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 in which 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.

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1 Introduction

Collateral is a fundamental building block of financial markets and affects economic growth and financial stability. Despite a significant amount of research that has been conducted on the benefits of collateral in mitigating conflicts of interest and enforcement frictions in lending (DeMarzo, 2019), the cost of pledging collateral has received less attention. The conventional wisdom is that the cost of pledging collateral is low in comparison to the benefits it provides to protect lenders and allow 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, or 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.[1] Firms could also lose financial flexibility because high asset encumbrance makes it harder to access liquidity through an asset sale (Donaldson, Gromb, and Piacentino, 2019) or obtain secured or unsecured financing (Rampini and Viswanathan, 2010; Donaldson, Gromb, and Piacentino, 2020).[2] Finally, firms in financial distress may lose flexibility 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 evidence on the economic magnitude of collateral costs for firms and their impact on financing decisions.

The lack of empirical evidence on the cost of pledging collateral could be partly due to the fact

[1] In a series of interviews with practitioners conducted by (Mann, 1997, p. 665), a CFO attributes his company's aversion to secured debt to "a question of flexibility and having to deal with it." He further explains that "in a secured loan, you just don't have the same flexibility of dealing with your properties as if you owned them unencumbered."

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

that it is a shadow cost, which is not explicitly recorded in 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 bunching at the collateral threshold, as shown in Figure 1. This pattern provides prima facie evidence that firms are averse to pledging collateral and would rather accept a smaller loan than they would naturally desire. Furthermore, bunching moves when the SBA changes the collateral threshold, suggesting that this pattern is unlikely the result of a behavioral tendency to cluster at a round number. Our empirical strategy uses the extent of bunching to infer the collateral cost: if many firms bunch at the threshold, the collateral cost is likely to be high; if only a few firms bunch, the collateral cost is likely to be low.

We develop a simple model to formalize the intuition and guide the estimation process. The model assumes that firms have different desired loan sizes, which follow a smooth distribution in the absence of regulatory distortion. The collateral requirement creates a discontinuity in firms' payoffs. Firms respond to the collateral threshold differently based on the distance between their desired loan size and the threshold. Firms just above the threshold choose to bunch at the threshold to avoid pledging collateral, while firms far away from the threshold choose not to bunch as it would require them to forgo too much funding and thus reduce their profits. Finally, a marginal firm exists that is indifferent between bunching and not bunching. The loan amount that the marginal firm is willing to give up to avoid pledging collateral can reveal the shadow cost of collateral.

We utilize the bunching estimation technique, which is commonly used in the public finance and labor literature (Saez, 2010; Kleven and Waseem, 2013; Chetty, Friedman, Olsen, and Pistaferri, 2011), to estimate the loan amount of the marginal firm. Firms bunching at the collateral threshold creates an excess mass of loans at the threshold and a missing mass of loans above it. The desired loan size of the marginal firm is identified when the missing mass equals the excess mass. By applying this technique to the Business Physical Disaster Loan (BPDL) program and the Economic Injury Disaster Loan (EIDL) program, we find that the collateral cost for the sample firms is equivalent to an interest rate of 4.4%. In terms of dollar value, the shadow cost of collateral amounts to approximately $1,100 per year for a loan of $25,000. The estimated collateral cost is significantly larger than the direct cost associated with pledging collateral, such as the fee to file a lien and is in the same order of magnitude as the secured–unsecured interest spreads faced by small firms.

We further investigate how the collateral cost varies across different types of collateral. 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 take advantage of a unique change in the collateral requirements of the EIDL program during the COVID-19 pandemic, which allowed floating assets to be pledged as collateral. We find that the estimated collateral cost decreases by around 22% after the change. This finding is consistent with the hypothesis that firms are more averse to pledging fixed assets than floating assets because fixed assets are typically less fungible and are essential to firms' operations.

Next, we investigate the sources of the collateral costs. Despite the lack of detailed information on firms' balance sheets, we provide some suggestive evidence for flexibility-based theories by exploring variations in secured creditor rights across states and over time. We posit that firms are less likely to lose flexibility in a secured transaction if the state collateral laws give weaker rights to secured creditors. As a result, firms may be less averse to borrowing secured loans. To test this hypothesis, we take advantage of 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.

The second channel for collateral costs is the opportunity cost of not being able to use the collateral for other purposes, such as obtaining a secured loan from the private sector. While this consideration can be broadly interpreted as a loss of financial flexibility (Rampini and Viswanathan, 2010), it is distinct from theories that propose pledging collateral has intrinsic inconvenience. We show that the magnitude of this channel depends on whether firms can obtain more favorable loan terms from private lenders than those offered by the SBA. If the current or future interest rates offered by private lenders are below the interest rate offered by the SBA, the value of preserving collateral is high. However, if the private interest rate remains above the interest rate offered by the SBA, the value of preserving collateral is low. Given that participants in the SBA disaster lending programs generally lack access to private financing and the interest rates of the SBA disaster lending programs are highly subsidized, the estimated collateral cost is more likely to reflect intrinsic inconvenience, rather than the option value of preserving collateral.

The third channel for collateral costs is the transaction costs associated with pledging collateral, such as the fees to file a lien or conduct an appraisal. While these transaction costs contribute to the total costs of pledging collateral, they are unlikely to be a major factor. Firstly, the fee for filing a lien is an order of magnitude smaller than the total collateral cost for a typical bunching loan. Additionally, appraisals are rare as the SBA provides free inspections in most cases. Finally, there is no significant difference in processing time between secured and unsecured loans in the disaster loan program.

We consider alternative explanations for the bunching pattern. One potential explanation is that firms do not have enough collateral to pledge so that they have to take unsecured loans. Although collateral scarcity is a crucial consideration in other settings, a closer examination of the institutional setting suggests it is unlikely to drive our estimated costs. For the BPDL program, repaired or replaced property typically serves as collateral for the loan. For the COVID EIDL program, generally available business assets such as inventory and accounts receivables can be used as collateral. Additionally, the SBA does not require the collateral value to fully cover the loan amount. Instead, it only requires firms to pledge what is available. Finally, we find significant collateral costs in industries in which collateral is widely available such as agriculture and manufacturing, further supporting the hypothesis that scarcity of collateral is not driving our results.

Another alternative explanation for the bunching pattern is that some business owners may not understand the collateral agreement and try to avoid it. Although it is difficult to completely rule out this explanation, we note that the SBA's security agreement is quite standard. A related concern is that some business owners may not have a clear idea of how much to borrow, so they choose a salient number mentioned in the SBA rule. However, this alternative explanation is unlikely to apply to the BPDL program as the verified loss incurred in the disaster serves as a natural benchmark for the borrowing amount.

We conduct various robustness checks to validate our results. Our analysis utilizes the bunching estimator, which assumes that the counterfactual distribution of loan sizes is smooth in the absence of the 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. Our results are also robust to alternative specifications of the bunching estimator, such as varying the degree of polynomials and bin sizes. We also assess the robustness of our results to different substitution margins and find that the order of magnitude of the collateral costs remains the same. Furthermore, we extend our analysis by modeling default, providing insight into how the collateral costs can be decomposed into components incurred in operation, in distress, and during default.

Our study sheds light on the shadow cost of collateral, which is otherwise difficult to observe. However, there are a few caveats to consider. 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—collateral cost is a crucial component of firms' secured borrowing decisions—is likely to remain valid.

The second caveat is that the lender is a government agency, which may not pursue the collateral with the same vigor as private lenders. This may result in an underestimation of the true collateral cost. However, it is worth noting that the SBA disaster loan program is not a grant and the security agreement and liquidation procedures are similar to those of private lenders.[3] A related concern is that some business owners may be reluctant to deal with a government agency because they engage in tax evasion (Gordon and Slemrod, 2000). This may result in an overestimation of the true collateral cost. Nevertheless, this concern is less severe for the BPDL and regular EIDL programs because the SBA takes fixed assets as collateral and does not monitor firms' bank accounts or accounting statements.

The third caveat is that firms may value flexibility more during natural disasters than in normal times. However, note that the estimated collateral costs reflect the average costs over the whole life span of the loan, so short-term variation in the value of flexibility may not have a first order impact on the estimates. A related concern is that collateral might be damaged or destroyed during natural disasters so it has a lower value than that in normal times. However, note that the value of collateral is conceptually different from the cost of pledging collateral: the collateral value is about the worth of the ownership, while the collateral cost is about the worth of the control rights. Furthermore, the collateral that firms pledge is the repaired or replaced property, rather than the damaged one.

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.

The fact that pledging collateral involves a substantial cost provides a new perspective on firm capital structure decisions. Since the seminal work of Myers and Majluf (1984), it is often believed that a pecking order exists between collateralized and uncollateralized borrowing: firms should first issue collateralized debt and then, after exhausting such claims, issue uncollateralized

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

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.

A substantial collateral cost also has important implications 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, our findings suggest two potential downsides associated with such requirements. First, requiring collateral would impose substantial costs on participating firms as they lose operational and financial flexibility. Second, because firms may strategically respond to the collateral threshold, such requirements may significantly reduce the program's take-up. The optimal program requires carefully weighing the benefit of collateral with these costs.

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 interest costs 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 solving this puzzle.

Our work is closely related to Benmelech, Kumar, and Rajan (2022), who find that secured debt issuance of investment-grade firms is uncorrelated with the spread between secured and unsecured debt. 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 et al. (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, using an instrumental variables (IV) estimation, that collateral reduces default rates by 35%. 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, Lopez-de Silanes, Shleifer, and Vishny (1998) and the subsequent literature, such as Levine (1998), Qian and Strahan (2007), Campello and Larrain (2016), and Calomiris et al. (2017), suggest that protecting creditor rights can foster financial development and improve financial access. 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 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 United States 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 macroeconomic dynamics (Kiyotaki and Moore, 1997; Bernanke, Gertler, and Gilchrist, 1999; Mendoza, 2010). This literature assumes that firms incur no cost to pledge collateral, so the collateral constraint is always binding. We introduce the collateral trade-off to the standard model of Kiyotaki and Moore (1997) and show that it can generate rich implications for the financial accelerator mechanism. This article also speaks to the extensive empirical research that has been devoted to investigating the magnitude of the financial accelerator mechanism (Lian and Ma, 2021; Catherine et al., 2022). 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. While the low sensitivity is typically rationalized by low asset 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 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 have been installed. Recent studies show that the pre-crisis banking relationship, bank market power, and racial biases of loan officers could significantly affect 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 mortgages (DeFusco and Paciorek, 2017; DeFusco, Johnson, and Mondragon, 2020), real estate (Anagol, Balasubramaniam, Ramadorai, and Uettwiller, 2022), 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 disburses the loans without the involvement of private banks. This feature allows us to hold the supply side constant when analyzing the demand.

2 Institutional Background and Data

2.1 SBA Disaster Loans

The U.S. Small Business Administration (SBA) provides low-interest, long-term loans to businesses and private nonprofits after a disaster. This SBA assistance is available only to small businesses when SBA determines they are unable to obtain credit elsewhere. There are two major loan programs: Business Physical Disaster Loans (BPDL) and Economic Injury Disaster Loans (EIDL).

Business Physical Disaster Loans (BPDL)

The first program, the Business Physical Disaster Loans (BPDL), assists businesses that experienced physical damages in declared disaster areas by covering the verifiable and uninsured portion of damages to their real estate, machinery, equipment, and fixtures. Firms are required to provide available collateral such as a lien on the repaired or replaced property unless the loan amount is below a certain threshold ($25,000 as of 2020). Furthermore, the SBA holds the interest rate fixed (usually around 4%) regardless of the loan size or collateral. Appendix A discusses the application process in more detail.

Funds of the disaster loan program are disbursed by the SBA itself. Firms can apply directly to SBA at no cost. This feature is different from other small business lending programs, such as the SBA 7(a) Program and the Paycheck Protection Program, which disburse funds through private lending institutions. Therefore, the concern that private lending institutions' market power or racial biases may affect firms' access to government lending programs (Bachas et al., 2021; Chernenko and Scharfstein, 2021) is less applicable in this setting.

If the requested loan size exceeds the collateral threshold, the SBA disburses the amount below the collateral threshold to the borrower immediately and then releases the remaining funds once all collateral is appropriately secured. Therefore, pledging collateral does not slow disbursement for the portion below the collateral threshold.

Economic Injury Disaster Loans (EIDL)

The second SBA disaster loan program provides Economic Injury Disaster Loans (EIDL). Unlike the BPDL program, the EIDL program assists businesses affected by declared disasters to meet their working capital needs, such as health care benefits, rent, and utilities. The regular EIDL program has features similar to 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 or collateral; and (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 are required to pledge collateral to secure the loan. The BPDL and regular EIDL use a fixed lien, which requires fixed assets such as real estate, machinery, equipment, and fixtures as collateral. In contrast, the COVID EIDL program allows firms to post floating assets, such as inventory and accounts receivables, as collateral.

The SBA typically does not require the collateral value to cover the full loan amount. Instead, the SBA requires the applicant to pledge the collateral SBA has determined is available.[4] The SBA will consider that collateral sufficient if an applicant pledges the collateral available to them. For the BPDL program, firms typically use the replaced or repaired property as collateral. Even if a property is damaged completely in a natural disaster, the firm can use the disaster loan to replace the damaged property and use it as collateral. For the COVID EIDL program, working capital is used as collateral, which is generally available.

To pledge assets as collateral, firms need to sign a security agreement, which is a document that provides a lender with a security interest in a specified asset or property.[5] The security agreement 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).

The security agreement may restrict firms' operational and financial flexibility. Consider an agricultural business that has taken a secured loan with a blanket lien on its assets. If the

[4]See page 122 of Small Business Administration Standard Operating Procedure, Section 50, NO.30, REV 9.

[5]See https://www.sba.gov/sites/default/files/2017-11/tools_sbf_finasst1059_0.pdf for an example of the SBA security agreement. See also Internet Appendix Figures IA1, IA2, and IA3, for examples of SBA and private security agreements.

firm wants to trade in its old equipment for a new one with an equipment dealer, the firm must contact its secured creditor to release the security interest. If the firm fails to do so, the creditor's security interest will continue in the equipment, which could create issues for the equipment dealer. Furthermore, because the security agreement is in the firm's public credit record, the equipment dealer may become less willing to deal with the firm in the first place. The security agreement may also restrict firms' financial flexibility. If the agricultural business is having troubles to pay its suppliers, it cannot sell its equipment to raise cash unless it obtains 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 bank account and commodity market transactions account would be subject to the secured creditor's discretion to withdraw, which may affect the firm's working capital and risk management in the commodity markets.

In addition to pledging business assets as collateral, the SBA may require a personal guarantee for loans above $200,000. We do not use the $200,000 threshold in this study because our focus is the cost of pledging business assets. Therefore, we restrict our sample to loans below $200,000. Note that there is some ambiguity in the SBA requirement of personal guarantee for loans below $200,000. The SBA Standard Operating Procedure mentions that "loans of $200,000 or less will not require the owner of the business to use their primary residence as collateral if it is determined the owner has other assets of equal quality and a value equal to or greater than the amount of the loan" on page 123. This statement seems to suggest that business owners may need to pledge their primary residence if they do not have sufficient business assets as collateral. However, it is unclear how often the SBA does so in practice because the SBA typically does not require the collateral value of business assets to cover the full loan amount. Evidence from examining SBA disaster loan security agreements with firms suggests personal assets are rarely pledged for loans below $200,000. Note that the CARES Act provides more clarity on this issue by explicitly waiving the requirement to obtain a personal guarantee on disaster loans of $200,000 or less.

2.3 Data

We obtain disaster loan data from the SBA website and from filing Freedom of Information Act (FOIA) requests. 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. At least one of the programs covers 88% of U.S. ZIP codes. Table 1 provides the summary statistics of our sample. The median loan amounts are $78,850, $30,200, and $26,000 for BPDLs, regular EIDLs, and COVID EIDLs, respectively. The total number of loans is around 17,000 for the BPDLs, 11,000 for regular EIDLs, and 3,604,000 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% of total loans. The whole sample covers more than 3.6 million 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 U.S. Federal Register. The SBA announces a single fixed interest rate for all businesses in one disaster. The majority of the regular disaster loans (58.54% for BPDLs and 62.36% for regular EIDLs) are offered at 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 1 shows the loan size distribution of BPDLs in 2014–2020.[6] We observe a sharp spike at the $25,000 collateral threshold. The spike at $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 these earlier samples. The fact that bunching moves with the collateral threshold provides compelling evidence that bunching is not driven by a behavioral

[6]Note that a small fraction of the BPDLs (general disaster BPDLs) changed 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.

tendency to cluster at a round number. Instead, firms are concerned about the cost of pledging collateral and behave strategically to avoid it.

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 disaster losses. 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 disaster losses along with the loan amounts of BPDLs. Indeed, we do not see any bunching in the distribution of the verified loss at the collateral thresholds.

These bunching patterns provide visual evidence that firms are averse to pledging collateral. Intuitively, more bunching at the collateral threshold implies a greater collateral cost perceived by firms. 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 programs and guide our estimation. Suppose there is a set of firms, which borrow K unit of capital to produce $F(K|A)$ unit of output. A is productivity, which 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. We define Z as the desired loan amount in the absence of the collateral requirement:

$$Z(A) = \arg\max_{K} = F(K|A) - RK. \tag{1}$$

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, as shown in Figure 2. Z is heterogeneous across firms, which follows a distribution f_0. Because there is a one-to-one mapping between Z and A for production functions, we use Z to index the firms in the following discussion. We define $\Pi(K|Z)$ as the profit when a firm with a natural loan size Z chooses a loan K,

$$\Pi(K|Z) \equiv F(K|Z) - RK. \tag{2}$$

Suppose firms now face a collateral requirement if their loan size K exceeds a threshold $\underline{K}$. Firms incur a cost of λZ when pledging collateral. We define the collateral cost as proportional to the loan size so that λ can be intuitively interpreted as a shadow interest rate. We scale the collateral cost with the undistorted loan size to capture the idea that the dollar value of collateral cost should be different for different sized firms. We discuss the robustness of our results to this assumption in Section 4.5.3. Note 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' problem in the presence of the collateral requirement is given by

$$\max_K \Pi(K|Z) - \lambda Z \mathbb{1}_{K>\underline{K}}. \tag{3}$$

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 $Z = \overline{K}$. Firms' optimal choices are given by

$$K^* = \begin{cases} \underline{K} & \text{if } Z \in [\underline{K}, \overline{K}] \\ Z & \text{if } Z \notin [\underline{K}, \overline{K}]. \end{cases} \tag{4}$$

The indifference condition of the marginal buncher is given by

$$\lambda Z = \Pi(\overline{K}|\overline{K}) - \Pi(\underline{K}|\overline{K}). \tag{5}$$

The indifference condition of the marginal buncher allows us to infer the collateral cost from the profit distortion of the marginal buncher.

Suppose the production function is Cobb-Douglas, $F(K|A) = AK^{\alpha}$. Using the indifference condition (5), we can derive the collateral cost as:

$$\lambda_1 = \left(\frac{1}{\alpha}(1 - (1-\theta)^{\alpha}) - \theta\right) R. \tag{6}$$

The Cobb-Douglas production function assumes a constant return to scale, which may be restrictive. To relax this assumption, we use a more general production function, $F(K|A) = AK^{\frac{\alpha\nu}{1-(1-\alpha)\nu}}$, where $\nu < 1$ indicates a decreasing return to scale.[7] Using the indifference condition (5), we can derive the collateral cost as:

$$\lambda_2 = \left(\frac{1-(1-\alpha)\nu}{\alpha\nu}(1 - (1-\theta)^{\frac{\alpha\nu}{1-(1-\alpha)\nu}}) - \theta\right) R. \tag{7}$$

In the following estimation, we will present results based on both production functions, with λ_2 being our preferred specification.

[7]The production function 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 $Y \propto K^{\frac{\alpha\nu}{1-(1-\alpha)\nu}}$.

4 Empirical Analysis

4.1 Bunching estimation

Section 3 shows the critical parameter to estimate is the loan size of the marginal buncher ($\overline{K}$). For this purpose, we use the bunching estimation approach developed by Kleven and Waseem (2013). Specifically, the collateral threshold induces firms whose preferred loan size in $[\underline{K}, \overline{K}]$ to bunch at the threshold, $\underline{K}$. Therefore, the actual probability density function, $f(K)$, should display some excess mass at the threshold relative to the smooth counterfactual density function, $f_0(K)$. We define the excess mass as

$$B \equiv \int_{K_L}^{\underline{K}} (f(K) - f_0(K))dK, \tag{8}$$

where K_L is set to $\underline{K}$.[8]

Since firms whose preferred loan size in $[\underline{K}, \overline{K}]$ choose to bunch at $\underline{K}$, there is also some missing mass above the threshold, which is defined as

$$M(\overline{K}) \equiv \int_{\underline{K}}^{\overline{K}} (f_0(K) - f(K))dK. \tag{9}$$

The bunching mass should equal the missing mass:

$$B = M(\overline{K}). \tag{10}$$

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

The above specification implies that the abnormal mass at the collateral threshold comes from the right, that is, the bunching firms are those who want to borrow more in the absence of the collateral requirements. One may wonder whether the bunching mass could come from the left, that is, firms which want to borrow less. Note that there is no benefit of pledging collateral in our

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

setting: firms do not get lower interest rates or preferential loan terms if they pledge collateral. Therefore, there is no incentive to borrow more than what a firm would naturally prefer. Another possible argument for bunching from the left is that firms may want to take a loan as large as possible given the subsidized interest rate. However, this argument only means that firms want to borrow more relative to a counterfactual in which the interest rate is higher. It does not mean that the collateral requirement makes firms want to borrow more. Moreover, in the model presented in Section 3, the incentive to take a loan as large as possible given the subsidized interest rate is already captured by $Z(R)$, the ideal borrowing amount in the absence of collateral requirement. The bunching pattern that we use to estimate the collateral cost is the distortion in loan size relative to this ideal amount.

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

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

$$N_j = \sum_{p=0}^{P} \beta_p (K_j)^p + \sum_{i=K_L}^{K_U} \gamma_i \cdot \mathbb{1}(K_j = i) + \sum_{r \in \{5000, 10000\}} \delta_r \mathbb{1}(K_j / r \in \mathbb{N}) + \epsilon_j, \tag{11}$$

where N_j denotes the number of observations in bin j. K_j is the loan amount within bin j using the midpoint of the bin. P is the degree of the polynomial, which we set as five in our baseline. $[K_L, K_U]$ is the excluded region. In our data, loan sizes corresponding to round numbers such as \$5,000 and \$10,000 tend to appear more frequently than other values. Since the collateral thresholds are located at salient round numbers, using the total excess mass at the collateral threshold would overstate the strategic response to the collateral requirements. We follow Kleven and Waseem (2013) to include a set of dummies, δ_r, for multiples of the round numbers to absorb the round-number bunching.[9] 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 (11) subtracting the contribution of the exclusion region dummies:

$$\hat{N}_j = \sum_{p=0}^{P} \hat{\beta}_p (K_j)^p + \sum_{r \in \{5000, 10000\}} \hat{\delta}_r \mathbb{1}(K_j / r \in \mathbb{N}). \tag{12}$$

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:

$$\hat{B} = \frac{1}{N} \sum_{j=K_L}^{\underline{K}} (N_j - \hat{N}_j), \tag{13}$$

$$\hat{M} = \frac{1}{N} \sum_{j>\underline{K}}^{K_U} (\hat{N}_j - N_j), \tag{14}$$

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

$$\hat{B} = \hat{M}(K_U). \tag{15}$$

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

The value of K_U that satisfies the above convergence condition is the marginal buncher, $\overline{K}$. We then plug the marginal buncher into equation (6) and (7) to solve the collateral costs. The interest rate, R, is set to the observed gross interest rates of the loans.

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 (11). Then, for each generated data sample, we estimate its marginal buncher $\overline{K}$, distortion ratio θ, and collateral cost λ with the same approach as above. Finally, the standard error is measured as the standard deviation of the 1,000 estimates.

The validity of the bunching estimate relies on several assumptions. First, the counterfactual distribution would be smooth in the absence of the collateral threshold. It effectively means that there are no other policies at the threshold that would induce firms to bunch. Second, other loan terms do not change discontinuously at the collateral threshold. We verify both assumptions are indeed true by carefully examining the SBA rules. Third, the counterfactual distribution can be approximated by a polynomial. Blomquist et al. (2021) argue that when the counterfactual distribution is unrestricted, bunching itself is insufficient to identify the underlying parameters. In other words, certain restrictions have to be placed on the functional form of the counterfactual distribution. In the estimation, we follow Kleven and Waseem (2013) to use a flexible polynomial to approximate the counterfactual distribution. We view it as rather weak restriction because any smooth function can be approximated by a polynomial of certain degree through a Taylor expansion. Nevertheless, we vary the degree of polynomials to verify our results are not sensitive to the choice of a particular polynomial degree.

Another caveat of the bunching estimation is that it captures intensive margin responses, but not the extensive margin responses, such as borrowers forgoing a SBA loan completely and switching to a private lender. However, this may not be a major issue in our setting because the SBA typically lends to firms that cannot obtain credit elsewhere. The data also suggest the extent of extensive responses is likely to be quite small.[10] Nevertheless, we carry out sensitivity analyses

[10]Note that we can empirically evaluate the extent of extensive responses because our setting features changes in the threshold. For instance, the collateral threshold increased from \$14,000 to \$25,000 in 2014. If there are significant

with respect to the polynomial degree P following Kleven and Waseem (2013), which notes that the extensive margin bias will mainly enter via functional form misspecification.

4.2 Estimation results

4.2.1 Baseline estimates

Figure 4 provides the visualization of the bunching estimates in the BPDL data. Each panel plots the loan size distribution for each subsample. 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 (12). 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. Note that the region between K_L and K_U has a positive mass. 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).

Table 2 presents the bunching estimates in the BPDL 2014–2020 sample, with a collateral threshold of \$25,000. Each column uses a different degree of polynomials. We find around 10% of firms bunch at the collateral threshold. The marginal firm's undistorted loan amount, $\overline{K}$, is around \$43,000, which implies a distortion ratio of around 42%. The estimates are statistically significant and are robust to the specification of the counterfactual distribution.

extensive responses, we would expect the densities in the \$22,500 to \$24,500 interval to increase substantially after the change. Instead, we find the densities are quite similar before and after the threshold change, changing from 4.67% to 5.17%. Note that we exclude the region below marginal buncher \$22,000 because it may be affected by intensive responses to the \$14,000 threshold.

Given the bunching estimates, we then use equation (6) and (7) to translate the distortion in loan size to an estimate of the collateral cost. The values of the collateral costs depend on the functional form of the production function. We start with the simplest Cobb-Douglas production function $F(K|A) = AK^{\alpha}$ with $\alpha = \frac{1}{3}$. The implied collateral cost is around 8% of the loan value annually. Note that this estimate relies on a strong assumption that the production function exhibits constant returns to scale. To relax this assumption, we consider a more general production $F(K|A) = AK^{\frac{\alpha\nu}{1-(1-\alpha)\nu}}$, where the shape of the return to scale is given by ν. $\nu < 1$ implies a decreasing return to scale. The literature estimates a value around 0.83 (Veracierto, 2001; Garicano et al., 2016). Using this value to calibrate the production function, the implied collateral cost is around 4.4%. We take this value as our preferred estimate because it uses an empirically founded production function. Table IA1 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 3.18% to 4.61%.

The estimated collateral cost is economically significant. Consider a loan of $25,000; the baseline estimate of 4.4% translates to a dollar cost of $1,100 per year, which is an economically significant cost for the small businesses in our sample. As a benchmark, the interest spread between secured and unsecured loans is around 7% for small businesses.[11] Therefore, the estimated collateral costs are in the same order of the magnitude as the secured-unsecured interest spreads.

Our estimates are pertinent to small businesses. These firms face greater external financing frictions so pledging collateral and losing flexibility could be particularly costly 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

[11]The average interest rate of secured small business loans is around 7% based on the RateWatch data from 2001 to 2020. The interest rate of unsecured small business loans for an average credit score borrower is around 14% based on the quote from American Express as of Oct 28, 2021 (https://www.americanexpress.com/us/business/business-funding/).

collateralized and uncollateralized borrowing even if their collateral cost is smaller.

4.2.2 Heterogeneity across collateral type

The cost of pledging collateral may differ depending on the type of collateral requirement. We compare two broad types of collateral: fixed assets and 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 machinery it uses for production. In contrast, floating assets such as account receivables are more fungible and less central to business operations. To test this hypothesis, we exploit a unique change in the collateral requirement in the EIDL program during the COVID-19 pandemic when the SBA changed the collateral requirement to allow firms to post floating assets as collateral. Table 3 presents the estimates in the COVID EIDL sample. We find that the implied shadow cost of collateral is only around 3.4%, which is significantly lower than the estimates for the BPDLs.

One may worry that the difference in the estimated collateral cost may be driven by 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 Table 3, we find the shadow cost of collateral is around 4.2% for the regular EIDLs, which is consistent with the BPDL estimates in Table 2.[12] 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.

[12]Figures IA4a and IA4b provide the visualization of the bunching estimates in the regular and COVID EIDL data, respectively. COVID EIDLs exhibit stronger round-number bunching, possibly because the uncertainty to assess the actual economic damage of the disaster. The flexible round-number dummies included in our estimation successfully capture the round number bunching in this sample, as shown by the spikes at round numbers in the counterfactual distribution. The excess mass at the $25,000 collateral threshold in the actual distribution is significantly larger than the predicted value due to round-number bunching, suggesting that the collateral threshold creates additional bunching mass. Note that the excess mass at $10,000 appears to be quite significant as well. This is likely due to the provision of the Emergency EIDL Grant, which allows firms to request an advance on the loan of up to $10,000. Our results are robust if we restrict sample to loans that are far above $10,000, as shown in Table IA2.

4.3 Sources of collateral costs

The high degree of bunching implies that the cost of pledging collateral is surprisingly high, equivalent to 3%–5% of the loan value annually. What are the underlying sources of the collateral costs? Pinpointing the exact channels are 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 Flexibility

We first provide some suggestive evidence for flexibility-based theories using the variations in secured creditor rights. In particular, we explore the staggered adoption of the Uniform Voidable Transactions Act (UVTA) across different states in the United States. The UVTA was proposed in 2014 as an amendment to the Uniform Fraudulent Transfer Act (UFTA). The UVTA weakens secured creditors' rights by making certain collateral transfer voidable.[13] 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.

Note that UVTA also contains broader changes that may affect all credit transactions. 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." We isolate the effect specific to secured creditor rights by comparing firms with verified losses above and below the collateral threshold. The idea is that firms with verified losses above the collateral threshold will likely face the trade-off of borrowing secured versus unsecured. In contrast, firms with verified losses below the threshold will only borrow unsecured. By using firms with verified losses below the threshold as a control group, we can difference out the effects of broader changes

[13] 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)). As suggested by Forster and Boughman (2015), "creditors with an Article 9 security interest can no longer foreclose on the property and retain it without risking the transfer being avoided."

that affect both secured and unsecured transactions. Note that we do not use the loan size to assign firms into treatment and control groups because firms can strategically choose the loan size to avoid collateral requirements. Using the verified loss to assign firms into treatment and control groups alleviate the endogeneity concern as there is no bunching pattern in the distribution of verified loss, as shown in Figure 2. Because this test requires information on the verified losses, we restrict our sample to the BPDLs.

Table 4 shows the adoption year of the UVTA in 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 secured creditor rights. The sample period is from 2014 to 2020.

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:

$$\textit{Take-up}_{i,t} = \beta_1 \textit{Adoption}_{i,t} \times \textit{Loss>25k}_{i,t} + \beta_2 \textit{Adoption}_{i,t} + \beta_3 \textit{Loss>25k}_{i,t} + \tau_t + \tau_s + \varepsilon_{i,t}. \tag{16}$$

The dependent variable, $\textit{Take-up}_{i,t}$, is defined as the ratio of the loan amount over the verified losses. $\textit{Adoption}_{i,t}$ is a dummy variable that equals one if the state where firm i is located has adopted the UVTA. This dummy captures the law changes that affect both secured and unsecured debt. β_1, the coefficient of the interaction of $\textit{Adoption}_{i,t}$ and the $\textit{Loss>25k}_{i,t}$ dummy captures the impact of the law change on firms that are more likely to borrow secured debt. Table 5 presents the results. Before the law change, the take-up ratio of firms with losses above $25,000 was around 30% lower than firms with losses below $25,000, consistent with our earlier evidence that firms bunch to avoid pledging collateral. 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 the 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 6 presents the estimated collateral costs in the UVTA and UFTA states, respectively. Consistent with the results in Table 5, the collateral cost is significantly lower in the UVTA states in which secured creditor rights are weaker.

4.3.2 Opportunity costs of outside option

Another reason why firms are averse to pledging collateral is that they want to preserve the collateral to secure loans from private lenders. While this consideration can be broadly interpreted as financial flexibility because firms care about the option value of collateral (Rampini and Viswanathan, 2010), it is still different from the theories in which pledging collateral has intrinsic inconvenience.

To study this channel, we introduce 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. We assume the outside option is available now but one could interpret K_s and R_s as discounted values if the outside option is only available in the future. Firms' problem is given by the following:

$$\max_{K,K_s} \Pi(K|Z) = F(K + K_s|A) - RK - R_sK_s - \lambda Z \mathbb{1}_{K>\underline{K} \text{ or } K_s>0}. \tag{17}$$

If $R_s < R$, it is more profitable to take only $\underline{K}$ from the SBA and save the collateral for a private secured loan K_s. However, if $R_s > R$, it is more profitable for firms to max out the subsidized loans by pledging the collateral to the SBA and take $K = \underline{K} + K_s$ from the disaster loan program. Therefore, the value of the outside option depends on whether the private secured borrowing cost R_s is lower than the public one, R.

We note several institutional reasons why this channel may not be a main component of the estimated collateral costs. First, firms participating in the SBA disaster loan programs typically do not have access to external financing. Indeed, we find that firms' tendency to bunch does not vary across regions with different numbers of banks, as shown in Table 7. Second, even if some firms have access to external financing, the secured loan rates that firms can get from the SBA are much lower than those from the private sector. A caveat of this argument is that it is possible that the future private secured loan rates could fall below the current rate from the SBA when firms grow larger and become more credit worthy in the future. In this case, our estimated collateral cost partially reflects the opportunity costs of not being able to borrow from private lenders in the future.

4.3.3 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 $1,100 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. Furthermore, there are typically no fees involved with appraisal because the SBA provides the inspection services free of charge.[14]

In addition to the explicit transaction costs, there could also be implicit costs such as tedious paperwork and delay in disbursement of funds. However, the application forms are the same for loans above and below the collateral threshold, except that firms need to sign a four-page security agreement and provide notations on certificates of title for secured loans. The processing times for secured and unsecured loans around the collateral thresholds are similar.[15] Finally, pledging collateral does not slow the disbursement process because the SBA disburses the amount below the collateral threshold to the borrower immediately and then releases the remaining funds once all collateral is appropriately secured. Overall, the evidence suggests that although transaction

[14]Note that formal appraisals performed by professional, licensed public appraisers are rare, although they may occasionally be deemed appropriate. See page 115 of the SBA Standard Operating Procedure (SOP 50 30 9), Disaster Assistance Program.

[15]See Internet Appendix Table IA3 for the average processing times of loans around the collateral thresholds.

costs contribute to the total costs of pledging collateral, they are unlikely to explain most of the estimated collateral costs.

4.4 Alternative explanations

So far, we show that firms bunch at the collateral threshold to avoid the costs associated with pledging collateral. This section discusses a few alternative explanations for bunching at the collateral threshold.

4.4.1 Collateral scarcity

One alternative explanation is that firms do not have collateral to pledge so that they have to bunch at the collateral threshold. However, a careful examination of the institutional setting suggests that collateral scarcity is unlikely to be a main driving force of bunching in our setting. For the BPDL program, the repaired or replaced property serves as the collateral for the loan. For the COVID EIDL program, broadly available working capital, such as inventory and account receivables, can be used as collateral.

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."[16] Therefore, firms would not be forced to give up a secured loan because of insufficient collateral.

The last piece of evidence comes from the cross-industry heterogeneity. Table 8 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.[17] We find substantial collateral

[16] 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.

[17] 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 a scarcity of collateral is driving our estimates.

4.4.2 Behavioral biases

Another alternative explanation for bunching is that some business owners may not understand the collateral requirements. They borrow at the collateral threshold simply to avoid the hassle. We think this alternative explanation is unlikely to apply to our setting because 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 to explain the implications of the collateral requirement on the SBA disaster loan programs.[18]

A related concern is that business owners may not have a clear idea of how much to borrow. They borrow at the collateral threshold amount because it is a salient number. We argue that this concern is unlikely to apply to the BPDL program, in which 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.

4.5 Extension and Robustness

This section discusses robustness checks on our baseline results. First, we conduct placebo tests on the sample periods 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 introducing alternative substitution margin for borrowers. Finally, we extend the baseline framework by

[18] For instance, see "Beware: That EIDL loan may come with unexpected strings attached" at `https://www.cpabr.com/article-beware-that-eidl-loan`.

explicitly modeling default.

4.5.1 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 IA4. 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.

4.5.2 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 IA5. 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.

4.5.3 Fixed versus 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 then to $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 IA1 presents the results. We find the dollar collateral cost is considerably higher for bigger marginal bunchers. It increases from \$807 to \$1,879 when the marginal buncher increases from \$17,500 to \$43,000. 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.

4.5.4 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 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:

$$\max_{K,K_u} \Pi(K|Z) = A(Z)(K+K_u)^{\alpha} - RK - R_u K_u - \lambda Z \mathbb{1}_{K>\underline{K}}. \tag{18}$$

Note that equation (18) differs from equation (17) because borrowing unsecured loans 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. The results are shown in Table 9. 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.

4.5.5 Model defaults explicitly

Our baseline model does not model defaults explicitly. In this section, we introduce defaults into our model. This extension does not change our baseline estimate of the collateral cost. Instead, it allows us to decompose this cost into three components: the loss of flexibility in operation, the loss of flexibility in financial distress, and the loss of flexibility in default.

Formally, we assume that there are three states of the world, bad, intermediate, and good, which occur with probability, p, q, and $1-p-q$, respectively. In the bad state, the firm always defaults. In the good state, the firm never defaults. In the intermediate state, the firm has a choice whether to default. We assume equity holders may get positive recovery value when the firm defaults, instead of being completely wiped out. This assumption is consistent with the empirical evidence that the absolute priority rule is not always followed (Bharath et al., 2010). Pledging assets as collateral may reduce equity recovery in bankruptcy because it prevents equity holders from fire selling assets before the bankruptcy and gives creditors stronger bargaining power in bankruptcy (Benmelech et al., 2020; Ma et al., 2022). Define κ_s as the equity recovery rate when firms take a secured loan, and κ_u as the equity recovery rate when firms take an unsecured loan. We have $\kappa_u \geq \kappa_s$.

In the intermediate state, equity holders can choose whether to inject additional cash C to the firm to avoid default. If the firm has not pledged its assets as collateral, the recovery rate in default is high so that equity holders would prefer to let the firm fail rather than injecting additional cash, $\kappa_u Z \geq \Pi - C$. However, if the firm has pledged its assets as collateral, the recovery rate in default is low so equity holders prefer to inject cash to avoid costly default, $\Pi - C \geq \kappa_s Z$. To simplify the notation, we define κ^* as the profits after netting the cash injection, per dollar of assets, $\kappa^* = (\Pi - C)/Z$, so $\kappa_u \geq \kappa^* \geq \kappa_s$. The firm's ex-ante optimization is given by

$$\begin{aligned} \max_K \mathbb{1}_{K>\underline{K}} &\left[(1-q-p)(\Pi(K|Z)-\rho Z)+(q\kappa^*+p\kappa_s)Z\right] \\ &+\mathbb{1}_{K\leq\underline{K}}\left[(1-q-p)\Pi(K|Z)+(q+p)\kappa_u)Z\right]. \end{aligned} \tag{19}$$

where ρ is the collateral cost when the firm is in operation.

The indifference condition of the marginal firm is given by

$$\Pi(\overline{K}|\overline{K}) - \Pi(\underline{K}|\overline{K}) = \left(\rho + \frac{q}{1-q-p}(\kappa_u - \kappa^*) + \frac{p}{1-q-p}(\kappa_u - \kappa_s)\right) Z = \lambda Z, \tag{20}$$

where $\kappa_u - \kappa^* \geq 0$ is the difference in returns between not defaulting and defaulting in the intermediate state. Comparing the above equation with the indifference condition of the baseline model, equation (5), we can see that the λ parameter estimated from the bunching estimation contains three types of collateral costs: (1) loss of flexibility in operation, ρ, (2) loss of strategic default value in distress, $\kappa_u - \kappa^* \geq 0$, and (3) reduced recovery rates in default, $\kappa_u - \kappa_s \geq 0$.

To evaluate the magnitude of these components, we calibrate $p + q$, the probability of default when borrow unsecured debt, to 24% according to Government Accountability Office (GAO) statistics.[19] We then calibrate the reduction in charge-off rates q due to pledging collateral to be 9% by fitting a Cox proportional-hazards model to the charge-off status of the loans in the SBA data.[20] Calibrating equity recovery rates is difficult because of a lack of data. Therefore, we consider a reasonable range of 1%-10% using the estimates from Bharath et al. (2010) and Kim (2018). Note that the literature does not provide estimates on how equity recovery rates vary with the usage of secured debt, so we consider the upper bound of this effect by assuming $\kappa_s = \kappa^* = 0$. We assume the total collateral cost is 4.37% based on the estimate of Table 2 and decompose it into three components according to equation (20). Table IA6 presents the results. We find the collateral cost in default due to the changes in equity recovery rates ranges from 0.20% to 1.97%, and the loss of strategic default value in distress ranges from 0.12% to 1.18%. These estimates suggest that the cost of flexibility in financial distress could be substantial for the small businesses in our sample.

[19] See page 14, "Small Business Administration: Physical Disaster Loan Performance Before and After Changes in Statutory Collateral Requirements."

[20] We find secured loans have a 37.5% lower hazard rate, which results in a 9% reduction in the charge-off rate. See Internet Appendix IA7 for more detail.

5 Implications of Collateral Costs

This section discusses the implications of collateral costs for capital structure decisions, financial accelerator mechanisms, and the design of government lending programs.

5.1 Capital structure decisions

Our results have important implications on the role of collateral in capital structure decisions. Since the influential work by Myers and Majluf (1984), it is often believed that there is 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 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 implications for macrofinance studies. A large body of literature following the seminal work of Kiyotaki and Moore (1997) shows that the 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. The details of the setup and equilibrium dynamics are presented in Appendix B. The key difference is that the equilibrium quantity of secured borrowing now depends on the trade-off between the net investment return μ and the collateral cost λ:

$$B_t = \frac{1-\delta}{R} q_{t+1} K_t \mathbb{1}_{\mu_t > \lambda}, \tag{21}$$

where B is the quantity of secured borrowing, R is the discount rate, q is the price of the capital, and K is the quantity of capital of borrowers. When the investment return μ exceeds the collateral cost λ, the collateral constraint is binding and the equilibrium borrowing equals the collateral value, $\frac{1-\delta}{R} q_{t+1} K_t$. When the investment return μ is below the collateral cost λ, the collateral constraint is slack and the equilibrium borrowing drops to zero. In comparison, in the original Kiyotaki and Moore (1997) model, the collateral constraint is always binding and the equilibrium borrowing always equals the collateral value. We examine the impact of a shock to the productivity of the borrowers. Two new patterns emerge.

State-dependency. The collateral trade-off makes the impulse responses state-dependent. The solid line in Figure 5 shows the impulse responses of borrowers' capital 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, a temporary productivity shock leads to a large and persistent drop in the price and quantity of capital. The financial amplification comes from the fact that, on top of the direct productivity shock, the depreciation in collateral prices further reduces borrowers' net worth. Because the collateral 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 capital 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., 2022), 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. (2022) 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 the collateral trade-off generates a new amplification mechanism in which borrowers endogenously reduce the borrowing amount below the debt capacity. We compare the impulse response of borrowers' 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 borrowers' 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, $\mu_t < \lambda$, borrowers find it too costly to borrow collateralized debt. As a result, borrowers' 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, 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 (4). ℓ is the charge-off rate for uncollateralized loans. The collateral requirement can lower the charge-off rate by β fraction. However, it imposes a shadow cost λZ on firms. Furthermore, the collateral requirement may distort the loan size choice from the desired level, $K^*(Z) \leq Z$. Finally, a fixed transaction cost is associated with the collateral requirement, ϕ.

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

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

$$\begin{aligned} W(\underline{K}) = (1-\gamma) \int \left[F(K^*(Z)) - \ell K^*(Z) + \mathbb{1}_{K^*>\underline{K}}(\beta \ell K^*(Z) - \lambda Z - \phi)\right] f_0(Z) dZ \\ +\gamma \int \left[F(Z) - \ell Z + \mathbb{1}_{Z>\underline{K}}(\beta \ell Z - \lambda Z - \phi)\right] f_0(Z) dZ. \end{aligned} \tag{22}$$

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

We first calibrate the model parameters to the corresponding moments in the data. First, the collateral cost λ is set to 5% based on the estimates in Table 2. Second, the distribution of firms' desired loan size f_0 is calibrated using the estimated counterfactual distribution in equation (12) in the 2014–2020 BPDL sample. Third, the charge-off rate of uncollateralized loans ℓ is calibrated to $\ell = 24\%$ according to Government Accountability Office (GAO) statistics.[21] We calibrate the reduction in charge-off rates β to be 37.5%.[22] Fourth, the fraction of the non-optimizing firms γ is calibrated to the fraction of firms in the bunching range $[\underline{K}, \overline{K}]$, which is 0.63. Finally, the fixed transaction cost of pledging collateral ϕ is calibrated to \$100.

[21] See page 14, "Small Business Administration: Physical Disaster Loan Performance Before and After Changes in Statutory Collateral Requirements."

[22] 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 IA7 for more detail.

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 default loss βZ—dominate the explicit transaction cost of collateral requirement ϕ. Therefore, welfare is maximized when most of the loans are subject to collateral requirements, except for the tiny ones because of the fixed transaction cost.

We then introduce the collateral costs into the welfare calculation. Interestingly, Figure 7b shows the relation between welfare and the 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 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, there would be a trade-off between reducing the expected default loss for taxpayers and imposing the collateral cost on borrowers. The policymakers need to carefully weigh the collateral costs with the benefits of reducing default loss. In addition, our 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 may 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 benefits of pledging collateral have been the subject of extensive studies, the costs are less well understood. This article empirically estimates the shadow cost of collateral by exploiting a unique setting in which firms can be exempted from collateral requirements if the loan amount is below a threshold. 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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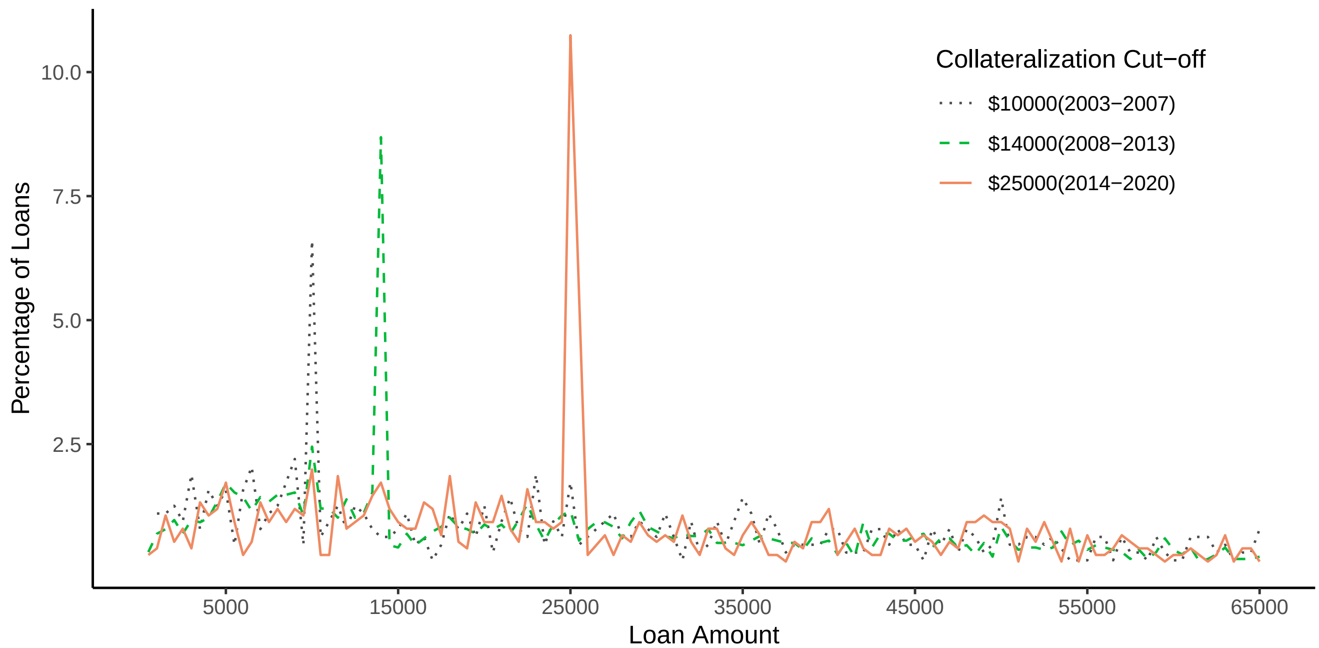
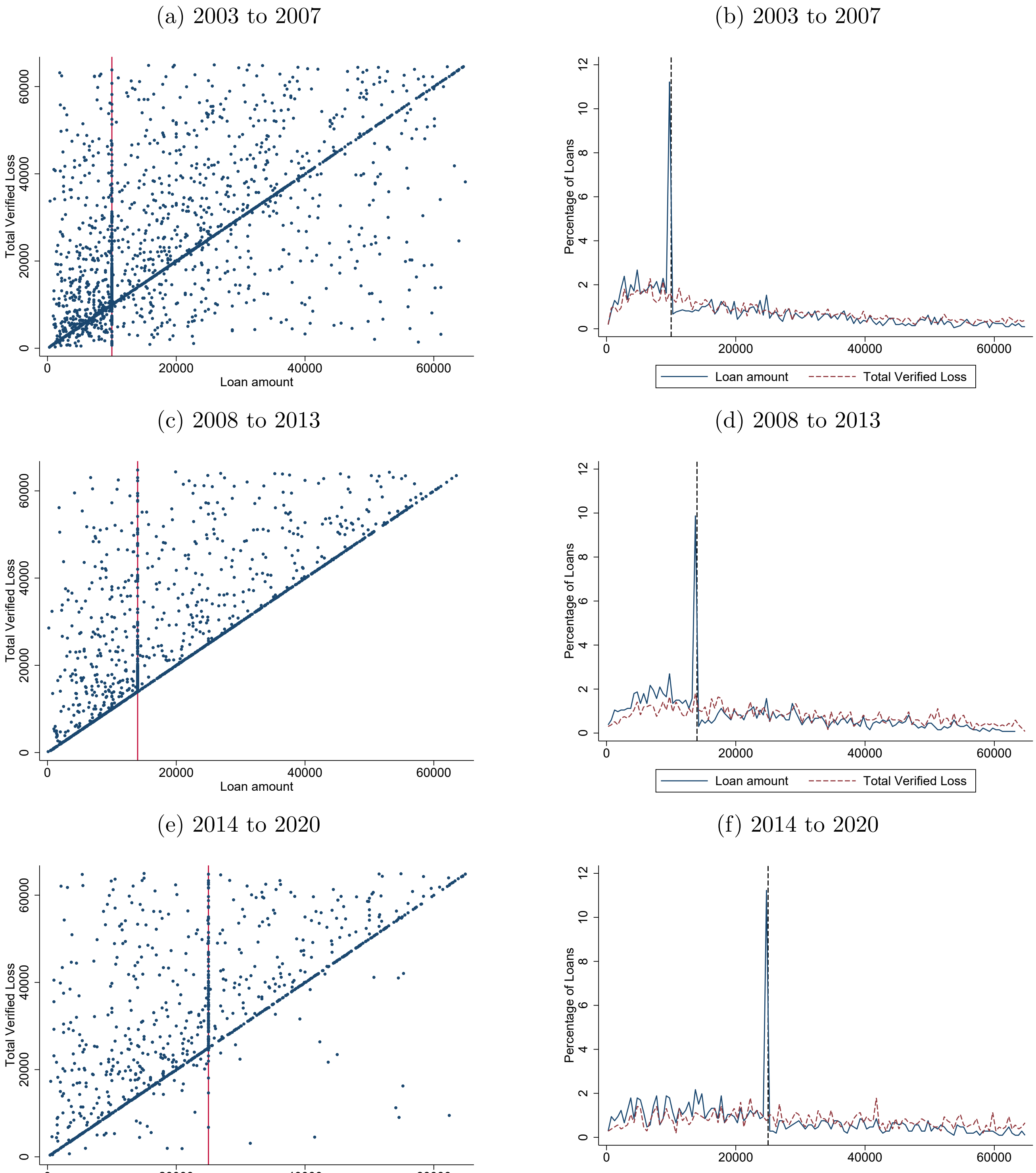
Figure 1: Loan size distribution of the SBA BPDL program



Note: The figure shows the loan size distribution of BPDL. Data source: SBA.

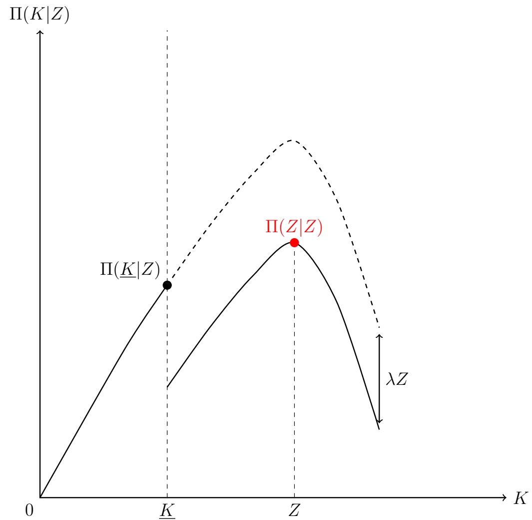
Figure 2: Distributions for BPDLs: loan amounts vs. verified losses



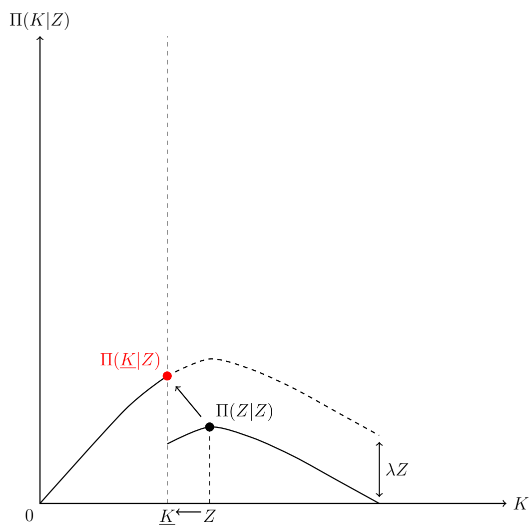
Note: The figure shows the verified loss and loan size distribution for BPDLs. The vertical lines indicate the collateral thresholds. Data source: SBA.

Figure 3: Bunching condition with collateral costs

(a) No bunching



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



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

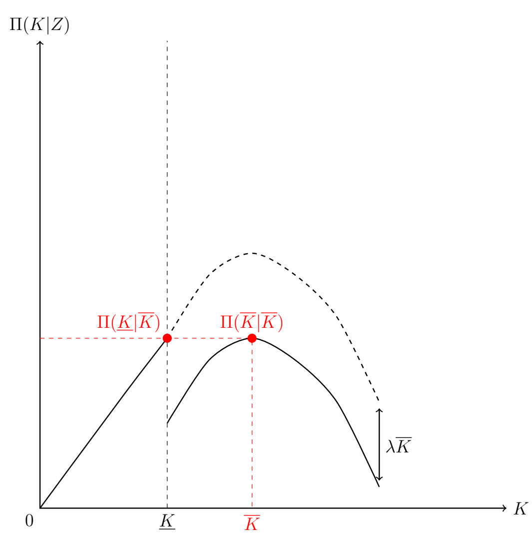
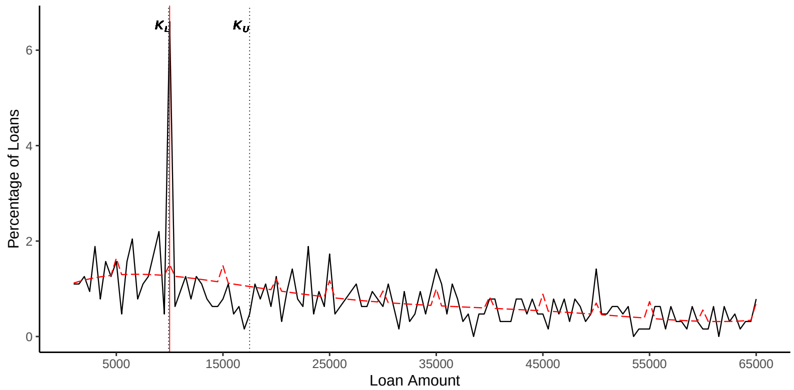
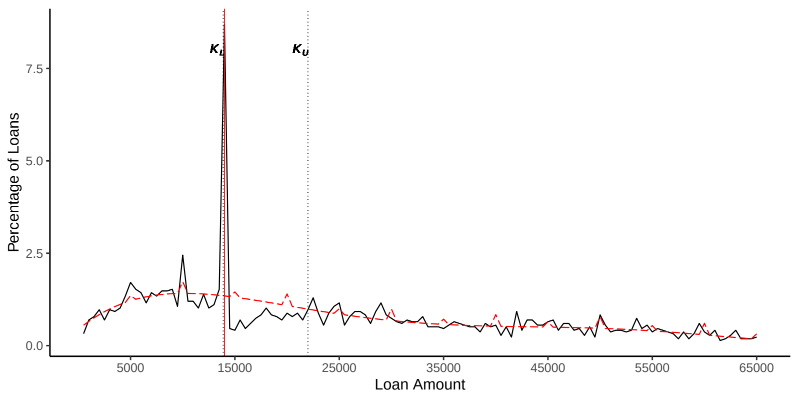


Figure 4: Counterfactual distribution and marginal buncher of BPDLs

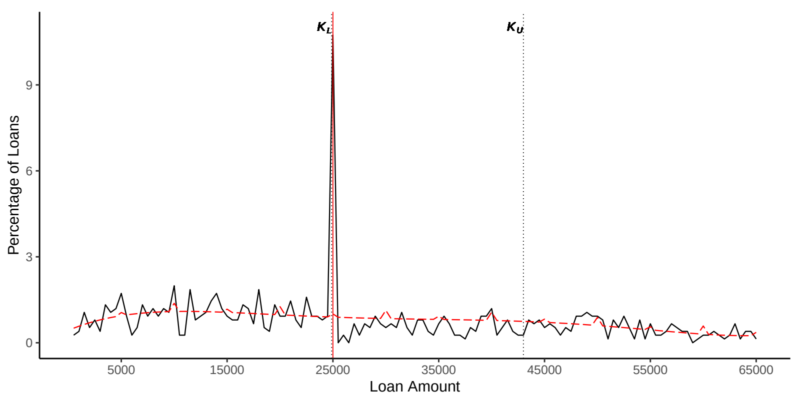
(a) 2003 to 2007



(b) 2008 to 2013

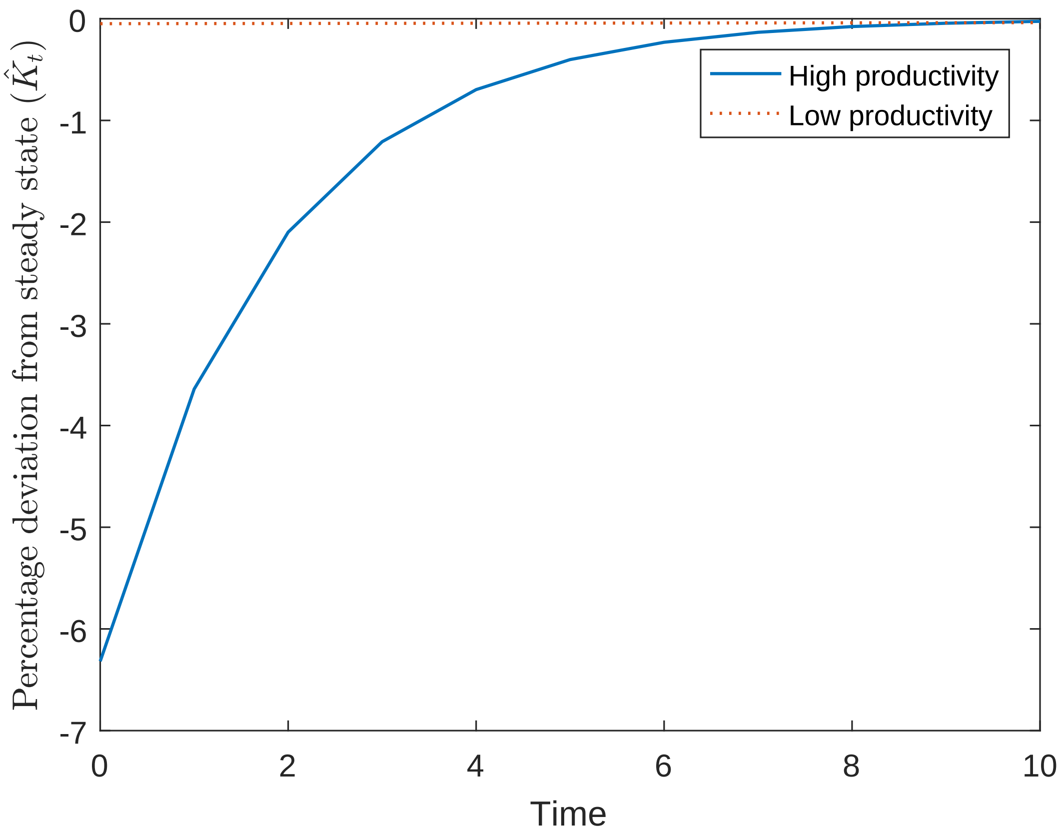


(c) 2014 to 2020



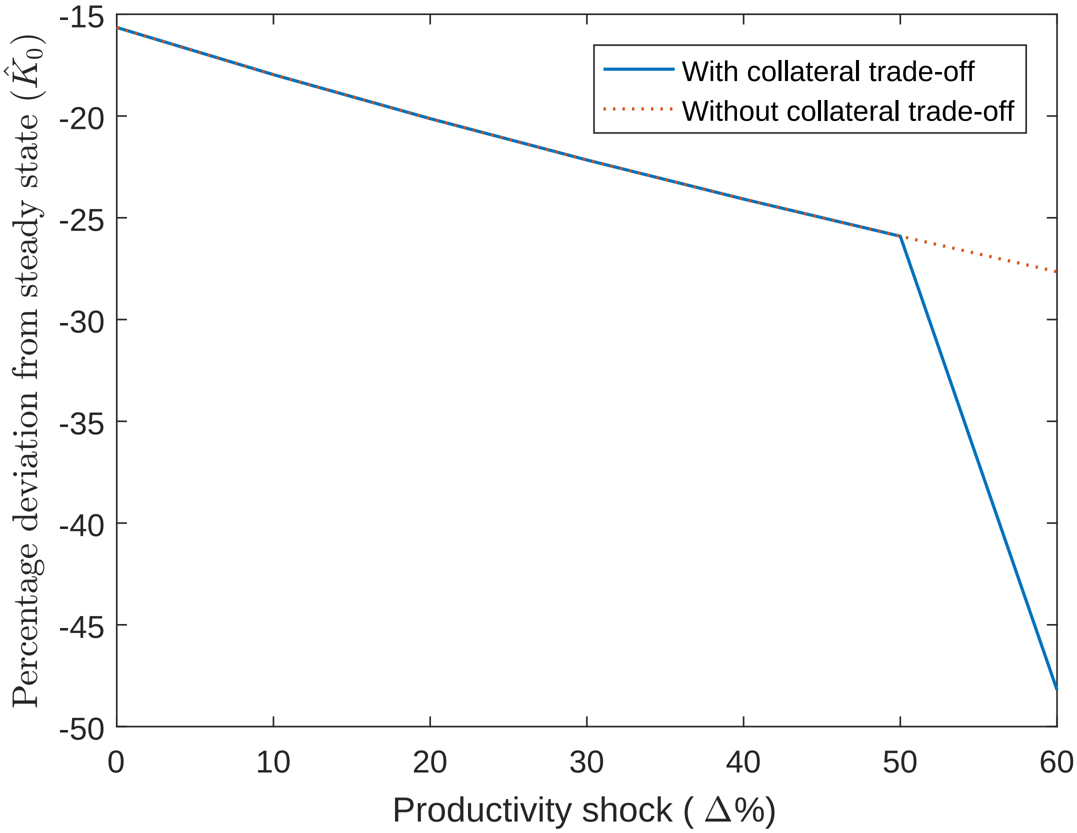
Note: This figure shows the observed (black) and counterfactual (red) percentage of loans in each bin. The counterfactual is estimated for each sample separately by fitting a fifth-order polynomial with round number dummies to the observed distribution using a bin size of \$500, excluding data in the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

Figure 5: 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 5%. The gross interest rate R is set to 1.01. The depreciation rate δ is set to 0.05. The elasticity of the residual land supply to the farmers to the user cost at the steady state η is set to 1.5.

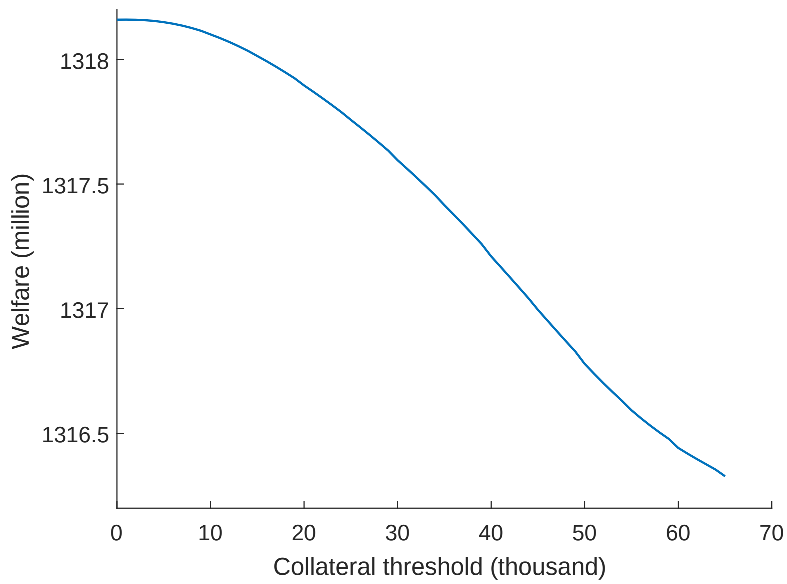
Figure 6: Time-0 impulse responses in a Kiyotaki and Moore (1997) model with vs. without collateral cost



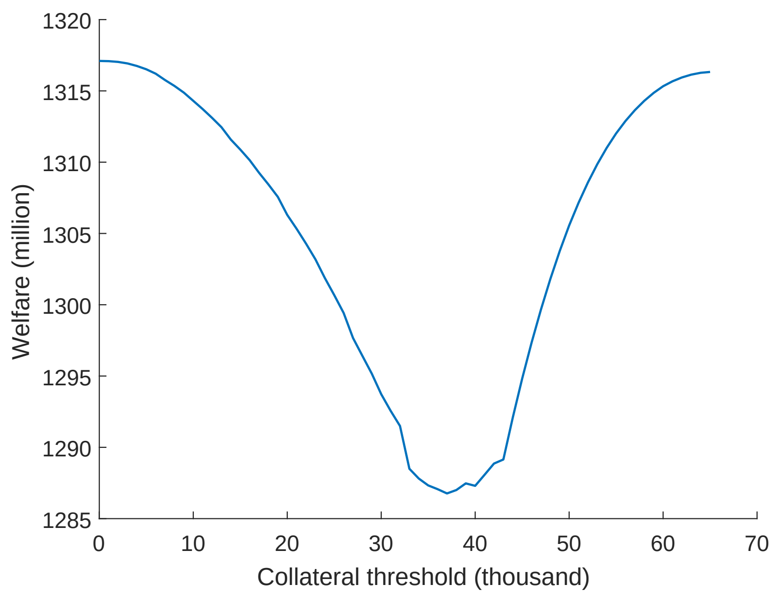
Note: This figure shows time-0 impulse responses for shocks of different sizes in a Kiyotaki and Moore (1997) model with collateral cost. The vertical axis is the percentage deviation of farmers' land at time 0 from the steady state, $\hat{K}_0$. The horizontal axis is the size of the productivity shock. 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 5%. The gross interest rate R is set to 1.01. The depreciation rate δ is set to 0.05. The elasticity of the residual land supply to the farmers to the user cost at the steady state η 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 ($\underline{K}$).

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 Loans (BPDL), Panel B reports statistics for the full sample of the Economic Inquiry Disaster Loans (EIDL), and Panel C reports statistics for the full sample of the COVID Economic Inquiry Disaster Loans (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)						
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)						
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: Bunching estimates for BPDLs

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for BPDL 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 costs λ_1 and λ_2 are calculated as in equation (6) and (7). The bin size is set to \$500 and the degree of the polynomial is set to 4 in column 1, 5 in column 2, and 6 in column 3. Bootstrapped standard errors are presented in parentheses.

	BPDL		
		Bin Size = 500	
Estimates Collateral requirement	$\underline{K} = 25,000$ Fixed lien $P = 4$ (1) 2014–2020	$\underline{K} = 25,000$ Fixed lien $P = 5$ (2) 2014–2020	$\underline{K} = 25,000$ Fixed lien $P = 6$ (3) 2014–2020
Bunching mass (B)	9.59%	9.74%	9.74%
	(0.14%)	(0.15%)	(0.16%)
Marginal buncher ($\overline{K}$)	46,000	43,000	43,000
	(3221.14)	(2,563.48)	(2809.61)
Distortion ratio (θ)	45.65%	41.86%	41.86%
	(4.53%)	(3.61%)	(3.94%)
Collateral cost (λ_1)	9.91%	8.06%	8.06%
	(1.95%)	(1.56%)	(1.71%)
Collateral cost (λ_2)	5.34%	4.37%	4.37%
	(1.03%)	(0.82%)	(0.90%)

Table 3: Bunching estimates: regular vs. COVID EIDLs

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for EIDLs. Columns 1 and 2 report the regular and COVID EIDL samples respectively. The collateral threshold is $25,000 for both samples. 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 costs λ_1 and λ_2 are calculated as in equation (6) and (7). The bin size is set to $500 and the degree of the polynomial is set to 5. Bootstrapped standard errors are presented in parentheses.

	EIDL	
	Bin Size = 500	
Estimates	$\underline{K} = 25,000$	$\underline{K} = 25,000$
Collateral requirement	Fixed lien	Floating lien
	$P = 5$	$P = 5$
	(1) Regular EIDL	(2) COVID EIDL
Bunching mass (B)	8.97%	2.58%
	(0.13%)	(0.07%)
Marginal buncher ($\overline{K}$)	42,500	40,000
	(2,358.62)	(2,913.65)
Distortion ratio (θ)	41.18%	37.50%
	(3.23%)	(4.15%)
Collateral cost (λ_1)	7.76%	6.23%
	(1.44%)	(1.76%)
Collateral cost (λ_2)	4.21%	3.40%
	(0.76%)	(0.93%)

Table 4: UVTA adoption status by state

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

Table 5: The effects of secured creditor rights on loan take-up

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

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

Table 6: 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 subsamples 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 costs λ_1 and λ_2 are calculated as in equation (6) and (7). The degree of the polynomial is set to 5, and the bin size is set to \$500. Bootstrapped standard errors are presented in parentheses.

COVID EIDL		
	Bin Size = 500	
Estimates	$\underline{K} = 25,000$ $P = 5$ (1) UVTA	$\underline{K} = 25,000$ $P = 5$ (2) UFTA
Bunching mass (B)	2.66%	2.51%
	(0.79%)	(0.07%)
Marginal buncher ($\overline{K}$)	40,000	44,500
	(2,957.97)	(2,982.41)
Distortion ratio (θ)	37.50%	43.82%
	(4.40%)	(4.11%)
Collateral cost (λ_1)	6.23%	8.96%
	(1.77%)	(1.81%)
Collateral cost (λ_2)	3.40%	4.84%
	(0.94%)	(0.95%)

Table 7: Local banking access

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for subsamples of COVID EIDL 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, that is, borrowers in counties with financial access lower than the national average. Column 2 reports the results for the high banking access subsample, that is, borrowers in counties with financial access higher than the national average. The sample contains loans between $1,000 and $65,000 for COVID EIDLs. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral costs λ_1 and λ_2 are calculated as in equation (6) and (7). The degree of the polynomial is set to 5, and the bin size is set to $500. Bootstrapped standard errors are presented in parentheses.

	COVID EIDL	
	Bin Size = 500	
Estimates	$\underline{K} = 25,000$ $P = 5$ (1) Low financial access	$\underline{K} = 25,000$ $P = 5$ (2) High financial access
Bunching mass (B)	2.43%	2.72%
	(0.06%)	(0.07%)
Marginal buncher ($\overline{K}$)	40,000	40,500
	(2,867.47)	(2,915.92)
Distortion ratio (θ)	37.50%	38.27%
	(4.14%)	(4.15%)
Collateral cost (λ_1)	6.23%	6.53%
	(1.72%)	(1.76%)
Collateral cost (λ_2)	3.40%	3.56%
	(0.91%)	(0.93%)

Table 8: Collateral cost by industry

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for different industries' 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 costs λ_1 and λ_2 are calculated as in equation (6) and (7). The degree of the polynomial is set to 5 and the bin size is set to $500. Bootstrapped standard errors are presented in parentheses.

Sector	NAICS	B	$\overline{K}$	θ	λ_1	λ_2
Agriculture	11	6.37%	40,500	38.27%	6.53%	3.56%
		(0.28%)	(2842.49)	(3.86%)	(1.73%)	(0.91%)
Construction	23	5.40%	40,000	37.50%	6.23%	3.40%
		(0.11%)	(1,830.70)	(2.74%)	(1.10%)	(0.58%)
Manufacturing	31-33	6.56%	40,000	37.50%	6.23%	3.40%
		(0.14%)	(1,705.19)	(2.57%)	(1.02%)	(0.54%)
Wholesale Trade	42	6.00%	40,000	37.50%	6.23%	3.40%
		(0.14%)	(2,158.15)	(3.28%)	(1.29%)	(0.68%)
Retail Trade	44-45	4.24%	37,500	33.33%	4.76%	2.62%
		(0.09%)	(1,923.89)	(3.54%)	(1.08%)	(0.58%)
Transportation	48-49	4.23%	40,000	37.50%	6.23%	3.40%
		(0.07%)	(1,879.50)	(2.80%)	(1.13%)	(0.60%)
Information	51	4.56%	40,000	37.50%	6.23%	3.40%
		(0.11%)	(3,989.37)	(7.86%)	(2.15%)	(1.16%)
Finance and Insurance	52	6.02%	40,500	38.27%	6.53%	3.56%
		(0.11%)	(2,271.37)	(3.17%)	(1.38%)	(0.73%)
Real Estate	53	2.98%	35,000	28.57%	3.38%	1.87%
		(0.09%)	(1,966.58)	(4.12%)	(1.02%)	(0.56%)
Professional Services	54	5.69%	40,000	37.50%	6.23%	3.40%
		(0.10%)	(1,651.60)	(2.49%)	(0.99%)	(0.52%)
Waste Management	56	4.80%	44,000	43.18%	8.66%	4.68%
		(0.11%)	(3,467.98)	(4.97%)	(2.09%)	(1.10%)
Educational Services	61	6.17%	46,000	45.65%	9.88%	5.32%
		(0.10%)	(2,222.59)	(2.85%)	(1.36%)	(0.71%)
Health Care	62	5.02%	43,500	42.53%	8.35%	4.52%
		(0.12%)	(2,381.92)	(3.22%)	(1.45%)	(0.76%)
Recreation	71	4.73%	40,000	37.50%	6.23%	3.40%
		(0.11%)	(3,534.91)	(5.46%)	(2.10%)	(1.11%)
Accommodation and Food	72	5.11%	44,500	43.82%	8.96%	4.84%
		(0.13%)	(2,472.71)	(3.37%)	(1.51%)	(0.79%)
Other Services	81	4.69%	40,000	37.50%	6.23%	3.40%
		(0.09%)	(1,681.16)	(2.41%)	(1.02%)	(0.54%)

Table 9: Collateral cost estimates with private unsecured loans

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) with private unsecured loans. The collateral cost λ_2 is calculated as in equation (7). The degree of the polynomial is set to 5, and the bin size is set to $500.

Outside unsecured loan interest rate	λ_{2BPDL}	λ_{2EIDL}	$\lambda_{2COVIDEIDL}$
15%	3.25%	3.18%	2.80%
20%	3.97%	3.86%	3.29%
25%	4.32%	4.18%	3.39%

Internet Appendix for

The Shadow Cost of Collateral

Appendix A SBA disaster loan application process

The application process of the SBA disaster loan program 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 the 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 two to three weeks after receiving complete application packages. The SBA uses credit score as a key underwriting criterion to approve or decline a loan application.[1] The SBA will not decline a loan if a borrower lacks a particular amount of collateral as long as it is reasonably sure that the borrower can repay the loan.[2] The SBA requires borrowers to pledge what is available if the loan size exceeds the collateral threshold.

Step 3: Loan closure and disbursement

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

[1]See page 47 of the United States Government Accountability Office July 2021 Report to Congressional Addressees on Economic Injury Disaster Loan Program.

[2]See 13 CFR §123.11 (d).

Appendix B Kiyotaki and Moore (1997) with collateral costs

We consider a discrete-time, infinite-horizon economy with two goods: durable land and a non-durable fruit, and two groups of agents: farmers and gatherers. We maintain the terminology in Kiyotaki and Moore (1997). However, note that land and fruit can be interpreted as capital and consumption goods, while farmers and gatherers 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 special case of Rampini and Viswanathan (2020) that the implicit collateralizability of firms' residual value is zero. Our results still hold if agents can borrow unsecured as long as unsecured debt capacity is lower than secured debt.

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

$$E_t\left(\sum_{s=0}^{+\infty}\beta^s x_{t+s}\right), \tag{23}$$

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

$$y_{t+1}=F\left(k_t\right)=\left(a+c\right)k_t, \tag{24}$$

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

$$E_t\left(\sum_{s=0}^{+\infty}\left(\beta'\right)^s x'_{t+s}\right), \tag{25}$$

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

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

$$y'_{t+1} = G\left(k'_t\right), \tag{26}$$

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

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

$$Rb_t \leq q_{t+1}\left(1-\delta\right)k_t. \tag{27}$$

Markets. There is a competitive spot market in which land is exchanged for fruit 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 fruit at date $t+1$. In equilibrium, as farmers are more impatient, they borrow from gatherers, and thus the rate of interest is always determined by gatherers' time preferences $R_t = \frac{1}{\beta'} = R$.

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

$$q_t\left(k_t - \left(1-\delta\right)k_{t-1}\right) + Rb_{t-1} + x_t + \lambda b_{t-1}\mathbb{1}_{b_{t-1}>0} = (a+c)k_{t-1} + b_t \tag{28}$$

$$q_t\left(k'_t - \left(1-\delta\right)k'_{t-1}\right) + Rb'_{t-1} + x'_t + \lambda b'_{t-1}\mathbb{1}_{b'_{t-1}>0} = G\left(k'_{t-1}\right) + b'_t \tag{29}$$

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

$$x_t = ck_{t-1}. \tag{30}$$

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

$$\mu_t \equiv a + c - u_t, \tag{31}$$

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

$$u_t = q_t - \frac{1-\delta}{R} q_{t+1}. \tag{32}$$

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

$$b_t = \frac{1-\delta}{R} q_{t+1} k_t \mathbb{1}_{\mu_t > \lambda}. \tag{33}$$

Plugging equation (33) into equation (28), a farmer's land holding is given by

$$k_t = \frac{1}{u_t} \left[(a + q_t(1-\delta))k_{t-1} - Rb_{t-1} - \lambda b_{t-1} \mathbb{1}_{\mu_t > \lambda} + \frac{1-\delta}{R} q_{t+1} k_t (\mathbb{1}_{\mu_t > \lambda} - 1). \right] \tag{34}$$

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

$$B_t = \frac{1-\delta}{R} q_{t+1} K_t \mathbb{1}_{\mu_t > \lambda}, \tag{35}$$

$$K_t = \frac{1}{u_t} \left[(a + q_t(1-\delta))K_{t-1} - RB_{t-1} - \lambda B_{t-1} \mathbb{1}_{\mu_t > \lambda} + \frac{1-\delta}{R} q_{t+1} K_t (\mathbb{1}_{\mu_t > \lambda} - 1) \right]. \tag{36}$$

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

$$\frac{1}{R}G'\left(k_t'\right) = u_t. \tag{37}$$

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

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

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,

$$q_t = \sum_{s=0}^{+\infty}\left(\frac{1-\delta}{R}\right)^s u(K_{t+s}). \tag{39}$$

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 in which the net investment return exceeds the collateral cost at the steady state $\mu \geq \lambda$, we have:

$$\left(1 - \frac{1-\delta}{R}\left(1-\lambda\right)\right) q = a, \tag{40}$$

$$B = \frac{1-\delta}{R} qK, \tag{41}$$

$$\frac{1}{R}G'\left(\bar{K} - K\right) = u, \tag{42}$$

$$u = \left(1 - \frac{1-\delta}{R}\right) q. \tag{43}$$

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

$$\delta q = a, \tag{44}$$

$$B = 0, \tag{45}$$

$$\frac{1}{R} G' \left(\bar{K} - K \right) = u, \tag{46}$$

$$u = \left(1 - \frac{1 - \delta}{R} \right) q. \tag{47}$$

Appendix C Additional figures

Figure IA1: Example of UCC financing statement: BPDL

[redacted]

UCC FINANCING STATEMENT
FOLLOW INSTRUCTIONS

A. NAME & PHONE OF CONTACT AT FILER (optional)

B. E-MAIL CONTACT AT FILER (optional)

C. SEND ACKNOWLEDGMENT TO: (Name and Address)
U.S. SMALL BUSINESS ADMINISTRATION
PROCESSING AND DISBURSEMENT CENTER
14925 KINGSPORT ROAD FORT WORTH, TX 76155-2243
ATTN: LEGAL DEPARTMENT, RE: 1000571915

FLORIDA SECURED TRANSACTION REGISTRY
FILED
2018 Jan 08 09:32 AM
****** 20180374893X ******

THE ABOVE SPACE IS FOR FILING OFFICE USE ONLY

1. DEBTOR'S NAME: Provide only one Debtor name (1a or 1b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 1b, leave all of item 1 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

1a. ORGANIZATION'S NAME: GALBREATH RESTAURANT GROUP, LLC

OR

1b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME		ADDITIONAL NAME(S)/INITIAL(S)	SUFFIX
1c. MAILING ADDRESS	**CITY**	**STATE**	**POSTAL CODE**	**COUNTRY**
253 RIVER RD	OAK HILL	FL	32759	USA

2. DEBTOR'S NAME: Provide only one Debtor name (2a or 2b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 2b, leave all of item 2 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

2a. ORGANIZATION'S NAME

OR

2b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME		ADDITIONAL NAME(S)/INITIAL(S)	SUFFIX
2c. MAILING ADDRESS	**CITY**	**STATE**	**POSTAL CODE**	**COUNTRY**

3. SECURED PARTY'S NAME (or NAME of ASSIGNEE of ASSIGNOR SECURED PARTY): Provide only one Secured Party name (3a or 3b)

3a. ORGANIZATION'S NAME: U.S. SMALL BUSINESS ADMINISTRATION

OR

3b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME		ADDITIONAL NAME(S)/INITIAL(S)	SUFFIX
3c. MAILING ADDRESS	**CITY**	**STATE**	**POSTAL CODE**	**COUNTRY**
801 TOM MARTIN DRIVE SUITE 120	BIRMINGHAM	AL	35211	USA

4. COLLATERAL: This financing statement covers the following collateral:

ALL FIXTURES AND MACHINERY AND EQUIPMENT, EXCLUDING AUTOMOTIVE NOW OWNED, HEREAFTER ACQUIRED, OR PURCHASED IN WHOLE OR IN PART FROM THE PROCEEDS OF THIS SBA LOAN DLB 1719307007, AND/OR THE PROCEEDS OF ANY DISPOSITION THEREOF

ALL DOCUMENTARY STAMPS DUE AND PAYABLE OR TO BECOME DUE AND PAYABLE, HAVE BEEN PAID.

5. Check only if applicable and check only one box: Collateral is ☐ held in a Trust (see UCC1Ad, item 17 and Instructions) ☐ being administered by a Decedent's Personal Representative

6a. Check only if applicable and check only one box: ☐ Public-Finance Transaction ☐ Manufactured-Home Transaction ☐ A Debtor is a Transmitting Utility

6b. Check only if applicable and check only one box: ☐ Agricultural Lien ☐ Non-UCC Filing

7. ALTERNATIVE DESIGNATION (if applicable): ☐ Lessee/Lessor ☐ Consignee/Consignor ☐ Seller/Buyer ☐ Bailee/Bailor ☐ Licensee/Licensor

8. OPTIONAL FILER REFERENCE DATA:

FILING OFFICE COPY — UCC FINANCING STATEMENT (Form UCC1) (Rev. 04/20/11)
International Association of Commercial Administrators (IACA)

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

Figure IA2: Example of UCC financing statement: COVID EIDL

[redacted]

UCC FINANCING STATEMENT
FOLLOW INSTRUCTIONS

FLORIDA SECURED TRANSACTION REGISTRY
FILED
2020 May 27 11:30 AM
****** 202001819143 ******

A. NAME & PHONE OF CONTACT AT FILER (optional)
CSC 1-800-858-5294

B. E-MAIL CONTACT AT FILER (optional)
SPRFiling@cscglobal.com

C. SEND ACKNOWLEDGMENT TO: (Name and Address)
1828 38538
CSC
801 Adlai Stevenson Drive
Springfield, IL 62703
Filed In: Florida (S.O.S.)

THE ABOVE SPACE IS FOR FILING OFFICE USE ONLY

1. DEBTOR'S NAME: Provide only one Debtor name (1a or 1b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 1b, leave all of item 1 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

1a. ORGANIZATION'S NAME Galbreath Restaurant Group LLC

OR

1b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)		SUFFIX
1c. MAILING ADDRESS 253 River Rd	CITY Oak Hill	STATE FL	POSTAL CODE 32759	COUNTRY USA

2. DEBTOR'S NAME: Provide only one Debtor name (2a or 2b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 2b, leave all of item 2 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

2a. ORGANIZATION'S NAME

OR

2b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)		SUFFIX
2c. MAILING ADDRESS	CITY	STATE	POSTAL CODE	COUNTRY

3. SECURED PARTY'S NAME (or NAME of ASSIGNEE of ASSIGNOR SECURED PARTY): Provide only one Secured Party name (3a or 3b)

3a. ORGANIZATION'S NAME U.S. Small Business Administration

OR

3b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)		SUFFIX
3c. MAILING ADDRESS 2 North Street, Suite 320	CITY Birmingham	STATE AL	POSTAL CODE 35203	COUNTRY USA

4. COLLATERAL: This financing statement covers the following collateral:

All documentary stamps due and payable or to become due and payable pursuant to s. 201.22 F.S., have been paid. All tangible and intangible personal property, including, but not limited to: (a) inventory, (b) equipment, (c) instruments, including promissory notes (d) chattel paper, including tangible chattel paper and electronic chattel paper, (e) documents, (f) letter of credit rights, (g) accounts, including health-care insurance receivables and credit card receivables, (h) deposit accounts, (i) commercial tort claims, (j) general intangibles, including payment intangibles and software and (k) as-extracted collateral as such terms may from time to time be defined in the Uniform Commercial Code. The security interest Borrower grants includes all accessions, attachments, accessories, parts, supplies and replacements for the Collateral, all products, proceeds and collections thereof and all records and data relating thereto.

ALL DOCUMENTARY STAMPS DUE AND PAYABLE OR TO BECOME DUE AND PAYABLE, HAVE BEEN PAID.
651452 7405

5. Check only if applicable and check only one box: Collateral is ☐ held in a Trust (see UCC1Ad, item 17 and Instructions) ☐ being administered by a Decedent's Personal Representative

6a. Check only if applicable and check only one box: ☐ Public-Finance Transaction ☐ Manufactured-Home Transaction ☐ A Debtor is a Transmitting Utility

6b. Check only if applicable and check only one box: ☐ Agricultural Lien ☐ Non-UCC Filing

7. ALTERNATIVE DESIGNATION (if applicable): ☐ Lessee/Lessor ☐ Consignee/Consignor ☐ Seller/Buyer ☐ Bailee/Bailor ☐ Licensee/Licensor

8. OPTIONAL FILER REFERENCE DATA: 1828 38538

FILING OFFICE COPY — UCC FINANCING STATEMENT (Form UCC1) (Rev. 04/20/11)

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

Figure IA3: Example of UCC financing statement: private lender

[redacted]

710434 **2020 Jan 23 PM10:23**

UCC FINANCING STATEMENT

FOLLOW INSTRUCTIONS (front and back) CAREFULLY

A. NAME & PHONE OF CONTACT AT FILER [optional]
Lien Solutions 800-331-3282

B. SEND ACKNOWLEDGMENT TO: (Name and Address)

Lien Solutions
P.O. Box 29071
Glendale, CA 91209-9071, USA
uccfilingreturn@wolterskluwer.com
(Fax)818-662-4141

THE ABOVE SPACE IS FOR FILING OFFICE USE ONLY

1. DEBTOR'S EXACT FULL LEGAL NAME - insert only one debtor name (1a or 1b) - do not abbreviate or combine names

1a. ORGANIZATION'S NAME **Jin Ramen Corporation**

OR 1b. INDIVIDUAL'S LAST NAME | FIRST NAME | MIDDLE NAME | SUFFIX

1c. MAILING ADDRESS **3183 BROADWAY** | CITY **NEW YORK** | STATE **NY** | POSTAL CODE **10027** | COUNTRY **USA**

1d. SEE INSTRUCTIONS | ADD'L INFO RE ORGANIZATION DEBTOR | 1e. TYPE OF ORGANIZATION **Corporation** | 1f. JURISDICTION OF ORGANIZATION **NY** | [redacted] | X NONE

2. ADDITIONAL DEBTOR'S EXACT FULL LEGAL NAME - insert only one debtor name (2a or 2b) - do not abbreviate or combine names

2a. ORGANIZATION'S NAME

OR 2b. INDIVIDUAL'S LAST NAME | FIRST NAME | MIDDLE NAME | SUFFIX

2c. MAILING ADDRESS | CITY | STATE | POSTAL CODE | COUNTRY

2d. SEE INSTRUCTIONS | ADD'L INFO RE ORGANIZATION DEBTOR | 2e. TYPE OF ORGANIZATION | 2f. JURISDICTION OF ORGANIZATION | 2g. ORGANIZATIONAL ID #, if any | NONE

3. SECURED PARTY'S NAME (or NAME of TOTAL ASSIGNEE of ASSIGNOR S/P) - insert only one secured party name (3a or 3b)

3a. ORGANIZATION'S NAME **JPMorgan Chase Bank, NA**

OR 3b. INDIVIDUAL'S LAST NAME | FIRST NAME | MIDDLE NAME | SUFFIX

3c. MAILING ADDRESS **Collateral Mgmt Small business, P.O. Box 33035** | CITY **Louisville** | STATE **KY** | POSTAL CODE **40232-9891** | COUNTRY **USA**

4. This FINANCING STATEMENT covers the following collateral:
All Inventory, Chattel Paper, Accounts, Equipment and General Intangibles; whether any of the foregoing is owned now or acquired later; all accessions, additions, replacements, and substitutions relating to any of the foregoing; all records of any kind relating to any of the foregoing; all proceeds relating to any of the foregoing (including insurance, general intangibles and other accounts proceeds)

5. ALTERNATIVE DESIGNATION [if applicable]: LESSEE/LESSOR | CONSIGNEE/CONSIGNOR | BAILEE/BAILOR | SELLER/BUYER | AG. LIEN | NON-UCC FILING

6. This FINANCING STATEMENT is to be filed [for record] (or recorded) in the REAL ESTATE RECORDS. Attach Addendum [if applicable] | 7. Check to REQUEST SEARCH REPORT(S) on Debtor(s) [ADDITIONAL FEE] [optional] | All Debtors | Debtor 1 | Debtor 2

8. OPTIONAL FILER REFERENCE DATA **NY-0-73485179-58458593**

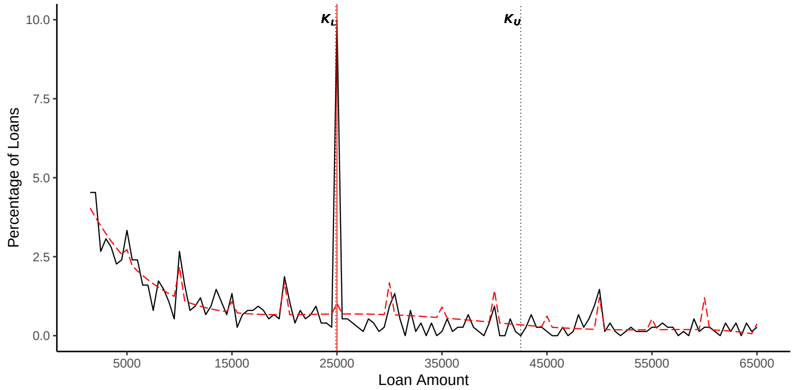
FILING OFFICE COPY — NATIONAL UCC FINANCING STATEMENT (FORM UCC1) (REV. 05/22/02)

Filing Number-202001235104061

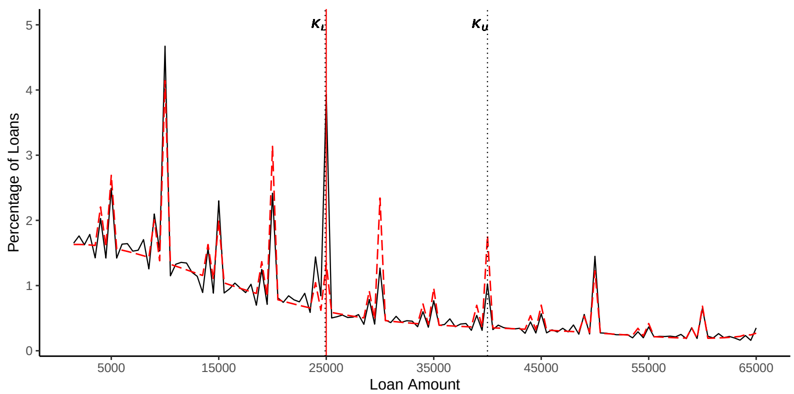
Note: The figure shows the UCC financing statement between Jin Ramen and JP Morgan. Data source: National Association of Secretaries of State (NASS).

Figure IA4: Loan size distribution and marginal buncher of EIDLs

(a) Regular EIDL

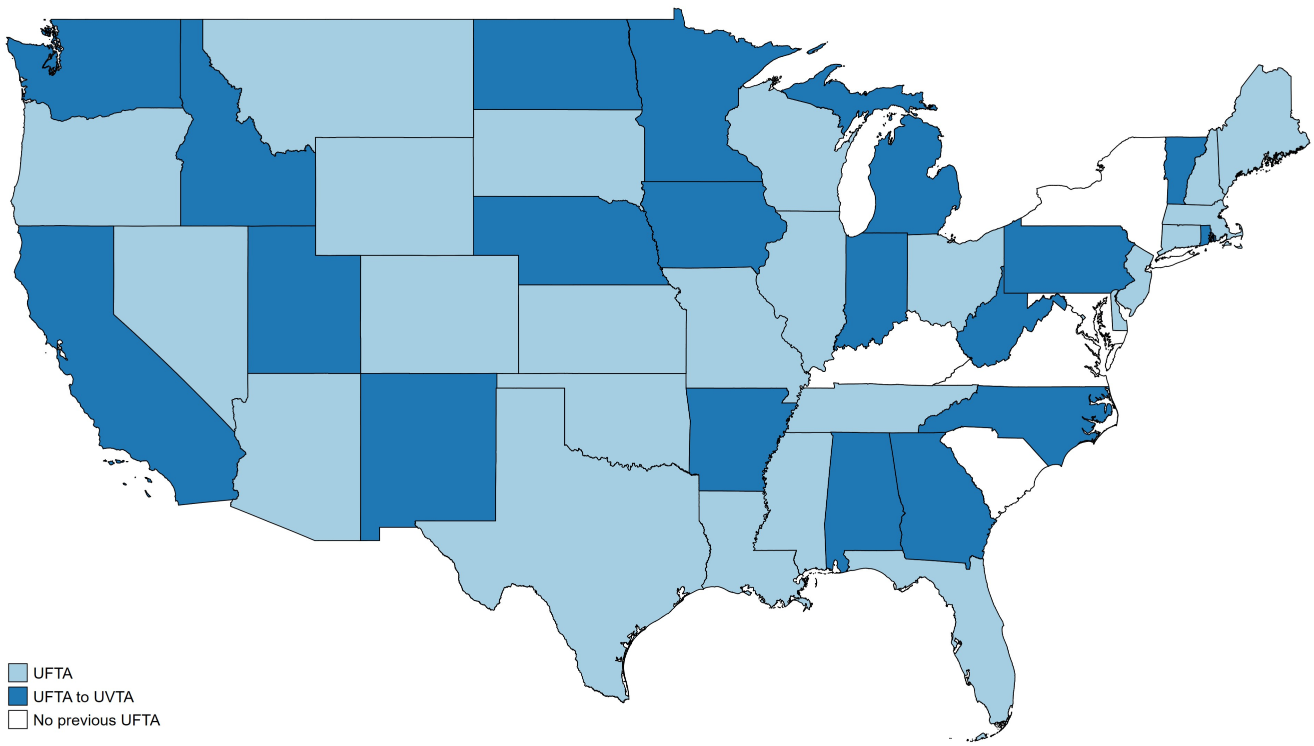


(b) COVID EIDL



Note: This figure shows the observed (black) and counterfactual (red) percentage of loans in each bin. The counterfactual is estimated for each sample separately by fitting a fifth-order polynomial with round number dummies to the observed distribution using a bin size of $500, excluding data in the bunching region. We set estimation ranges to be from $1,000 to $65,000 for both regular EIDLs and COVID EIDLs.

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 Additional tables

Table IA1: Bunching estimates for BPDL: fixed versus variable costs

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 costs λ_2 are calculated as in equation (7). The bin size is set to \$500 and the degree of the polynomial is set to 5. Bootstrapped standard errors are presented in parentheses.

BPDL			
	Bin Size = 500		
Estimates	$\underline{K} = 10,000$	$\underline{K} = 14,000$	$\underline{K} = 25,000$
Collateral requirement	Fixed lien	Fixed lien	Fixed lien
	$P = 5$	$P = 5$	$P = 5$
	(1) 2003–2007	(2) 2008–2013	(3) 2014–2020
Bunching mass (B)	5.10%	7.34%	9.74%
	(0.16%)	(0.08%)	(0.15%)
Marginal buncher ($\overline{K}$)	17,500	22,000	43,000
	(2,788.59)	(1,704.67)	(2,563.48)
Distortion ratio (θ)	42.86%	36.36%	41.86%
	(4.04%)	(4.14%)	(3.61%)
Proportional collateral cost (λ_2)	4.61%	3.18%	4.37%
	(0.89%)	(0.96%)	(0.82%)
Dollar collateral cost ($\lambda_2\overline{K}$)	807	700	1,879

Table IA2: Bunching estimates for COVID EIDL: alternative samples

This table reports the bunching estimation results on excess mass (B) and marginal buncher ($\overline{K}$) for COVID EIDL using different starting points larger than \$10,000. Column 1 shows results using the sample contains loans with a loan amount between \$13,000 and \$65,000. Column 2 shows results using the sample contains loans with a loan amount between \$15,000 and \$65,000. Column 3 shows results using the sample contains loans with a loan amount between \$17,000 and \$65,000. The distortion ratio is calculated as $\theta = (\overline{K} - \underline{K})/\overline{K}$. The collateral costs λ_1 and λ_2 are calculated as in equation (6) and (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.

COVID EIDL			
	Bin Size = 500		
Estimates	$\underline{K} = 25,000$	$\underline{K} = 25,000$	$\underline{K} = 25,000$
Collateral requirement	Floating lien	Floating lien	Floating lien
Sample coverage	$[13,000, 65,000]$	$[15,000, 65,000]$	$[17,000, 65,000]$
	$P = 5$	$P = 5$	$P = 5$
	(1) COVID EIDL	(2) COVID EIDL	(3) COVID EIDL
Bunching mass (B)	3.74%	4.08%	5.65%
	(0.10%)	(0.13%)	(0.29%)
Marginal buncher ($\overline{K}$)	40,000	40,000	40,000
	(2,834.03)	(3,388.55)	(2,002.37)
Distortion ratio (θ)	37.50%	37.50%	37.50%
	(4.87%)	(5.39%)	(3.05%)
Collateral cost (λ_1)	6.23%	6.23%	6.23%
	(1.64%)	(1.96%)	(1.20%)
Collateral cost (λ_2)	3.40%	3.40%	3.40%
	(0.88%)	(1.04%)	(0.63%)

Table IA3: Loan processing days below and above collateral thresholds

This table presents the average loan processing days near collateral thresholds for different BPDL subsamples between 2003 and 2020. The loan processing days are estimated as the number of days between the date a loan is approved by the 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 BPDL 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

Table IA4: 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 costs λ_1 and λ_2 are calculated as in equation (6) and (7).The bin size is set to \$500 and the degree of the polynomial is set to 4 in column 1, 5 in column 2, and 6 in column 3. Bootstrapped standard errors are presented in parentheses.

BPDL			
	Bin Size = 500		
Estimates Collateral requirement	$\underline{K} = 25,000$ Fixed lien $P = 4$ (1) 2008–2013	$\underline{K} = 25,000$ Fixed lien $P = 5$ (2) 2008–2013	$\underline{K} = 25,000$ Fixed lien $P = 6$ (3) 2008–2013
Bunching mass (B)	0.07%	0.19%	0.20%
	(0.09%)	(0.09%)	(0.08%)
Marginal buncher ($\overline{K}$)	25,000	25,000	25,000
	(578.88)	(6,117.11)	(6,071.58)
Distortion ratio (θ)	0.00%	0.00%	0.00%
	(1.41%)	(14.32%)	(15.43%)
Collateral cost (λ_1)	0.00%	0.00%	0.00%
	(0.25%)	(2.73%)	(2.48%)
Collateral cost (λ_2)	0.00%	0.00%	0.00%
	(0.14%)	(1.48%)	(1.36%)

Table IA5: 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 and COVID EIDL 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 costs λ_1 and λ_2 are calculated as in equation (6) and (7). The degree of the polynomial is set to 5 and the bin size is set to \$100 in column 1, \$250 in column 2, and \$500 in column 3. Bootstrapped standard errors are presented in parentheses.

	BPDL		
	Bin Size = 100	Bin Size = 250	Bin Size = 500
Estimates	$\underline{K} = 25,000$	$\underline{K} = 25,000$	$\underline{K} = 25,000$
Collateral requirement	Fixed lien	Fixed lien	Fixed lien
	$P = 5$	$P = 5$	$P = 5$
	(1) 2014–2020	(2) 2014–2020	(3) 2014–2020
Bunching mass (B)	9.72%	9.78%	9.74%
	(0.06%)	(0.10%)	(0.15%)
Marginal buncher ($\overline{K}$)	42,900	43,000	43,000
	(2963.47)	(2922.23)	(2,563.48)
Distortion ratio (θ)	41.72%	41.86%	41.86%
	(4.21%)	(4.17%)	(3.61%)
Collateral cost (λ_1)	8.00%	8.06%	8.06%
	(1.79%)	(1.77%)	(1.56%)
Collateral cost (λ_2)	4.34%	4.37%	4.37%
	(0.94%)	(0.93%)	(0.82%)

	COVID EIDL		
	Bin Size = 100	Bin Size = 250	Bin Size = 500
Estimates	$\underline{K} = 25,000$	$\underline{K} = 25,000$	$\underline{K} = 25,000$
Collateral requirement	Floating lien	Floating lien	Floating 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%
	(0.06%)	(0.09%)	(0.07%)
Marginal buncher ($\overline{K}$)	40,000	40,000	40,000
	(4,969.71)	(4,727.21)	(2,913.65)
Distortion ratio (θ)	37.50%	37.50%	37.50%
	(8.76%)	(7.76%)	(4.15%)
Collateral cost (λ_1)	6.23%	6.23%	6.23%
	(2.81%)	(2.74%)	(1.76%)
Collateral cost (λ_2)	3.40%	3.40%	3.40%
	(1.50%)	(1.46%)	(0.93%)

Table IA6: Model with defaults

This table presents estimates of three sources of collateral costs under different equity recovery rates when the firm borrows unsecured debt, κ_u. The equity recovery rate when the firm borrows secured debt and the per dollar profits netting the cash injection are assumed to be zero, $\kappa_s = \kappa^* = 0$. The collateral cost λ could be decomposed into three sources as in equation (20).

κ_u	Cost in operatons	Cost in financial distress	Cost in default
1%	4.06%	0.12%	0.20%
2%	3.75%	0.24%	0.39%
3%	3.43%	0.36%	0.59%
4%	3.12%	0.47%	0.79%
5%	2.80%	0.59%	0.99%
6%	2.49%	0.71%	1.18%
7%	2.17%	0.83%	1.38%
8%	1.85%	0.95%	1.58%
9%	1.54%	1.07%	1.78%
10%	1.22%	1.18%	1.97%

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. We use the Cox proportional-hazards model to examine whether borrowers are less likely to default when they borrow secured loans:

$$\textit{Charge-off}_i(t) = \textit{Charge-off}_0(t) \times exp(\beta_1 \textit{Secured}_i + \beta_2 \textit{log(loan amount)}_i + \varepsilon_i). \tag{48}$$

The dependent variable, $\textit{Charge-off}_i(t)$, is the charge-off status of the loan. $\textit{Charge-off}_0(t)$ captures the baseline hazard if both independent variables are equal to zero. $\textit{Secured}_i$ is a dummy variable that equals one if the loan is secured. $HR_1 = exp(\beta_1)$, the hazard ratio of the $\textit{Secured}_i$ 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 IA7 presents the results. Secured loans are around 40% or seven percentage points less likely to be charged off compared to unsecured loans.

Table IA7: Cox proportional-hazards model of charge-off

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 a dummy variable that indicates whether the loan is paid in full or charged off as in year t: 1 is charged off, and 0 is paid in full. The results presented in the table are the hazard ratios: $HR_i = \exp(\beta_i)$. The coefficients β_i are estimated in equation (48). $HR_i = 1$ indicates the independent variable has no effects on charge-off; $HR_i > 1$ indicates the independent variable increases charge-off hazard; $HR_i < 1$ indicates the independent variable reduces charge-off hazard. Secured is a dummy variable that indicates whether the loan is a secured loan or 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 of the full sample. Column 2 reports results for loan amounts between $10,000 below the collateral threshold and $10,000 above 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:	Hazard ratio		
	(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