

We first investigate if the collateral costs depend on the secured creditor rights, which vary across states and over time due to statute changes. If the statutes give weaker rights to secured creditors, firms will likely lose less flexibility when pledging assets as collateral. Consequently, firms may be less averse to borrowing secured debt.

To assess the relationship between secured creditor rights and the collateral cost, we explore the staggered adoption of the Uniform Voidable Transactions Act (UVTA) across different states in the U.S. The UVTA was proposed in 2014 as an amendment to the Uniform Fraudulent Transfer Act (UFTA). Under the UVTA, strict foreclosure of UCC Article 9 security interests will no longer be exempted from being treated as voidable transactions (UVTA § 8(e)(2)). Forster and Boughman (2015) suggest that under the UVTA, "creditors with an Article 9 security interest can no longer foreclose on the property and retain it without risking the transfer being avoided." In other words, secured creditors' rights would be weakened as the collateral transfer becomes voidable under the UVTA. It is worth noting that UVTA also contains other changes that affect both secured and unsecured creditors.<sup>18</sup> We isolate the effect of secured creditor rights by comparing firms with

<sup>&</sup>lt;sup>18</sup>For instance, Ersahin et al. (2021) suggest that the UVTA could allow creditors to have "the power to undo a much broader set of transactions than those that fall within the scope of fraud." However, the Uniform Law Commission, the commission which wrote this law, argues that the general purpose of the UVTA introduction is to "address a few narrowly defined issues, … not a comprehensive revision". See "Uniform Voidable Transactions Act: a Summary" by the Uniform Law Commission.

verified losses above and below the collateral threshold. The idea is that firms with verified losses above the collateral threshold will likely face the trade-off of borrowing secured versus unsecured. In contrast, firms with verified losses below the threshold do not face this trade-off. Because this test requires information on the verified losses, we restrict our sample to the BPDLs.

Table 4 shows the adoption year of UVTA of each state. Note that six states—Alaska, South Carolina, Kentucky, Maryland, New York, and Virginia—used state-specific laws different from the UFTA. We exclude these states to ensure that the adoption of the UVTA captures the same change in the secured creditor rights. The sample period is from 2014, when the UVTA is first introduced, to 2020, when the BPDL sample ends.

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

$$Take-up_{i,t} = \beta_1 Adoption_{i,t} \times Loss > 25k_{i,t} + \beta_2 Adoption_{i,t} + \beta_3 Loss > 25k_{i,t} + \tau_t + \tau_s + \varepsilon_{i,t}.$$
 (14)

The dependent variable,  $Take-up_{i,t}$ , is defined as the ratio of the loan amount over the verified losses.  $Adoption_{i,t}$  is a dummy variable that equals one if the state where firm i locates has adopted UVTA. This dummy captures the law changes that affect both secured and unsecured debt.  $\beta_1$ , the coefficient of the interaction of  $Adoption_{i,t}$  and the  $Loss>25k_{i,t}$  dummy captures the impact of the law change on firms that are more likely to borrow secured debt. Table 3 presents the results. Before the law change, the take-up ratio of firms with losses above \$25,000 is around 30% lower than those with losses below \$25,000, consistent with our earlier evidence that firms bunch to avoid pledging collateral. The take-up increased by around 10% after the law change, consistent with the idea that weakened secured creditor rights reduce collateral costs. The increase in take-up ratio accounts for a third of the take-up ratio gap between firms above and below the \$25,000 threshold.

We further verify our results by estimating the implied collateral cost in UVTA and UFTA states using the bunching estimator. We can only do this exercise in the COVID EIDLs because

the BPDL sample does not have enough observations to construct densities for the bunching estimator. Figure IA5 illustrates each state's collateral law as of 2021. Table 5 presents the estimated collateral costs in the UVTA and UFTA states, respectively. Consistent with the results in Table 3, the collateral cost is significantly lower in the UVTA states in which secured creditor rights are weaker.

#### 4.3.2 Transaction costs

Another source of collateral costs is the transaction costs associated with pledging collateral, such as the fees to file for a lien and the costs to conduct an appraisal. To understand these transaction costs' importance, we consider a typical \$25,000 loan. Based on our estimates, the dollar value of the collateral cost is around \$2,300 annually. The estimate seems to be an order of magnitude larger than the explicit transaction costs. Specifically, as of 2020, firms must pay the SBA a \$100 fee for filing a lien on business assets. However, there are typically no fees involved with appraisal because the SBA would also provide the inspection services free of charge.<sup>19</sup>

In addition to the explicit transaction costs, there could also be implicit costs such as a long time for paperwork. However, the application forms are very similar for loans of different sizes, except that firms need to sign a 4-page security agreement and provide notations on certificates of title for secured loans.<sup>20</sup> The processing times for secured and unsecured loans around the collateral thresholds are similar.<sup>21</sup> Finally, pledging collateral does not seem to slow down the disbursement process because the SBA typically does a partial disbursement of the amount below the collateral threshold to the borrower and releases the remaining funds once all collateral is appropriately secured.<sup>22</sup> Therefore, pledging collateral does not seem to slow down the disbursement, at least for the portion below the collateral threshold.

<sup>&</sup>lt;sup>19</sup>Note that formal appraisals performed by professional, licensed public appraisers are rare, although may occasionally be deemed appropriate. See page 115 of the SBA Standard Operating Procedure (SOP 50 30 9), Disaster Assistance Program.

<sup>&</sup>lt;sup>20</sup>See the security agreement for the COVID EIDL program at https://www.sba.gov/document/sba-form-1059-security-agreement.

<sup>&</sup>lt;sup>21</sup>See Internet Appendix Table IA7 for the average processing times of loans around the collateral thresholds.

 $<sup>^{22}\</sup>mathrm{See}$  SBA Disaster Loan FAQ at https://wisconsinsbdc.org/services/covid-19/disasterloans/disaster-loan-inquiry/sba-disaster-loan-faq/.

Overall, the evidence suggests that although transaction costs contribute to the total costs of pledging collateral, they are unlikely to explain most of the estimated collateral costs.

#### 4.3.3 Collateral scarcity

So far, we have discussed the sources of collateral costs based on flexibility-based theories and transaction costs. Now we discuss a few alternative explanations. One possibility is that the collateral cost may reflect the scarcity of collateral rather than firms' aversion to pledge it. To elaborate, if some firms in our sample do not have any collateral in the first place, they would have to bunch at the threshold regardless of how much they would like to borrow. However, a careful examination of the institutional setting suggests that collateral scarcity is unlikely to be a main driving force in our data. For the BPDL program, the loans are used to repair or replace damaged property or machinery. The repaired or replaced property or machinery typically serves as collateral. Therefore, firms in our sample have the option to pledge the collateral if they deem it beneficial to do so. Similarly, for the COVID EIDL program, general business assets can be used as collateral. These assets are broadly available. This feature also makes it unlikely that collateral scarcity is a key driving force.

Another important institutional feature is that the SBA typically does not require the collateral value to cover the loan amount fully. In the disaster loan program guidance, the SBA states that "SBA will not decline a loan for lack of collateral, but requires the applicant to pledge the collateral SBA has determined is available." Therefore, the estimated collateral cost is more likely to reflect the aversion to pledge collateral rather than the scarcity of the collateral.

The last piece of evidence comes from the cross-industry heterogeneity. Table 6 reports the estimated collateral costs by industry. Note that we can only do this exercise in a subsample of COVID EIDLs for which the industry information is available.<sup>24</sup> We find substantial collateral

<sup>&</sup>lt;sup>23</sup>See page 21 of the SBA Standard Operating Procedure (SOP 50 30 9), Disaster Assistance Program at www.sba.gov/document/sop-50-30-9-disaster-assistance-program.

<sup>&</sup>lt;sup>24</sup>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.

costs in industries that have plenty of tangible assets, such as agriculture and manufacturing.

Therefore, it is unlikely the scarcity of collateral is driving our estimates.

#### 4.3.4 Preserve collateral for private secured financing

Another possibility is that firms take the unsecured credit from the SBA because they want to preserve the collateral to assess secured financing from the private sector. In this way, firms can maximize the total credit they can get. While this consideration can be broadly interpreted as financial flexibility because firms care about the option value of collateral, it is still different from the theories in which pledging collateral has intrinsic costs.

We argue that this channel may not be the main driver of the bunching pattern. The reason is that the secured loan rates that firms can get from the SBA are much lower than those from the private sector. If firms want to maximize the total credit at a lower cost, they should take a bigger secured loan from the SBA instead of splitting it into an unsecured SBA loan and a secured private loan. In other words, the payoff to exercise the collateral option now with the SBA is much higher than that with a private lender, given the subsidized rates from the SBA. Furthermore, the typical loan sizes of the bunching firms are much smaller than the maximum loan size cap allowed by the SBA, \$2 million, so in principle, bunching firms can take a larger secured loan from the SBA if they prefer doing so.

We formalize this intuition by introducing an outside option of borrowing a secured private loan to the baseline model. Suppose firms can access private secured loans  $K_s$  with interest rate  $R_s$ ,  $R < R_s$ .

$$\max_{K,K_s} \Pi(K|Z) = A(Z)(K + K_s)^{\alpha} - RK - R_s K_s - \lambda Z \mathbb{1}_{K > \underline{K}|K_s > 0}, \tag{15}$$

If a firm takes  $\underline{K}$  from SBA and a private secured loan  $K_s$ , the payoff is  $A(\underline{K} + K_s)^{\alpha} - R\underline{K} - R_sK_s - \lambda Z$ . In comparison, if this firm takes a full secured loan from the SBA with the loan amount equal to the sum of the two loans,  $K = \underline{K} + K_s$ , then the payoff is  $A(\underline{K} + K_s)^{\alpha} - R(\underline{K} + K_s) - \lambda Z$ . It is easy to see the former option generates a lower payoff than the latter, so  $K_s = 0$  if  $R_s > R$ . In

other words, it would be suboptimal to give up the subsidized public funding to preserve collateral for more expensive private funding.

We provide another piece of evidence by exploring the cross-region variations in the local banking access. We measure the county-level banking access by the number of bank branches divided by the number of establishments in the county. If firms' bunching is indeed driven by their intention to save collateral for private sector funding, local banking access would affect the extent of bunching. However, we do not observe significant differences in firms' tendency to bunch across regions with different banking accesses, as shown in Table 7, suggesting that the intention to preserve collateral for private secured financing is unlikely to drive our results.

#### 4.3.5 Behavioral biases

Another alternative explanation for the bunching pattern at the collateral threshold is business owners' behavioral biases. For instance, one may worry that many business owners do not understand the implications of collateral agreement or have a clear idea of how much to borrow. They borrow at the collateral threshold simply because it is a salient number. There are two reasons why this alternative explanation is unlikely to apply to our setting. First, the SBA's security agreement is quite standard and should be comprehensible for business owners who have engaged in private security transactions before. For inexperienced business owners, there are plenty of sources from the internet and professional advisors for the implications of the collateral requirement on the SBA disaster loan programs.<sup>25</sup> Second, regarding the concern that business owners may not have a clear idea of how much to borrow, it is worth noting that in the BPDL program, the verified loss incurred in the disaster is a natural benchmark for the borrowing amount. As shown in Figure 2, the sizes of many loans coincide with the verified losses when they are away from the collateral threshold. Therefore, it is unlikely that borrowers do not know how much to borrow at least for the BPDL program.

<sup>&</sup>lt;sup>25</sup>For instance, see "Beware: That EIDL loan may come with unexpected strings attached" at https://www.cpabr.com/article-beware-that-eidl-loan.

## 4.4 Robustness checks

This section discusses robustness checks on our baseline results. First, we conduct placebo tests on the samples where thresholds have not been introduced. Second, we evaluate the sensitivity of our results to alternative specifications of the bunching estimator. Third, we examine whether proportional or fixed costs can better describe the collateral cost. Fourth, we consider alternative production functions to translate the observed bunching into collateral costs. Finally, we investigate whether fixed or proportional costs describe the nature of collateral costs.

#### 4.4.1 Placebo tests

The key identification assumption of the bunching estimator is that the counterfactual distribution is smooth in the absence of the discontinuity of the collateral requirement. To verify this assumption, 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 IA3. 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 unrelated to the collateral requirement.

#### 4.4.2 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 noise when the sample size is small. Therefore, we check the robustness of our results using alternative bin sizes in Table IA4. 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.

#### 4.4.3 Fixed vs proportional costs

Our baseline estimation assumes that the collateral cost is proportional to loan size. This assumption is natural because larger loans typically involve more collateral, and the economic costs associated with losing control rights are likely greater. Nevertheless, we now examine this assumption by exploiting the changes in the collateral thresholds. Specifically, the SBA has changed the collateral threshold several times during our sample period, from \$10,000 to \$14,000 and \$25,000. These changes allow us to identify the collateral costs for different marginal bunchers. If the collateral cost is a fixed cost, we expect the dollar values estimated from different thresholds to be similar. If the collateral cost scales with the loan size, we expect the proportional cost to be similar. Table IA2 presents the results. We find the dollar collateral cost is considerably larger for bigger marginal bunchers. It increases from \$1,491 to \$4,368 when the marginal buncher increases from \$17,500 to \$45,500. However, if we express the collateral costs as a percentage of the loan value, the magnitude is more similar across thresholds. This result suggests that the collateral cost is unlikely to be fixed. Instead, it appears to scale proportionally with the loan size.

#### 4.4.4 Alternative production functions

In the baseline estimation, we use the simplest Cobb-Douglas production function with a constant return to scale. In this section, we consider alternative production functions with a decreasing return to scale:

$$\Pi(K|Z) = A(Z)K^{\frac{\alpha\nu}{1-(1-\alpha)\nu}} - RK - \lambda Z \mathbb{1}_{K>\underline{K}},\tag{16}$$

where  $\nu < 1$  indicates decreasing return to scale.<sup>26</sup> We calibrate  $\nu$  to the various values estimated in the literature as shown in Panel B of Table 8. Although the exact value of the collateral costs depends on the value of  $\nu$ , the order of magnitude remains the same as our baseline results. Specifically, the values of collateral costs estimated from the BPDLs and regular EIDLs vary from 4% to 11%, and the values of collateral costs estimated from the COVID EIDLs vary from 3% to

<sup>&</sup>lt;sup>26</sup>The production function in equation (16) can be derived as follows: start from a Cobb-Douglas production function with decreasing return to scale:  $Y \propto (K^{\alpha}L^{1-\alpha})^{\nu}$ ; optimize in labor so that the output  $Y \propto K^{\frac{\alpha\nu}{1-(1-\alpha)\nu}}$ .

7%. More importantly, the relative order of collateral costs between fixed and floating assets is preserved no matter what production functions are used.

#### 4.4.5 Alternative substitution margin

In the baseline estimation, we assume firms would cut investment if they bunch their loans below the collateral threshold. While this assumption is consistent with the fact that the firms participating in the SBA disaster loan programs typically do not have access to external financing, we would like to assess the robustness of the results to this assumption. To this end, we allow firms to borrow unsecured financing  $K_u$  with a flat rate  $R_u$ . Firms' payoff function becomes the following:

$$\max_{K,K_u} \Pi(K|Z) = A(Z)(K + K_u)^{\alpha} - RK - R_u K_u - \lambda Z \mathbb{1}_{K > \underline{K}}.$$
 (17)

It is worth noting that equation (17) differs from equation (15) because borrowing unsecured would not trigger collateral costs. In this case, getting an unsecured loan from the private sector is not necessarily dominated by getting a bigger secured loan from the SBA because collateral is not required. We consider various unsecured lending rates ranging from 15% to 25%. We find that the estimated collateral costs tend to be lower if firms have access to lower unsecured lending rates from the private sector. The intuition is that bunching becomes less costly when firms can find funding substitutes and avoid cutting investments. Nevertheless, the order of magnitude of the estimated collateral costs and the relative order between different collateral requirements remain the same as our baseline results.

# 5 Implications of Collateral Costs

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

## 5.1 Capital structure decisions

Our results have important implications on the role of collateral in capital structure decisions. Since the influential work by Myers and Majluf (1984), it has long been 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., 2022). This intuition seems consistent with the observation that collateralized debt usually entails lower interest rates than uncollateralized debt. However, our results show that pledging collateral imposes a considerable shadow cost on firms. Our result supports a more recent theoretical literature that shows that pledging collateral could be costly because it limits firms' operational and financial flexibility and bargaining power (Mello and Ruckes, 2017; Rampini and Viswanathan, 2010; Donaldson et al., 2020; Benmelech et al., 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. However, the standard macro-finance model with collateral constraints does not consider the collateral cost. Since firms incur no cost when pledging collateral, they always borrow up to the collateral limit. We now examine the implications of our findings by incorporating the collateral cost into the standard Kiyotaki and Moore (1997) model.

We consider a discrete-time, infinite-horizon economy with two goods: a durable land and a nondurable fruit, and two groups of agents: farmers and gatherers. We maintain the terminology in Kiyotaki and Moore (1997). Still, it is worth noting that land and fruit can be interpreted as capital and consumption goods, while farmers and gathers can be interpreted as firms and lenders.

There is no aggregate uncertainty in the model aside from an initial unanticipated shock, so given rational expectations, agents have perfect foresight. Following Kiyotaki and Moore (1997), we assume that agents can only borrow secured debt. This assumption can be viewed as a limiting case of Rampini and Viswanathan (2020) that the implicit collateralizability of firms' residual value is zero. Our results still hold if agents can borrow unsecured as long as unsecured debt capacity is lower than secured debt.

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

$$E_t \sum_{s=0}^{+\infty} \beta^s x_{t+s}$$
 (18)

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

$$y_{t+1} = F(k_t) = (a+c)k_t,$$
 (19)

where  $k_t$  denotes the farmer's landholding at the end of time t,  $ak_t$  is the tradable output, while the  $ck_t$  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

$$E_t \quad \sum_{s=0}^{+\infty} \left( \beta' \right)^s x'_{t+s} \right) \left( \tag{20} \right)$$

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

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

$$y'_{t+1} = G\left(k'_{t}\right) \tag{21}$$

where  $G'>0,\,G''<0$  and  $G'\left(0\right)>aR>G'\left(\bar{K}\right)$  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 the rate of  $\delta$ ) at t + 1:

$$Rb_t \le q_{t+1} \left( 1 - \delta \right) k_t. \tag{22}$$

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

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

$$q_t (k_t - (1 - \delta) k_{t-1}) + Rb_{t-1} + x_t + \lambda b_{t-1} \mathbb{1}_{b_{t-1} > 0} = (a + c)k_{t-1} + b_t$$
(23)

$$q_{t}\left(k'_{t}-(1-\delta)\,k'_{t-1}\right) \notin Rb'_{t-1}+x'_{t}+\lambda b'_{t-1}\mathbb{1}_{b'_{t-1}>0}=G\left(k'_{t-1}\right) \notin b'_{t}$$
(24)

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

$$x_t = ck_{t-1}. (25)$$

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

$$\mu_t \equiv a + c - u_t, \tag{26}$$

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

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

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

$$b_t = \frac{1 - \delta}{R} q_{t+1} k_t \mathbb{1}_{\mu_t > \lambda}. \tag{28}$$

Substituting equation (28) into equation (23), a farmer's land holding is given by

$$k_{t} = \frac{1}{u_{t}} \left[ (a + q_{t}(1 - \delta))k_{t-1} - Rb_{t-1} - \lambda b_{t-1} \mathbb{1}_{\mu_{t} > \lambda} + \frac{1 - \delta}{R} q_{t+1} k_{t} (\mathbb{1}_{\mu_{t} > \lambda} - 1) \right]$$
 (29)

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

$$B_t = \frac{1-\delta}{R} q_{t+1} K_t \mathbb{1}_{\mu_t > \lambda},\tag{30}$$

$$K_{t} = \frac{1}{u_{t}} \left[ (a + q_{t}(1 - \delta))K_{t-1} - RB_{t-1} - \lambda B_{t-1} \mathbb{1}_{\mu_{t} > \lambda} + \frac{1 - \delta}{R} q_{t+1} K_{t} (\mathbb{1}_{\mu_{t} > \lambda} - 1) \right] \left( (31)^{t} \right]$$

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,  $u_t$ :

$$\frac{1}{R}G'(k_t') = u_t. \tag{32}$$

Market Clanilearing. 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

$$u_t = u(K_t) \equiv \frac{1}{R} G' \left( \bar{K} - K_t \right) \tag{33}$$

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

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

$$q_t = \sum_{s=0}^{+\infty} \left(\frac{1-\delta}{R}\right)^s u(K_{t+s}). \tag{34}$$

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

$$\left(1 - \frac{1 - \delta}{R} \left(1 - \lambda\right)\right) \left(q = a, \right) \tag{35}$$

$$B = \frac{1 - \delta}{R} qK,\tag{36}$$

$$\frac{1}{R}G'\left(\bar{K} - K\right) \not\models u,\tag{37}$$

$$\frac{1}{R}G'(\bar{K} - K) \not= u,$$

$$u = \left(1 - \frac{1 - \delta}{R}\right) \not q.$$
(37)

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

$$\delta q = a, (39)$$

$$B = 0, (40)$$

$$\frac{1}{R}G'\left(\bar{K} - K\right) \not\models u,\tag{41}$$

$$\frac{1}{R}G'\left(\bar{K} - K\right) = u, \tag{41}$$

$$u = \left(1 - \frac{1 - \delta}{R}\right) u. \tag{42}$$

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

We first show that the collateral trade-off makes the impulse responses state-dependent. The solid line in Figure 5 shows the impulse responses of farmers' landholding to the productivity shock when the economy was originally in a high productivity state. We assume that the negative productivity shock is small such that the net investment return is still above the collateral cost,  $\mu_t > \lambda$ . Because the collateral constraint is binding before and after the shock hits the economy, a temporary productivity shock leads to a large and persistent drop in landholding and asset prices. The financial amplification comes from the fact that, on top of the direct productivity shock,  $\Delta a$ , the depreciation in land prices further reduces farmers' net worth. Because the land price is forward-looking, the dynamic effect is much larger than the static effect due to the productivity shock. Note that this case is equivalent to Kiyotaki and Moore (1997).

The solid line in Figure 5 shows the impulse responses of farmers' landholding to the productivity shock when the economy is originally in a low productivity state. The shock has a limited impact because the collateral constraint is not binding. In other words, the financial accelerator mechanism is muted when the economy is originally at a low productivity state.

This result speaks to the extensive empirical studies on the magnitude of the financial accelerator mechanism (Lian and Ma, 2021; Catherine et al., 2018), which often find that the sensitivity of firm-level investment to collateral values is well below the magnitude predicted by the standard Kiyotaki and Moore (1997) model. For instance, Catherine et al. (2018) find the sensitivity of investment to asset prices is 0.06 while the standard Kiyotaki and Moore (1997) model implies

a sensitivity of 1. The existing literature often uses low asset pledgeability, to rationalize this discrepancy. While asset pledgeability is crucial, we suggest that the collateral cost can also contribute to the low sensitivity. If the collateral cost is substantial, firms may choose not to pledge their assets even if lenders are willing to accept them as collateral. Therefore, the fluctuations in asset prices would have a smaller impact on firms' investments.

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

Figure 6 compares the impulse responses of farmers' capital at time t when the productivity shock hits with and without the collateral trade-off for different shock sizes. When the shock size is small, the impulse responses are almost identical. However, when the shock size is large, the model with the collateral trade-off generates greater amplification. The intuition is that when the net investment return falls below the collateral cost,  $\mu_t < \lambda$ , farmers find it too costly to borrow collateralized debt. Instead, they will pay the full price in cash to buy lands without borrowing. As a result, the farmers' demand for capital falls more than that in Kiyotaki and Moore (1997).

## 5.3 Design of the 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).  $\ell$  is the charge-off rate for uncollateralized loans. The

collateral requirement can lower the charge-off rate by  $\beta$  fraction. However, it imposes a shadow cost  $\lambda Z$  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,  $\phi$ .

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 in the dominated region above the threshold. We refer to them as the non-optimizing firms following the terminology of Kleven and Waseem (2013). We denote the fraction of non-optimizing firms as  $\gamma$ .

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

$$W(\underline{K}) = (1 - \gamma) \iint [AK^*(Z)^{\alpha} - \ell K^*(Z) + \mathbb{1}_{K^* > \underline{K}} (\beta \ell K^*(Z) - \lambda Z - \phi)] f_0(Z) dZ$$

$$+ \gamma \iint [AZ^{\alpha} - \ell Z + \mathbb{1}_{Z > \underline{K}} (\beta \ell Z - \lambda Z - \phi)] f_0(Z) dZ.$$

$$(43)$$

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  $\lambda$  is set to 9% based on the estimates in column 1 of 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 rate of uncollateralized loans  $\ell$  is calibrated to  $\ell = 24\%$  according to the Government Accountability Office (GAO) statistics.<sup>27</sup> We calibrate the reduction in charge-off rates  $\beta$  to be 37.5%.<sup>28</sup> Fourth, the fraction of the non-optimizing firms  $\gamma$  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  $\phi$  is calibrated to \$100.

We index different program designs using the collateral threshold,  $\underline{K}$  and calculate the welfare for each program. 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

<sup>&</sup>lt;sup>27</sup>See "Small Business Administration: Physical Disaster Loan Performance Before and After Changes in Statutory Collateral Requirements".

<sup>&</sup>lt;sup>28</sup>We fit a Cox proportional-hazards model to the charge-off status of the loans and find secured loans have a 37.5% lower hazard rate. See Internet Appendix IA6 for more detail.

default loss  $\beta Z$ —dominate the explicit transaction cost of collateral requirement  $\phi$ . Therefore, welfare is maximized when most of the loans, except those tiny ones below \$1,000, are subject to collateral requirements.<sup>29</sup>

We then introduce the collateral costs into the welfare calculation. Interestingly, 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 program design would exempt all the firms from the collateral requirements because of the collateral cost and the resulting manipulation.

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

## 6 Conclusion

Collateral plays a crucial role in the economy. While the benefit of pledging collateral has received extensive studies, the cost is less well understood. This article empirically estimates the shadow

<sup>&</sup>lt;sup>29</sup>The tiny loans are exempted because the fixed transaction cost is large relative to the benefits of the collateral.

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. A bunching estimation shows that the collateral cost is in the same magnitude as the interest differential between secured and unsecured debt. 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. Moreover, we show that the collateral cost depends on collateral types, business sectors, and collateral laws. These results have important implications for understanding firms' borrowing constraints, the financial accelerator mechanism, and the design of government lending programs.

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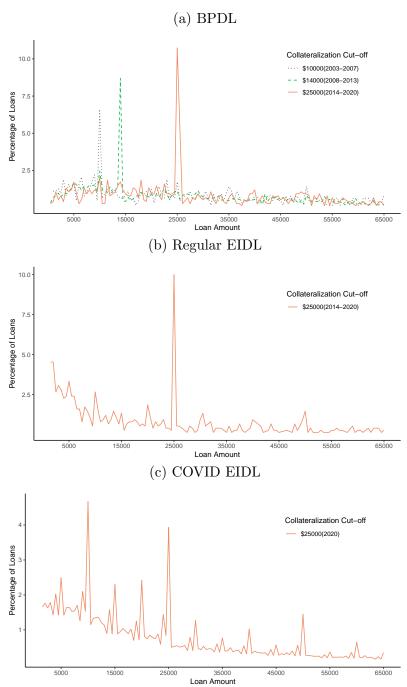
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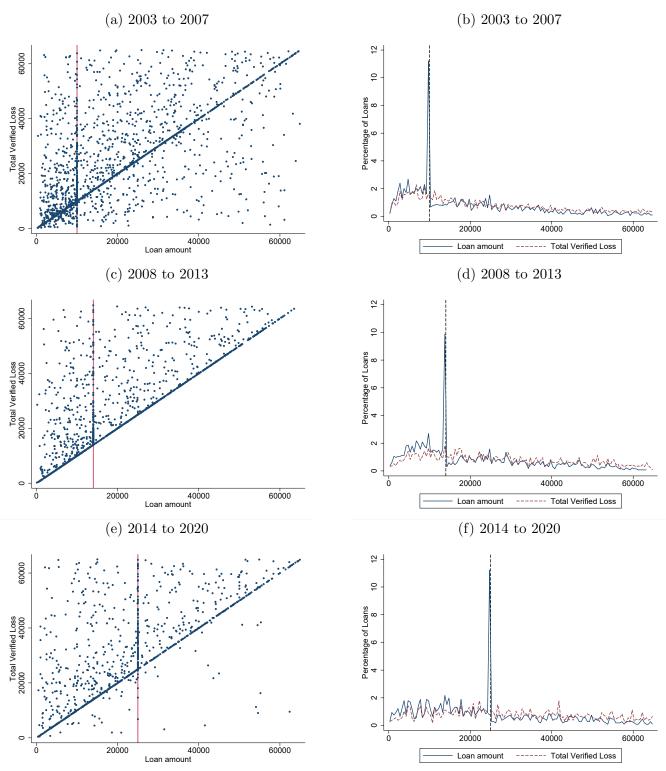
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Figure 1: Loan size distribution



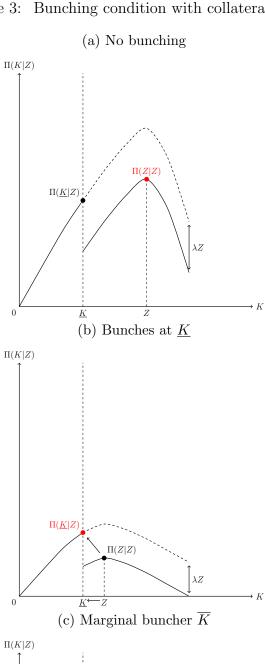
**Note:** The figure shows the loan size distribution of BPDLs, regular EIDLs, and COVID EIDLs, respectively. Data source: SBA.

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



**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



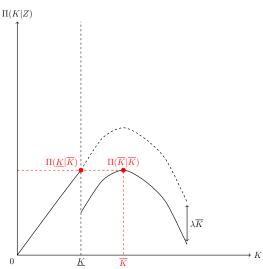
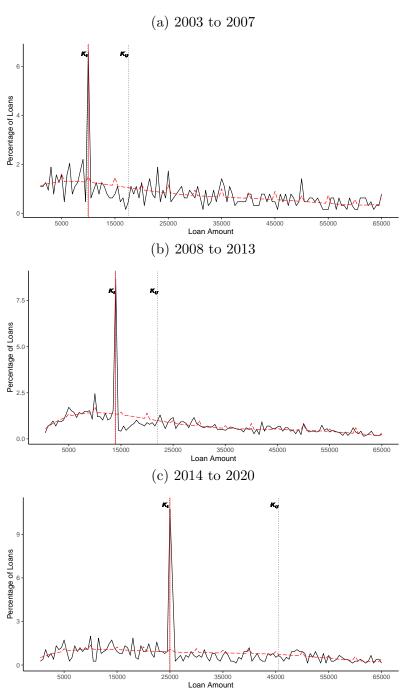
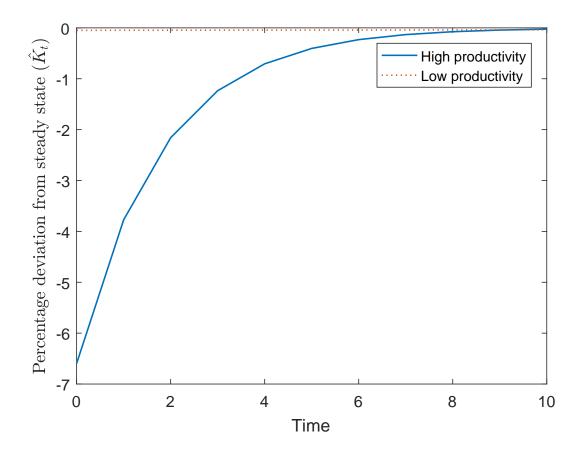


Figure 4: Counterfactual distribution and marginal buncher of BPDLs



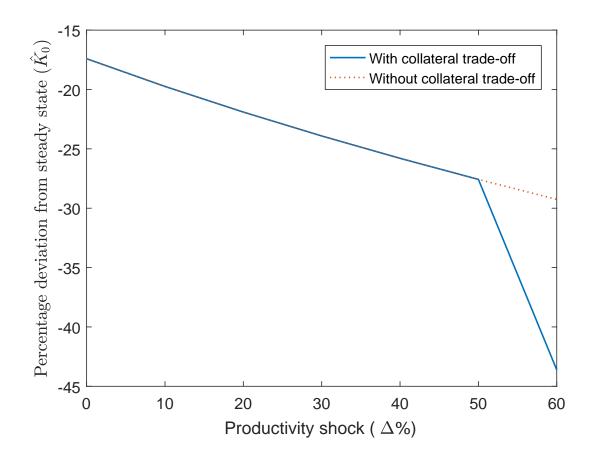
**Note:** This figure shows the observed (black) and counterfactual (red) percentage of loans in each bin. The counterfactual is estimated for each sample separately by fitting a fifth-order polynomial with round number dummies to the observed distribution using a bin size of \$500, excluding data in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

Figure 5: Impulse response functions in a Kiyotaki and Moore (1997) model with collateral cost



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

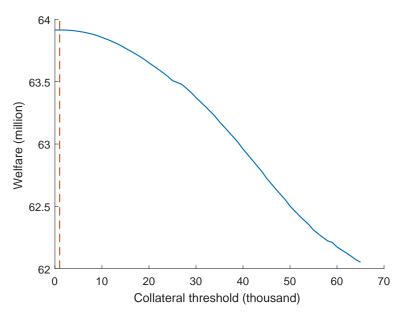
Figure 6: Time-0 impulse responses in a Kiyotaki and Moore (1997) model with vs. without collateral cost



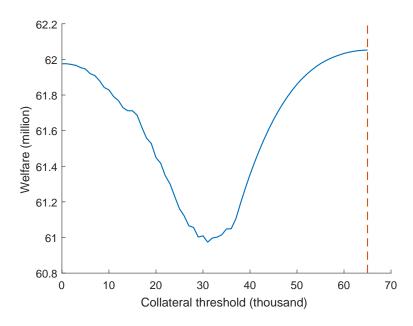
Note: This figure shows time-0 impulse response for shocks of different sizes in Kiyotaki and Moore (1997) model with collateral cost. The vertical axis is the percentage deviation of farmers' land at time 0 from the steady state,  $\hat{K}_0$ . The horizontal axis is the size of the productivity shock.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

Figure 7: Counterfactual policy simulation

(a) Without collateral cost



(b) With collateral cost



**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 10th percentile, median, and 90th percentile, respectively. Panel A reports summary statistics for the full sample of the Business Physical Disaster Loan (BPDL), panel B reports statistics for the full sample of the Economic Inquiry Disaster Loan (EIDL), and panel C reports statistics for the full sample of the COVID Economic Inquiry Disaster Loan (COVID EIDL). The loan amount is the approved loan amount of a given loan in the sample. The 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.	10th Pctl.	Median	90th Pctl.	Observations
Loan amount (\$)	586,104	3,313,977	10,000	78,850	944,900	17,238
Interest rate (%)	3.61	0.46	2.90	4.00	4.00	16,630
Verified losses (\$)	1,766,036	$13,\!147,\!101$	0	102,796	2,162,268	17,238
Loans per disaster	223.75	284.62	8	110	544	17,238
Loans per zip code	3.98	5.65	1	3	8	17,238

Panel B: EIDL (	2003-2020)	
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Outcome	Mean	Std.Dev.	10th Pctl.	Median	90th Pctl.	Observations
Loan amount (\$)	126,676	384,592	2,300	30,200	294,500	11,202
Interest rate (%)	3.55	0.46	2.90	3.67	4.00	11,185
Loans per disaster	192.19	249.32	6	77	501	11,600
Loans per zip code	3.17	3.91	1	2	6	11,600

#### Panel C: COVID EIDL (2020)

	3.1	Ct I D	10/1 D /1	) / 1·	0041 D 41	01
Outcome	Mean	Std.Dev.	10th Pctl.	Median	90th Pctl.	Observations
Loan amount (\$)	53,240	58,207	4,000	26,000	150,000	3,604,257
Interest rate (%)	3.75	0.00	3.75	3.75	3.75	3,604,257
Loans per zip code	610.46	615.00	79	425	$1,\!407$	$3,\!604,\!257$

Table 2: Estimates of collateral cost

This table reports the bunching estimation results on excess mass (B) and marginal buncher  $(\overline{K})$ . The results cover three different disaster loan samples: BPDL, Covid EIDL and Regular EIDL. BPDL sample contains loans with a loan amount between \$0 and \$65,000 in 2014–2020. Covid EIDL sample contains loans with a loan amount between \$1,000 and \$65,000 in 2020. Regular EIDL sample contains loans with a loan amount between \$1,000 and \$65,000 in 2014-2020. The collateral threshold is at \$25,000. Columns 1, 2, and 3 include BPDLs, COVID EIDLs, and Regular EIDLs, respectively. The distortion ratio is calculated as  $\theta = (\overline{K} - \underline{K})/\overline{K}$ . The collateral cost  $\lambda$  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.

	Disast	ter Loans				
	Bin Size = 500					
Estimates	K = 25000	$\underline{K} = 25000$	$\underline{K} = 25,000$			
Sample period	2014-2020	2020	2014-2020			
Collateral requirement	Fixed lien	Floating lien	Fixed lien			
	P = 5	P = 5	P = 5			
	(1) BPDL	(2) COVID EIDL	(3) Regular EIDL			
Bunching mass $(B)$	9.65%	2.58%	8.83%			
- , ,	(0.15%)	(0.08%)	(0.13%)			
Marginal buncher $(\overline{K})$	45,500	40,000	45,000			
	(2277.11)	(3635.17)	(1673.92)			
Distortion ratio $(\theta)$	45.05%	37.50%	44.44%			
. ,	(2.73%)	(5.03%)	(2.18%)			
Collateral cost $(\lambda)$	9.60%	6.23%	9.29%			
	(1.39%)	(2.18%)	(1.02%)			

Table 3: The effects of secured creditor rights on loan take-up

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

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

Table 4: UVTA Adoption status by state

Uniform Voidable Transaction Act Non-Uniform Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act	1990 1990 1987 1986 1991 1991 1996 1996 1988	2018 2017 2015	SB152 HB2139 SB161
Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act	1987 1986 1991 1991 1996 1996 1988		
Uniform Voidable Transactions Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act	1987 1986 1991 1991 1996 1996 1988		
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Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act	1991 1991 1996 1996 1988	2015	SB161
Uniform Fraudulent Transfer Act Uniform Fraudulent Transfer Act Uniform Fraudulent Transfer Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act	1991 1996 1996 1988		
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Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act	1988		
Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act			
Uniform Fraudulent Transfer Act			
	2002	2015	SB65
· · · · · · · · · · · · · · · · · ·	1985		
Uniform Voidable Transactions Act	1987	2015	HB92
Uniform Fraudulent Transfer Act	1990		
Uniform Voidable Transactions Act	1994	2017	SB316
Uniform Voidable Transactions Act	1995	2016	HF2400
Uniform Fraudulent Transfer Act	1999		
Uniform Voidable Transactions Act		2015	SB204
Uniform Fraudulent Transfer Act	1985		
Uniform Fraudulent Transfer Act	1986		
Uniform Fraudulent Conveyance Act			
Uniform Fraudulent Transfer Act	1996		
Uniform Voidable Transactions Act	1998	2017	SB982
Uniform Voidable Transactions Act	1987	2015	HF1342 & SF181
Uniform Fraudulent Transfer Act	2006		
		2019	LB70
		2021	AB3384 & SB317
			HB85
			AB5622
	1997		SB123
			HB1135
		_010	1121100
		2017	SB629
			HB7334
	1000	2010	11D1001
	1987		
		2017	SB58
			HB35
	1930	4011	111000
	1088	2017	SB5085
			HB4233
		2010	11D4299
	Uniform Voidable Transactions Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Fraudulent Transfer Act Uniform Fraudulent Conveyance Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Voidable Transactions Act	Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Fraudulent Transfer Act Uniform Fraudulent Transfer Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act	Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Fraudulent Conveyance Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Fraudulent Transfer Act Uniform Fraudulent Transfer Act Uniform Voidable Transactions Act Uniform Fraudulent Transfer Act Uniform Fraudulent Transfe

Table 5: Impact of secured creditor rights on collateral costs

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

	COVID EIDL	
	Bin Siz	e = 500
Estimates	$\underline{K} = 25000$	$\underline{K} = 25,000$
	P = 5	P = 5
	(1) UVTA	(2) UFTA
Dunching mass $(D)$	2.66%	2.51%
Bunching mass $(B)$	· -	
	(0.12%)	(0.06%)
Marginal buncher $(\overline{K})$	40,000	44,500
	(3639.38)	(3461.23)
Distortion ratio $(\theta)$	37.50%	43.82%
Distortion ratio (v)	(5.10%)	(4.45%)
	(3.10/0)	(4.49/0)
Collateral cost $(\lambda)$	6.23%	8.96%
,	(2.19%)	(2.10%)

Table 6: Collateral cost by industry

This table reports the bunching estimation results on excess mass (B) and marginal buncher (K) for different industry's COVID EIDLs at the \$25,000 collateral threshold. The sample contains loans with a loan amount between \$1,000 and \$65,000. The distortion ratio is calculated as  $\theta = (\overline{K} - \underline{K})/\overline{K}$ . The collateral cost  $\lambda$  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	В	$\overline{K}$	Distortion ratio $\theta$	Collateral cost $\lambda$
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 Foo	d 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: Local banking access

This table reports the bunching estimation results on excess mass (B) and marginal buncher  $(\overline{K})$  for sub-samples of disaster loans at the \$25,000 collateral threshold. We define county-level banking access as the number of bank branches divided by the number of establishments in the county. Column 1 reports the results for the low banking access subsample, i.e. borrowers in counties with financial access lower than the national average. Column 2 reports the results for the high banking access subsample, i.e. borrowers in counties with financial access higher than the national average. The sample contains loans between \$1,000 and \$65,000 for COVID EIDLs and loans between \$0 to \$65,000 for BPDLs. The distortion ratio is calculated as  $\theta = (\overline{K} - \underline{K})/\overline{K}$ . The collateral cost  $\lambda$  is calculated as in equation (7). The degree of the polynomial is set to 5, and the bin size is set to \$500. Bootstrapped standard errors are presented in parentheses.

	COVID EIDL			
		e = 500		
Estimates	$\underline{K} = 25000$	$\underline{K} = 25,000$		
	P = 5	P = 5		
	(1) Low financial access	(2) High financial access		
Bunching mass $(B)$	2.43%	2.72%		
	(0.07%)	(0.08%)		
Marginal buncher $(\overline{K})$	40,000	40,500		
Triangular surrous (11)	(3579.91)	(3848.86)		
Distortion ratio $(\theta)$	37.50%	38.27%		
Distortion ratio (t)	(4.99%)	(4.94%)		
Collateral cost $(\lambda)$	6.23%	6.53%		
Condictal cost (X)	(2.15%)	(2.33%)		
	BPDL 2014-2020			
		e = 500		
Estimates	K = 25000	K = 25,000		
	P = 5	P=5		
	(1) Low financial access	(2) High financial access		
Bunching mass $(B)$	7.20%	12.05%		
0 ( )	(0.24%)	(0.18%)		
Marginal buncher $(\overline{K})$	47,000	46,500		
William Sunonor (11)	(4075.05)	(1374.04)		
Distortion ratio $(\theta)$	46.81%	46.24%		
	(5.02%)	(1.55%)		
Collateral cost $(\lambda)$	10.52%	10.21%		
Collaborat cost (A)	(2.48%)	(0.84%)		

Table 8: Alternative production functions and outside options

This table reports the bunching estimation results on excess mass (B) and marginal buncher  $(\overline{K})$  with alternative production functions and outside options. The collateral cost  $\lambda$  is calculated as in equation (7). The degree of the polynomial is set to 5, and the bin size is set to \$500.

Panel A: Cobb-Douglas production with CRS (baseline)

Calibration method	ν	$\alpha$	$\lambda_{BPDL}$	$\lambda_{EIDL}$	$\lambda_{COVIDEIDL}$
Baseline	1	$\frac{1}{3}$	9.60%	9.29%	6.23%

Panel B: Cobb-Douglas production with DRS

Calibration method	ν	$\alpha$	$\lambda_{BPDL}$	$\lambda_{EIDL}$	$\lambda_{COVIDEIDL}$
Veracierto (2001)	0.83	$\frac{1}{3}$	5.18%	5.01~%	3.40 %
Hsieh and Klenow (2009)	0.50	$\frac{1}{3}$	10.98%	10.63%	7.10 %
Garicano et al. (2016)	0.86	$\frac{1}{3}$	4.42%	4.28%	2.91%

Panel C: Incorporating outside unsecured financing in baseline model

Outside unsecured loan interest rate	ν	$\alpha$	$\lambda_{BPDL}$	$\lambda_{EIDL}$	$\lambda_{COVIDEIDL}$
15%	1	$\frac{1}{3}$	4.15%	4.09%	3.38%
20%	1	$\frac{1}{3}$	5.57%	5.47%	4.40%
25%	1	$\frac{1}{3}$	6.74%	6.61%	5.18%

Internet Appendix for
The Shadow Cost of Collateral

# Appendix A Application process of the SBA disaster loan program

This section describes the application process of the SBA disaster loan program. The application process consists of three steps.

#### Step 1: Apply

The application can be done online at disasterassistance.gov, by phone, or in person at any local disaster center. Borrowers are under no obligation to accept the loan if approved.

#### Step 2: Application processed

Application packages and required documents (including credit and income information) will be reviewed for completeness. Eligible applications are sent to SBA's loss verification team and property inspections may be necessary to decide the total physical damage. A loan officer on a case may ask for any additional information, review insurance or other recoveries, and recommend a loan amount. Loan determinations are typically made within 2–3 weeks after receiving complete application packages.

#### Step 3: Loan closure & disbursement

Loan closing documents are prepared for the applicant's signature. After receipt of the signed documents, an initial disbursement up to \$25,000 will be made within 5 business days. Loan may be increased up to 20% after closing due to changing circumstances, such as unexpected repair costs.

# Appendix B Examples of UCC financing statements

Figure IA1: Example of UCC financing statement: BPDL

UCC FINANCING STATEMENT		FLO	RIDA SECUI	RED TRANSACTIO	N REGISTR	
FOLLOW INSTRUCTIONS A. NAME & PHONE OF CONTACT AT FILER (optional)  B. E-MAIL CONTACT AT FILER (optional)		FILED 2018 Jan 08 09:32 AM ****** 20180374893X ******				
DEBTOR'S NAME: Provide only one Debtor name (1a or 1b) (use exa name will not fit in line 1b, leave all of item 1 blank, check here and pro		nit, modify, or abbreviate any	part of the Debtor	name); if any part of the I	ndividual Debtor's	
1a. ORGANIZATION'S NAME	THE STATE OF THE S			,	- ···- <b>,</b>	
GALBREATH RESTAURANT GROUP, LLC	FIRST P	ERSONAL NAME	ADDITIO	NAL NAME(S)/INITIAL(S)	SUFFIX	
c MAILING ADDRESS 253 RIVER RD	CITY	HILL	STATE:	POSTAL CODE 32759	USA	
D. INDIVIDUAL'S SURNAME  C. MAILING ADDRESS  SECURED PARTY'S NAME (or NAME of ASSIGNEE of ASSIGNOR	CITY	ERSONAL NAME  Provide only <u>one</u> Secured Pa	STATE	NAL NAME(S)/INITIAL(S)	SUFFIX	
20 OCCANIZATIONIC NAME						
38. ORGANIZATION'S NAME U.S. SMALL BUSINESS ADMINISTRATION		ERSONAL NAME	ADDITIO	NAL NAME(S)/INITIAL(S)	SUFFIX	
U.S. SMALL BUSINESS ADMINISTRATION	FIRST P		1			
DR U.S. SMALL BUSINESS ADMINISTRATION  BL. INDIVIDUAL'S SURNAME  BL. MAILING ADDRESS  801 TOM MARTIN DRIVE SUITE 120	CITY BIRM	MINGHAM	STATE AL	POSTAL CODE 35211	COUNTRY USA	
DIS. SMALL BUSINESS ADMINISTRATION  BI. INDIVIDUAL'S SURNAME  IN MAILING ADDRESS  801 TOM MARTIN DRIVE SUITE 120	CITY BIRM steral: ND EQUIPME ED IN WHOLE OCEEDS OF A	NT. EXCLUDING OR IN PART FRO NY DISPOSITION	AUTOMOT M THE PRO THEREOF	35211 IVE NOW OWI CEEDS OF THIS	USA NED, SBA	
D.S. SMALL BUSINESS ADMINISTRATION  D. INDIVIDUAL'S SURNAME  D. MAILING ADDRESS  BO1 TOM MARTIN DRIVE SUITE 120  4. COLLATERAL: This financing statement covers the following collaboration of the col	BIRM BIRM DEQUIPME ED IN WHOLE OCEEDS OF A D PAYABLE C	NT, EXCLUDING OR IN PART FRO NY DISPOSITION OR TO BECOME D	AUTOMOT M THE PRO THEREOF DUE AND PA	35211 IVE NOW OWI CEEDS OF THIS	USA NED, SBA EEN	

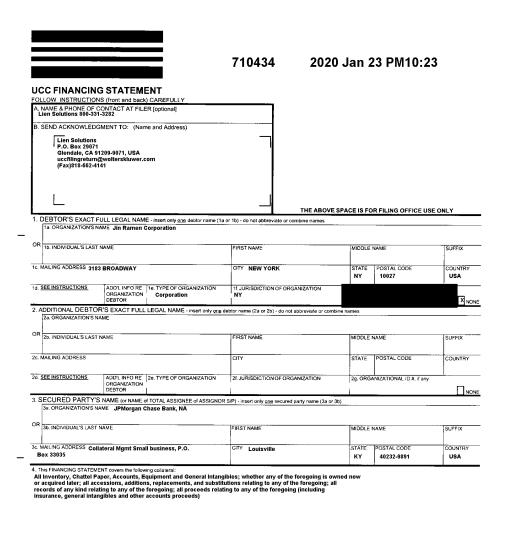
**Note:** The figure shows the UCC financing statement between Galbreath Restaurant Group LLC and Small Business Administration. Data source: Florida Secured Transaction Registry (FSTR).

Figure IA2: Example of UCC financing statement: COVID EIDL

CC FINANCING STATEMENT DLLOW INSTRUCTIONS  NAME & PHONE OF CONTACT AT FILER (optional)			FLORIDA	SECURED TRANSACTION R FILED 2020 May 27 11:30 AM	EGISTRY
CSC 1-800-858-5294			****	* 202001819143 **	****
. E-MAIL CONTACT AT FILER (optional) SPRFiling@cscglobal.com	1				
. SEND ACKNOWLEDGMENT TO: (Name and Address)					
1828 38538	71		•		
CSC 801 Adlai Stevenson Drive					
Springfield, IL 62703	Filed In: Florida				
<u>L</u>	(S.O.S.)				
DEBTOR'S NAME: Provide only one Debtor name (1a or 1b) (u	sa evant full name; do not omit medi			R FILING OFFICE USE	
name will not fit in line 1b, leave all of item 1 blank, check here	and provide the Individual Debtor info	ormation in item 10 of the	Financing St	atement Addendum (Form UC	C1Ad)
1a. ORGANIZATION'S NAME Galbreath Restaurant C	Group LLC				
1b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NA	ME	ADDITIO	NAL NAME(S)/INITIAL(S)	SUFFIX
			1		1
MAILING ADDRESS 253 River Rd	CITY Oak Hill		STATE	POSTAL CODE 32759	USA
DEBTOR'S NAME: Provide only one Debtor name (2a or 2b) (uname will not fit in line 2b, leave all of item 2 blank, check here	se exact, full name; do not omit, modi and provide the Individual Debtor info	ly, or abbreviate any part formation in item 10 of the	of the Debtor Financing St	's name); if any part of the In atement Addendum (Form UC	dividual Deb CC1Ad)
2a. ORGANIZATION'S NAME	<del></del>		<u>`</u> _	<del></del>	<u> </u>
2b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NA	ME	ADDITIO	NAL NAME(S)/INITIAL(S)	SUFFIX
: MAILING ADDRESS	CITY		STATE	POSTAL CODE	COUNTR
MALINO ABBALGO			JOINIE	I GOTAL GODE	10001111
SECURED PARTY'S NAME (or NAME of ASSIGNEE of ASS	IGNOR SECURED PARTY): Provide	only one Secured Party r	ame (3a or 3b	))	٠
38. ORGANIZATION'S NAME U.S. Small Business A	dministration				
36 INDIVIDUAL'S SURNAME	FIRST PERSONAL NA	ME	IADDITIO	NAL NAME(S)/INITIAL(S)	SUFFIX
35.112.112.5.12.5.35.112.112			1		
MAILING ADDRESS 2 North Street, Suite 320	CITY		STATE	POSTAL CODE	COUNTR
	Birmingham		AL	35203	USA
COLLATERAL: This financing statement covers the following coll. All documentary stamps due and payable o All tangible and intangible personal property	y, including, but not limit r, including tangible cha	ed to: (a) invent tel paper and e	tory, (b) e lectronic eceivabl	equipment, (c) inst chattel paper, (e) es and credit card g payment intangi	ruments bles an
documents, (f) letter of credit rights, (g) acc receivables, (h) deposit accounts, (i) common software and (k) as-extracted collateral as se Code. The security interest Borrower grant	ercial tort claims, (j) gen such terms may from tim s includes all accession	ne to time be de s, attachments,	fined in t	ries, parts, supplie	es and
documents, (f) letter of credit rights, (g) acc receivables, (h) deposit accounts, (i) comm software and (k) as-extracted collateral as s Code. The security interest Borrower grant replacements for the Collateral, all products ALL DOCUMENTARY STAMPS DUE AND	ercial tort claims, (j) gen such terms may from tim s includes all accession s, proceeds and collection	ne to time be de s, attachments, ons thereof and	fined in t accesso all record	ries, parts, supplie ds and data relatin	es and g theret
documents, (f) letter of credit rights, (g) acc receivables, (h) deposit accounts, (i) comm software and (k) as-extracted collateral as scode. The security interest Borrower grant replacements for the Collateral, all products ALL DOCUMENTARY STAMPS DUE AND 651452 7405	ercial tort claims, (j) gen such terms may from tim s includes all accession s, proceeds and collection PAYABLE OR TO BEC	ne to time be de s, attachments, ons thereof and OME DUE AND	fined in to accessor all record PAYAE	uries, parts, supplieds and data relating SLE, HAVE BEEN STEEN BEEN	es and g theret
including promissory notes (d) chattel pape documents, (f) letter of credit rights, (g) acc receivables, (h) deposit accounts, (i) comm software and (k) as-extracted collateral as s Code. The security interest Borrower grant replacements for the Collateral, all products ALL DOCUMENTARY STAMPS DUE AND 651452 7405  Check acity if applicable and check acity one box: Collateral ish a. Check acity if applicable and check acity one box:	ercial tort claims, (j) gensuch terms may from tim s includes all accession proceeds and collection PAYABLE OR TO BECO	ne to time be de s, attachments, ons thereof and OME DUE AND	fined in t accesso all record D PAYAE	ries, parts, supplieds and data relatin	es and g theret. PAID.  Al Representatione box:

**Note:** The figure shows the UCC financing statement between Galbreath Restaurant Group LLC and Small Business Administration. Data source: Florida Secured Transaction Registry (FSTR).

Figure IA3: Example of UCC financing statement: private lender



5. ALTERNATIVE DESIGNATION [if applicable]: LESSEE/LESSOR   CONSIGNEE/CONSIGNOR   BAILEE/BAILOR   SELLER/BUYER	AG. LIEN NON-UCCFILING
6. This FINANCING STATEMENT is to be filed (for record) (or recorded) in the REAL [7, Check to REQUEST SEARCH REPORT(S) on Debtor(s) [6] ESTATE RECORDS. Attach Addendum [6] Independent [7] Addendum [7] Addendum [8] Attach Addendum [8] Adde	All Debtors Debtor 1 Debtor 2
8. OPTIONAL FILER REFERENCE DATA NY-0-73485179-58458593	

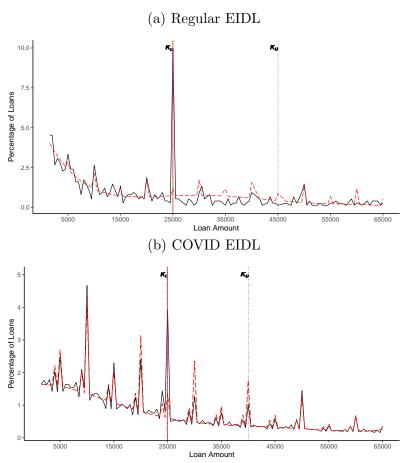
 $\textbf{FILING OFFICE COPY} = \texttt{NATIONAL UCC FINANCING STATEMENT (FORM UCC1)} \, (\text{Rev. } 05/22/02)$ 

#### Filing Number-202001235104061

**Note:** The figure shows the UCC financing statement between Jin Ramen and JP Morgan. Data source: National Association of Secretaries of State (NASS).

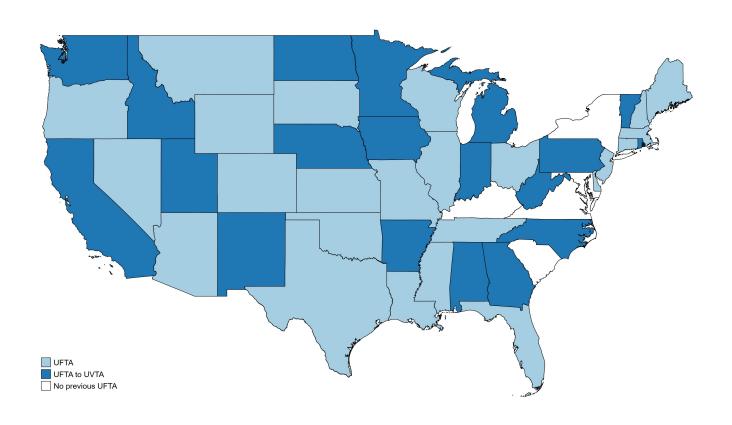
# Appendix C Additional figures

Figure IA4: Loan size distribution and marginal buncher of EIDLs



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 IA5: UVTA and UFTA status by state as of 2021



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

# Appendix D Robustness of bunching estimates

Table IA1: Bunching estimates for BPDLs: robustness

This table reports the bunching estimation results on excess mass (B) and marginal buncher  $(\overline{K})$  for BPDLs between 2014 and 2020 at the \$25,000 collateral threshold. The sample contains loans with a loan amount between \$0 and \$65,000. The distortion ratio is calculated as  $\theta = (\overline{K} - \underline{K})/\overline{K}$ . The collateral cost  $\lambda$  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%
Dunching mass $(D)$	(0.13%)	(0.15%)	(0.15%)
	(0.1370)	(0.1370)	(0.13%)
Marginal buncher $(\overline{K})$	47,500	45,500	45,000
	(2857.88)	(2277.11)	(2493.37)
Distortion ratio $(\theta)$	47.37%	45.05%	44.44%
(,)	(3.34%)	(2.73%)	(3.07%)
Collateral cost $(\lambda)$	10.83%	9.60%	9.29%
	(1.74%)	(1.39%)	(1.52%)

Table IA2: Bunching estimates for BPDL: alternative thresholds

This table reports the bunching estimation results on excess mass (B) and marginal buncher  $(\overline{K})$  for BPDLs in multiple sample periods at different collateral thresholds. The sample contains loans with a loan amount between \$0 and \$65,000. The distortion ratio is calculated as  $\theta = (\overline{K} - \underline{K})/\overline{K}$ . The collateral cost  $\lambda$  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
$\mathbf{p}_{\mathbf{p}} = \mathbf{p}_{\mathbf{p}} \cdot \mathbf{p}_{\mathbf{p}} \cdot \mathbf{p}_{\mathbf{p}} \cdot \mathbf{p}_{\mathbf{p}} \cdot \mathbf{p}_{\mathbf{p}}$	E 1107	7 2407	0.6507
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 $(\theta)$	42.86%	36.36%	45.05%
Distortion radio (t)	(3.40%)	(4.04%)	(2.73%)
	(0.1070)	(1.01/0)	(2.1970)
Proportional collateral cost $(\lambda)$	8.52%	5.82%	9.60%
	(1.79%)	(1.65%)	(1.39%)
Dollar collateral cost $(\lambda \overline{K})$	1,491	1,280	4,368

Table IA3: 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 a loan amount between \$0 and \$65,000. The distortion ratio is calculated as  $\theta = (\overline{K} - \underline{K})/\overline{K}$ . The collateral cost  $\lambda$  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) 2008-2013	(2) 2008-2013	(3) 2008-2013
Bunching mass $(B)$	0.07%	0.19%	0.20%
0 ( )	(0.08%)	(0.06%)	(0.07%)
Marginal buncher $(\overline{K})$	25,000	25,000	25,000
	(0.00)	(199.25)	(235.01)
Distortion ratio $(\theta)$	0.00%	0.00%	0.00%
	(0.00%)	(0.76%)	(0.90%)
Collateral cost $(\lambda)$	0.00%	0.00%	0.00%
	(0.00%)	(0.01%)	(0.07%)

Table IA4: 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 the \$25,000 collateral threshold. The sample contains loans with a loan amount between \$0 and \$65,000. The distortion ratio is calculated as  $\theta = (\overline{K} - \underline{K})/\overline{K}$ . The collateral cost  $\lambda$  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	ı	
	Bin Size $= 100$	Bin Size $= 250$	Bin Size $= 500$
Estimates	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
D 11 (D)	0 7004	2 724	0.0704
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 $(\theta)$	47.14%	46.52%	45.05%
(*)	(2.83%)	(1.88%)	(2.73%)
Collateral cost $(\lambda)$	10.71%	10.37%	9.60%
	(1.64%)	(1.13%)	(1.39%)

	COVID	EIDL	
	Bin Size $= 100$	Bin Size $= 250$	Bin Size $= 500$
Estimates	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
11101811101 (11)	(5307.12)	(5343.94)	(3635.17)
Distortion ratio $(\theta)$	37.50%	37.50%	37.50%
Distortion ratio (t)	(8.87%)	(8.36%)	(5.03%)
Collateral cost $(\lambda)$	6.23%	6.23%	6.23%
	(3.04%)	(3.12%)	(2.18%)

## Appendix E Effect of collateral on charge-off rates

We examine whether borrowers become less likely to default when they borrow secured loans by estimating the following regression model in the 2000-2020 sample of business disaster loans:

$$Charge-off_i = \beta_1 Secured_i + \beta_2 log(loan\ amount)_i + \tau_t + \tau_s + \varepsilon_i.$$
(44)

The dependent variable,  $Charge-off_i$ , is the charge-off status of the loan.  $Secured_i$  is a dummy variable that equals one if the loan is secured.  $\beta_1$ , the coefficient of the  $Secured_i$  dummy captures the impact of pledging collateral on the borrowing firm's charge-off probability. Table IA5 presents the results. Secured loans are four percentage points less likely to be charged-off compared to unsecured loans.

To explore the dynamics of loan default, we also use the Cox proportional-hazards model to examine if borrowers are less likely to default when they borrow secured loans:

$$Charge-off_i(t) = Charge-off_0(t) \times exp(\beta_1 Secured_i + \beta_2 log(loan\ amount)_i + \varepsilon_i). \tag{45}$$

The dependent variable,  $Charge-off_i(t)$ , is the charge-off status of the loan.  $Charge-off_0(t)$  captures the baseline hazard if both independent variables are equal to zero.  $Secured_i$  is a dummy variable that equals one if the loan is secured.  $HR_1 = exp(\beta_1)$ , the hazard ratio of the  $Secured_i$  captures the impact of pledging collateral on the borrowing firm's charge-off likelihood.  $HR_1 = 1$  indicates secured lending has no effects on charge-off;  $HR_1 > 1$  indicates secured lending increases charge-off hazard;  $HR_1 < 1$  indicates secured lending reduces charge-off hazard. Table IA6 presents the results. Secured loans are around 40% or seven percentage points less likely to be charged-off compared to unsecured loans.

Table IA5: Charge-off probability

This table presents estimates of the loan level effects of pledging collateral on the disaster loan charge-off probability between 2000 and 2020. The dependent variable charge-off is the dummy variable that indicates whether the loan is paid-in-full or charge-off as in 2021: 1 is charge-off, and 0 is paid-in full. Secured is the dummy variable that indicates whether the loan is a secured loan or an unsecured loan: 1 is secured, and 0 is unsecured. log(loan amount) is calculated as the log of the approved disaster loan amount. Column (1) reports the results without fixed effects. Column (2) reports results with approval year fixed effects. Column (3) reports results with state fixed effects. Column (4) reports results with both approval year and state fixed effects. All standard errors are clustered both at the approval year level and the state level.

Disaster loans 2000-2020							
Dependent variable:	Charge-off						
	(1)	(2)	(3)	(4)			
Secured	-0.065**	-0.048***	-0.048*	-0.040**			
	(0.030)	(0.016)	(0.023)	(0.015)			
log(loan amount)	0.028**	0.019***	0.025**	0.020***			
,	(0.012)	(0.007)	(0.010)	(0.006)			
Constant	-0.035	0.041	-0.019	0.032			
	(0.103)	(0.061)	(0.089)	(0.059)			
Year fixed effects	No	Yes	No	Yes			
State fixed effects	No	No	Yes	Yes			
Observations	36,350	36,350	36,349	36,349			
Adjusted $R^2$	0.002	0.016	0.025	0.034			

Table IA6: Cox proportional-hazards model

This table presents estimates of the loan level effects of pledging collateral on the disaster loan charge-off hazard between 2000 and 2020. The dependent variable charge-off is the dummy variable that indicates whether the loan is paid-in-full or charge-off as in year t: 1 is charge-off, and 0 is paid-in full. The results presented in the table are the hazard ratios:  $HR_i = \exp(\beta_i)$ . The coefficients  $\beta_i$  are estimated in equation (45).  $HR_i = 1$  indicates independent variable has no effects on charge-off;  $HR_i > 1$  indicates independent variable increases charge-off hazard;  $HR_i < 1$  indicates independent variable reduces charge-off hazard. Secured is the dummy variable that indicates whether the loan is a secured loan or unsecured loan: 1 is secured, and 0 is unsecured.  $\log(\log \alpha)$  amount) is calculated as the log of the approved disaster loan amount. Column (1) reports the results of the full sample. Column (2) reports results for loan amounts between \$10,000 below the collateral threshold. Column (3) reports results for loan amounts between \$5,000 below the collateral threshold and \$5,000 above the collateral threshold. All standard errors are clustered at the state level.

Disaster loans 2000-2020						
Coefficients:	s: Hazard ratio					
	$\overline{(1)}$	(2)	(3)			
	Full sample	$[\underline{K}-10,000, \underline{K}+10,000]$	$[\underline{K}-5,000, \underline{K}+5,000]$			
Secured	0.635***	0.597***	0.617***			
	(0.035)	(0.050)	(0.054)			
log(loan amount)	1.097***	1.539***	1.716***			
	(0.024)	(0.138)	(0.281)			
Observations	57,579	18,943	12,139			

# Appendix F Processing time around collateral thresholds

Table IA7: Loan processing days below and above collateral thresholds

This table presents the average loan processing days near collateral thresholds for different BPDL sub-samples between 2003 and 2020. The loan processing days are estimated as the number of days between the date a loan is approved by SBA and the date a related disaster is announced. Panel A presents the mean of loan processing days and Panel B presents the median of loan processing days. Column (1) reports the average loan processing days below the collateral threshold. Column (2) reports the average loan processing days above the collateral threshold.

Panel A: Average	<b>BPDL</b>	processing	days (	(Mean)	)
------------------	-------------	------------	--------	--------	---

Years	(1) Below threshold: $[\underline{K}$ -5,000, $\underline{K}]$	(2) Above threshold: ( $\underline{K}$ , $\underline{K}$ +5,000]
2003 to 2007	139.49	148.50
2008 to 2013	96.65	92.10
2014 to 2020	111.38	109.91

Panel B: Average BPDL processing days (Median)

Years	(1) Below threshold: $[\underline{K}$ -5,000, $\underline{K}]$	(2) Above threshold: $(\underline{K}, \underline{K}+5,000]$
2003 to 2007	136	145
2008 to 2013	76	77
2014 to 2020	89	91