The Cost of Consumer Collateral: Evidence from Bunching*

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Abstract

We show that borrowers are highly sensitive to the requirement of posting their homes as collateral. Using administrative loan application and performance data from the U.S. Federal Disaster Loan Program, we exploit a loan amount threshold above which households must post their residence as collateral. One-third of all borrowers select the maximum uncollateralized loan amount, and our bunching estimates suggest that the median borrower is willing to give up 40% of their loan amount to avoid collateral. Exploiting time variation in the loan amount threshold, we find that collateral causally reduces default rates by 35%. Our results help to explain high perceived default costs in the mortgage market, and uniquely quantify the extent to which collateral reduces moral hazard in consumer credit markets.

JEL Codes: D14, D82, G23, G28

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1 Introduction

How do collateral requirements impact consumer borrowing behavior? Eighty percent of household debt in the United States is collateralized, and real estate secures nearly 90% of these loans (Federal Reserve Bank of New York, 2020). Despite its economic importance, we know surprisingly little about how collateral influences consumer credit demand or default behavior. Isolating the causal effect of collateral is particularly difficult, as observed loan contract terms, including any collateral requirements, are determined jointly in equilibrium between lenders and borrowers. In addition, consumer debt markets are highly segmented: Some markets (e.g., mortgages and auto loans) always require collateral while others (e.g., credit cards) rarely do.

Understanding the role collateral plays in lending markets is critical given recent research on consumer repayment behavior. Collateral has been traditionally viewed as affecting consumers' behavior by increasing their "skin in the game." From this perspective, collateral addresses information frictions, thereby expanding access to credit markets (e.g., Bester, 1985; Chan and Thakor, 1987). However, examinations of mortgage defaults during the Great Recession and thereafter have found that collateral values have little bearing on mortgage defaults (Bhutta et al., 2017), with Ganong and Noel (2020b) estimating that 97% of defaults can be attributed instead to adverse life events. The connections between collateral and mortgage default (reviewed recently by Foote and Willen, 2018) suggest that it is an open question whether collateral directly influences consumer borrowing and default behavior.

In this paper, we pursue two related questions. First, how much do consumers value collateral? Lenders regularly limit access to credit based on collateral valuations, and may be allocating credit inefficiently if consumers are not sensitive to collateral requirements. Second, does collateral affect consumer defaults? If consumers' default behavior is unrelated to collateral, it would reduce concerns about moral hazard. Answering these two questions informs consumer lending decisions and government policies around mitigating harms from default and foreclosure.

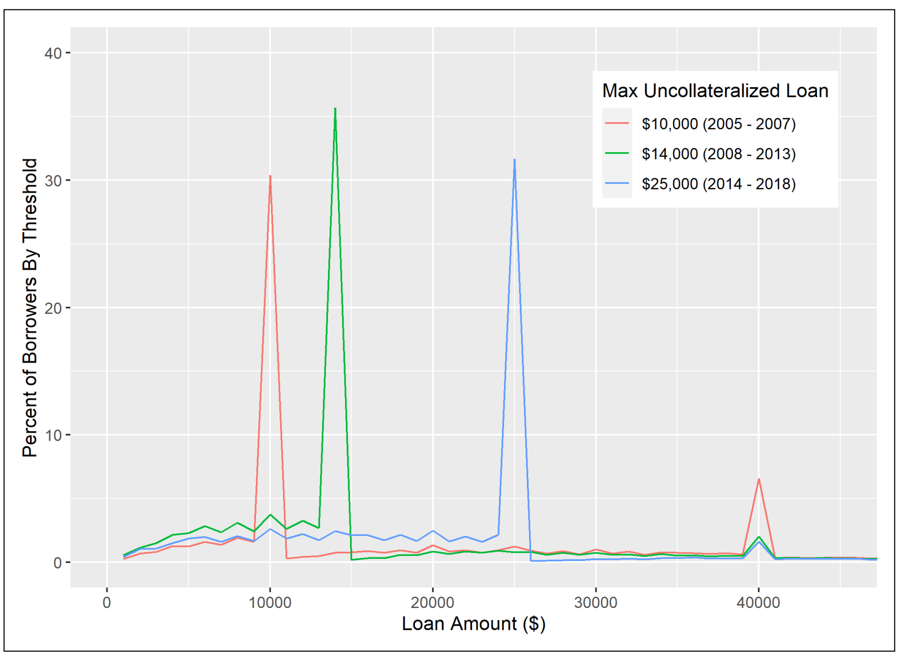
We examine the impact of collateral requirements on consumer borrowing behavior in a setting that is largely free from the standard endogeneity concerns. The Federal Disaster Loan (FDL) program offers low-interest loans directly to households who have experienced a natural disaster (e.g., hurricane, tornado, wildfire) towards the repair of damage to their primary residence and the replacement of destroyed belongings.[1] These disasters produce large, exogenous shocks: The median homeowner applying to this program has incurred $50,000 in uninsured damages.

[1]While this loan program lends to both households and businesses, our analyses exclusively consider household applicants. In 2020, this program's lending authority expanded to provide Economic Injury Disaster Loans for COVID-19, but our data do not cover that time frame.

If households choose a loan amount that is above a certain threshold, currently \$25,000, they are required to post their house as collateral. Alternatively, households can borrow at exactly the threshold and avoid collateral requirements. In other credit market settings, optional collateralization would likely bring certain benefits, such as an interest rate reduction. Our setting is unique in that no other loan terms change when borrowers choose a loan at the collateral threshold versus \$1 above. We can thus exploit borrower choices around this discontinuous threshold to identify the direct impact of collateral on loan demand *ex ante* and the propensity to default *ex post*.

Figure 1 shows the distribution of loan amounts under each of our three collateral thresholds. In 2005-2007, the maximum uncollateralized loan amount was \$10,000. This amount was increased to \$14,000 in 2008, and to \$25,000 in 2014. Households are eligible to borrow as much as the amount of their uninsured damages, up to a program maximum of \$240,000, or can instead choose to borrow a smaller amount. The figure shows that households frequently borrow at exactly the collateral threshold: 38% of all borrowers with losses above the threshold (and 31% of all borrowers in the program) choose to locate at the largest uncollateralized loan amount.

Figure 1: Bunching in Loan Amounts



Note: This figure plots the distribution of loan amounts. The maximum loan amount that does not require collateral changes over time from \$10,000 (2005-2007) to \$14,000 (2008-2013) to \$25,000 (2014-2018). The vertical axis shows, for each time period, the percent of borrowers choosing the loan amount. For example, 33% of borrowers in 2014-2018 chose a \$25,000 loan. Households can borrow up to \$240,000 from the program.

We can infer households' private value of collateral by measuring how much they move from their *ideal loan amount* – the amount that they would have borrowed in the absence of the collateral requirement – to avoid posting collateral. To estimate the counterfactual distribution of households' ideal loan amounts, we first use a traditional bunching estimator that extrapolates the distribution below the threshold to estimate the "missing" mass of the distribution above it (Kleven, 2016). We can then estimate households' collateral aversion using the difference between households' ideal loan amounts and their selected loan amounts.

We find that households are highly sensitive to collateral rules: Across all three bunching thresholds, the median borrower is willing to give up about 40% of their loan to avoid collateral, and 75% of borrowers in the bunching region reduce the size of their loans to avoid posting their home as collateral.[2] This magnitude of a reduction in demand is substantial: Based on the interest rate demand curve for the loan program estimated by Collier and Ellis (2021), the response to the collateral requirement is equivalent to the demand response from raising the program's average interest rate by 200 basis points (from 2.5% to 4.5%). In the aggregate, we estimate that bunchers have given up over $1.1 billion in loans to avoid collateral.

Bunching estimators generally rely on strong assumptions regarding extrapolating the shape of the distribution beyond the threshold. In our setting, we can relax these assumptions by using additional applicant information and variation in the program's rules over time to assess the robustness of traditional bunching estimates. Our first alternative approach is a difference-in-bunching (DiB) estimator with data on the amount of damages that the household incurred from the disaster, a strong predictor of its loan amount that is plausibly exogenous within the bunching region. To identify the impact of collateral, we compare the loan amounts for individuals with the same losses, but under different collateral threshold regimes. For consumers with losses between $10,000 and $25,000, the method generates individual estimates of the amount given up to avoid posting collateral in regressions that control for covariates that may correlate with collateral aversion.[3]

Our second alternative to the traditional approach leverages a strong proxy for the ideal loan amount of many borrowers. Households report the amount that they would like to borrow on the initial loan application, which we directly observe. A household can costlessly adjust this "original request" after completing the application and meeting with a loan officer, and many do: 70% of

[2]The bunching region is the range of ideal loan amounts from which borrowers move to instead borrow at the threshold. For example, the estimated bunching region for the $25,000 collateral threshold is from $25,000 to $49,900.

[3]Traditional bunching methods estimate the distribution (i.e., the count) of consumers who bunch, but data limitations typically preclude generating estimates for individual consumers. The information on household-level damages allow us to extend beyond the standard approach.

eventual bunchers originally requested a loan amount larger than the threshold. The benefit of this approach relative to the DiB method is that it can assess bunching behavior for consumers over a larger range of ideal loan amounts, yielding an estimate of the full CDF of collateral aversion for borrowers in the program.

Despite using different sources of identifying variation, these alternative methods yield similar estimates of collateral aversion as the traditional bunching estimator around the median: The median borrower is willing to give up between 40 and 47% of their loan to avoid posting collateral. However, these alternative methods suggest that variation in collateral aversion across borrowers may be much larger than estimates generated by the traditional method. In settings where the "marginal" buncher is of interest, traditional bunching estimators may substantially under-predict the degree of sensitivity to collateral requirements.

We then turn to heterogeneity in bunching across borrowers for insights into the mechanisms underlying collateral aversion. We find that more creditworthy borrowers (based on *ex ante* observables) are more likely to bunch. These collateral-averse individuals have higher credit scores and incomes, supporting an "advantageous selection" interpretation of bunching behavior. We find that financial incentives influence bunching decisions: Consumers are more likely to bunch when loan interest rates are higher. Yet, we also find behavioral or preference-related aspects of collateral aversion. For example, among borrowers who are already underwater on their existing home loans (i.e., their LTV ratios exceed 1) and have no equity at stake, about 30% bunch at the threshold to avoid posting their homes as collateral.

Finally, we examine the causal impact of collateral on consumer defaults. To identify the impact of collateral on defaults, we exploit time variation in the bunch point. Consumers are more likely to bunch if the collateral threshold is near their ideal loan amount. For example, a consumer with an ideal loan amount of $30,000 would be more likely to bunch if the collateral threshold were $25,000 than if it were $10,000. Changes in the threshold over time create variation in the distance from the borrowers' ideal loan amount to the threshold, which we use as an instrument for whether or not the borrower's loan is collateralized. This identification strategy provides the local average treatment effect for households who would bunch when the threshold is high ($25,000), but not when it is low ($10,000).

We find that collateral causes a large reduction in default rates, reducing default rates by about 35%. For context, a reduction of this magnitude is comparable to a 100 point increase in the borrower's credit score. Thus, our analysis shows that the likelihood of default is highly sensitive to the attachment of a primary residence as collateral, indicating the important role that collateral plays in addressing moral hazard in household lending.

Our primary contribution is to provide some of the first evidence of the impact of collateral requirements on household decision-making. Prior research on collateral has almost exclusively focused on decisions made by corporate borrowers and lenders, with a special focus on small businesses and entrepreneurs (Chaney et al., 2012; Jimenez et al., 2006; Benmelech and Bergman, 2009; Luck and Santos, 2019).[4] A number of recent papers have examined a variety of legal changes that altered the relative value of collateral or creditor rights, showing that these influence lending decisions on both the intensive and extensive margins (Cerqueiro et al., 2016; Ersahin et al., 2019; Costello, 2019; Zevelev, 2020). Our setting is unique in that the choice of collateral is entirely up to the borrower, and does not affect the likelihood of loan approval or any of the loan terms besides the loan amount.[5] Our results suggest that consumers' aversion to posting collateral is large: Many would give up thousands of dollars of a low-interest loan during a time of need to avoid posting an additional lien on their homes.

We also provide new estimates of the causal effect of collateral on the likelihood of default, informing an extensive banking literature on the role of collateral in mitigating moral hazard in lending environments (Boot and Thakor, 1994; Berger and Udell, 1995). Research examining the relationship between collateral and default has generally relied on observational data, where corporate collateral use reflects heightened borrower risk and subsequently higher default rates (Berger and Udell, 1990; Jiménez and Saurina, 2004; Berger et al., 2011; Ioannidou et al., 2019). Recent work, however, has sought well-identified settings to disentangle causal channels.[6] Our findings that collateral reduces default risks by one third offers empirical support for the important role that collateral can play in reducing asymmetric information to expand access to consumer credit (Bester, 1985; Chan and Thakor, 1987).

Our estimates suggest that collateral concerns sharply reduce homeowners' willingness to default, providing new evidence to the literature on household financial decision-making around mortgage default (Guiso et al., 2013; Agarwal et al., 2017). While Gupta and Hansman (2020) use exogenous changes in interest rate adjustments to separately identify adverse selection from moral hazard for payment size in the mortgage market, we exploit changes in collateral thresh-

[4]See Calomiris et al. (2017) for a cross-country examination of collateral laws, and Coco (2000) for a survey of the pre-2000s literature.

[5]In addition, our analysis provides one of the first investigations of a large and important government-backed lending program, which supports households experiencing natural disasters (Collier and Ellis, 2021; Billings et al., 2021; Begley et al., 2020). Understanding borrower choices—and their sensitivity to contract features—can help improve the targeting for a growing set of public programs using credit as a policy tool to assist consumers and businesses adversely affected by shocks (e.g., pandemics, natural disasters, and recessions).

[6]For instance, O'Malley (2020) finds a substantial increase in mortgage default rates after an unexpected Irish court ruling that blocked lenders' ability to repossess real estate. Also, Gertler et al. (2021) examine loans secured with digital assets, which the lender can disable if the borrower does not repay. In a field experiment, they find that digital collateral improved loan repayment by about 25%, primarily by reducing moral hazard.

olds to separate adverse selection from moral hazard in loan default. Loan default entails both pecuniary and non-pecuniary costs, and the possibility of losing one's residence appears to have a strong deterrent effect that may extend beyond the direct financial implications. Our findings help to rationalize prior findings that homeowners are averse to borrowing against their homes through reverse mortgages (Nakajima and Telyukova, 2017) and reluctant to walk away from their homes, even when severely underwater on their mortgages (Bhutta et al., 2017; Ganong and Noel, 2020a).

Finally, the richness of our setting allows us to extend the growing methodological literature on bunching (Saez, 2010; Chetty et al., 2011; Kleven and Waseem, 2013; Kleven, 2016; Cloyne et al., 2019; Best et al., 2020) as well as add to the recent literature using bunching in household finance (DeFusco and Paciorek, 2017; Bäckman et al., 2021). Our methodology is closest to Best et al. (2020), who exploit a difference-in-bunching estimator using individual-level panel data to examine interest rate sensitivity in the UK mortgage market. Most traditional bunching papers only observe the *ex post* distribution of the outcome of interest. We emphasize that the differences in our approach, only feasible with a sufficiently rich dataset, are critical when the parameter of interest involves identifying the marginal individual whose behavior is distorted by the collateral threshold.

2 Data and Setting

This section describes the Federal Disaster Loan (FDL) program and our data, using material from FEMA (2019) and the program's Office of Disaster Assistance (2018).

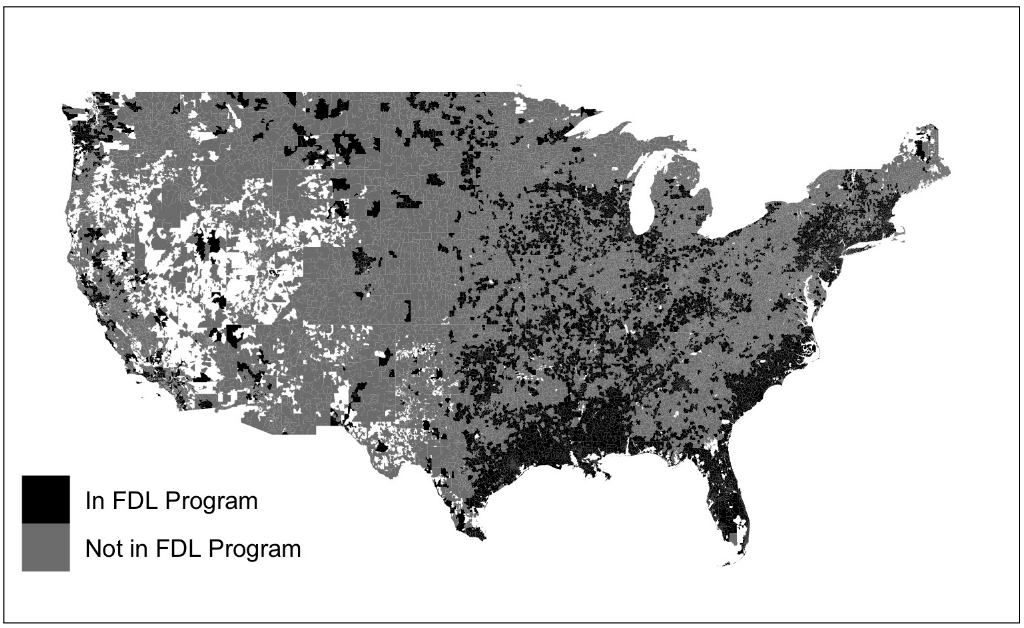
2.1 Federal Disaster Loan Program Overview

Since the FDL program began in 1953, it has made roughly $60 billion in recovery loans as of 2019. Administered by the Small Business Administration (SBA), the program is authorized to lend to households for the repair of uninsured damages to their primary residence, its contents (e.g., appliances, furniture), and their automobiles. Though it predominantly lends to households, the program also lends to businesses and non-profits. In 2017, households comprised 80% of applicants and 70% of the total loan volume. We limit our analysis to household lending.

Effectively all (98%) of household FDL applications are associated with a presidential disaster declaration. For these declarations, FEMA coordinates the local response, establishing temporary offices in affected neighborhoods. Households harmed by the disaster are encouraged to register with these FEMA offices. Households with incomes below a certain threshold (typically 125% of the federal poverty line) are referred to a FEMA grant program, which pays to repair or replace their lost property. FEMA refers households above the income threshold to the FDL program to apply for a loan. FEMA gives these households a summary sheet that describes disaster loans, including eligible loan amounts, interest rates, and collateral requirements. (Appendix A includes the summary sheet for Hurricane Harvey.) These households are then automatically contacted (via email, robocalls, and letters) by the FDL program.

A household's eligibility depends on the issuance of a disaster declaration for its county, incurring a loss from the disaster, and some portion of the loss being uninsured. Figure 2 shows the geographic distribution of the program, and illustrates its broad use across the contiguous U.S. with an emphasis on the Gulf and South Atlantic coasts. The black areas in the figure denote ZIP codes that have had at least one borrower in our data.

Figure 2: ZIP Codes with FDL Borrowers, 2005 to 2018



Note: Figure shows which ZIP codes had at least one borrower in our sample from 2005 to 2018.

2.2 Data, Lending Decisions, and Terms

Our data include all household FDL applications from 1 January 2005 to 31 May 2018 in the 50 U.S. states and the District of Columbia. During that time, the program received over 1 million applications and disbursed $12.5 billion in approved loans to 285,260 households. We restrict our analyses to borrowers who have incurred real estate losses to their primary residence, a sample of 222,436 households. Only real estate is used to secure loans in the program and so this restriction facilitates comparisons between homeowners who do and do not collateralize their loans.

Lending decisions. The program is "a good faith lender and will only make a disaster loan if there is reasonable expectation that the loan can be repaid" (SBA, 2020). It collects information on an applicant's income from the IRS, outstanding debts from credit reports, and property damages from an onsite loss inspection. Lending decisions largely depend on the interaction of the applicant's credit score and *existing* debt-service-to-income (DTI) ratio (that excludes the new disaster loan). While the rules vary over time, the program generally approves applicants with a credit score of at least 620 and an existing DTI below 40. Approximately 60% of homeowners who apply to the program are approved.

Table 1 describes the credit scores and DTIs of borrowers. The average credit scores of FDL borrowers is 695, below that of GSE mortgage borrowers, but around the national average. The average borrower has a DTI of 35, which is similar to GSE mortgage borrowers.[7]

Loan Terms. The program can lend up to $200,000 for damages to the residence and up to a combined total of $40,000 in damages to their contents and automobiles. The average loan amount is $50,139 (median of $25,319) with a 2.47% interest rate, 21 year maturity, and $254 monthly payment (Table 1).

Collateral requirements. The program does not make lending decisions based on borrower collateral, nor does the borrower's interest rate depend on the provision of collateral. However, the program requires homeowners to secure their loans with collateral if the loan amount exceeds a certain threshold.[8] Over our window of observation, the program used three different collateral thresholds, $10,000 from 2005-2007, $14,000 from 2008-2013, and $25,000 from 2014-2018. If the borrower secures the loan with collateral, the program places a lien on the home. About 70% of borrowers have an existing mortgage, and the disaster loan is a subordinated claim to existing home debt. As a result, the program's claim on the home may not fully collateralize the disaster loan.

[7]Specifically, the average U.S. FICO score was 689 in 2011 (the middle year of our data, Experian, 2020) and around 765 for the GSEs' mortgage borrowers (Fannie Mae, 2019; Freddie Mac, 2019). The program's underwriting requirements are less stringent regarding both DTI and credit score than the GSEs. For example in 2017, the 99$^{\text{th}}$ percentile borrower has a DTI of 50 for Fannie Mae, versus a DTI of 79 for the FDL program. Similarly, the 1$^{\text{st}}$ percentile borrower has a credit score of 632 for Fannie Mae, compared to 531 in the FDL program.

[8]Online Appendix B examines applicants with losses around the collateral threshold and shows that income, credit score, DTI, loan approval rates, loan decision times, and interest rates are all smooth through the collateral threshold.

Table 1: Summary Statistics of Federal Disaster Loan Borrowers

			Percentiles		
	Mean	SD	p10	p50	p90
Income	86,973	64,190	34,803	72,787	148,752
Credit Score	695	76	593	693	798
DTI (%)	34	110	9	32	55
Loss Amount	103,325	128,504	13,262	50,844	270,399
Insurance Claims	31,633	74,703	0	1,137	112,591
Loan Amount	52,816	66,881	10,025	25,609	144,928
Interest Rate (%)	2.47	0.82	1.69	2.69	3.12
Maturity (Years)	22	25	6	29	30
Monthly Payment	261	271	58	160	606

Note: Monetary values in 2018$. Table includes data 217,202 borrowers for whom data on all variables listed are available. "Income" is annual adjusted gross income and is winsorized at the 0.5% and 99.5% levels. "Credit Score" is the FICO score of the primary applicant. "DTI" divides a household's existing total monthly debt service payments (e.g., its mortgage) by its monthly income and is reported as a percentage. "Loss Amount" is the program's onsite assessment of property losses.

Decision and Disbursement Times. The median lending decision occurs 58 days after the disaster declaration date, and the median final loan disbursement occurs 61 days following the decision date. Larger loans take longer to disburse. The longer duration may be, in part, due to the additional processing needed to collateralize a loan. However, a longer duration can also come at the request of borrowers. According to program administrators, borrowers typically schedule disbursements to match contractor workflow and can receive disbursements in segments. The SBA processes the collateralization when total disbursements exceed the collateral threshold. The first disbursement is almost always smaller than the collateral threshold and comes a median of 51 days after the decision date. The second disbursement almost always pushes the total loan balance above the collateral threshold and comes a median of 82 days after the first disbursement. The agency's multiple disbursement approach reduces concerns that borrowers may avoid posting collateral in order to get their loan more quickly.

Collections. The program allows for loans to be adjusted in cases of hardship by suspending payments and/or extending the loan's maturity, though interest on the loan continues to accrue during a deferment (Federal Register, 1997). For example, all disaster loans were granted an automatic deferment during COVID-19 (SBA, 2021).

The program takes the following actions if the borrower defaults. First, the program transfers the delinquent debt to the Treasury Offset Program, which garnishes a portion of funds (e.g., tax refunds and social security payments) typically paid to an individual to pay down the loan balance (Treasury Offset Program, 2021). Second, the program reports the default to the credit bureaus who register it as charged-off Federal debt. Third, if the loan is collateralized, the program "may liquidate collateral securing a loan" (Federal Register, 2014).

2.3 Loss Amounts and Loan Amounts

The application process offers additional insights on households' borrowing needs and proceeds as follows. Households begin the loan application by providing their contact information and completing a set of forms allowing the program to verify their income, examine their credit report, and conduct an onsite loss inspection to determine the amount of property damages. After the loss inspection, the applicant meets with a loan officer to finalize the application. The applicant then requests a loan amount, which is capped at the loss amount. The program processes the application and renders a decision on whether to approve the loan. The lending decision does not depend on the loan amount, and the borrower can costlessly adjust the loan amount until its disbursement.

The median household incurred $51,000 in damages, only $1,000 of which was insured (Table 1). Almost 48% of borrowers received no insurance claims payment for their damages. The low amount of insurance claims reflects a combination of households who are uninsured and others who are underinsured against the disaster. For example, many consumers, even those in very vulnerable locations, do not buy flood insurance (Walsh, 2017). Similarly, an insured household might have insufficient coverage: The National Flood Insurance Program has a maximum coverage limit of $250,000 on the home structure and does not tend to cover basements. As a result, a large insurance coverage gap exists, especially for floods (e.g., about 70% of Hurricane Harvey-related flood damage was uninsured, Larsen, 2017).

Panel A of Figure 3 shows the distributions of the loss amount and disbursed loan amount. These values are centered based on the prevailing collateral threshold (e.g., 100% on the horizontal axis is $10,000 from 2005-2007 while 100% is $25,000 from 2014-2018). The loss amount is smooth across the collateral threshold. The figure shows substantial bunching in the loan amount: One third of all borrowers choose a final loan amount at the collateral threshold. Among borrowers whose losses exceed the collateral threshold, 38% choose a loan amount at the threshold.[9]

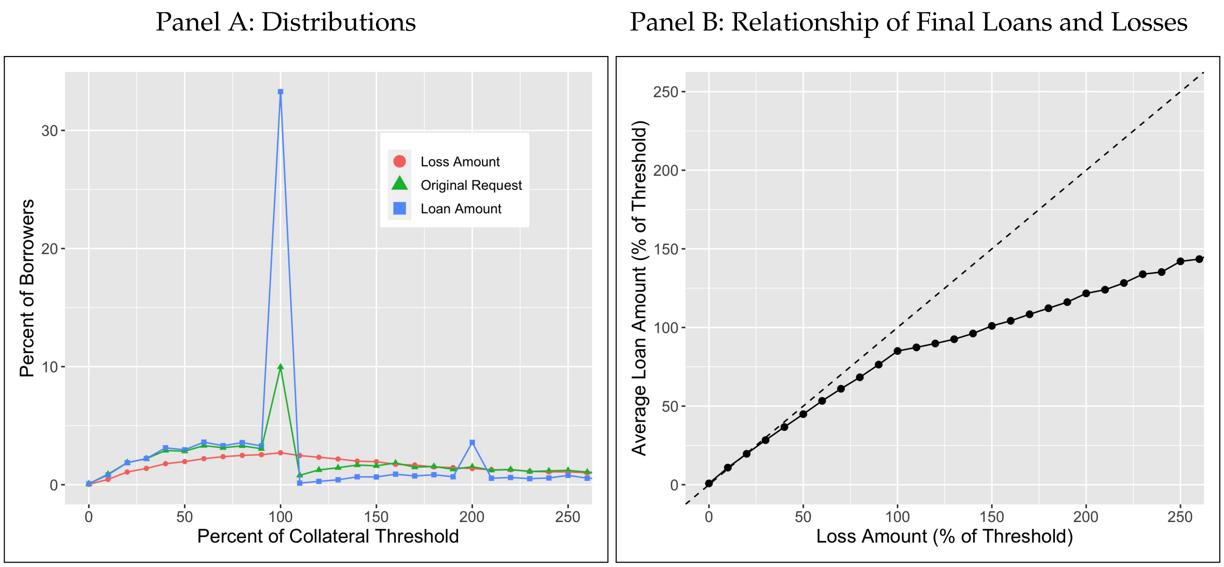
Panel B of Figure 3 illustrates the strong relationship between losses and loan amounts. The dashed, 45-degree line marks the case in which loan amounts equal loss amounts. The figure

[9] We also observe some bunching at 200% (which represents $50,000 in 2014-2018). This bunching is likely due to additional requirements on loan disbursements exceeding $50,000: the applicant must acquire a building permit, document the total estimated cost of the project, account for all financing for the project, and document completed work through receipts or an onsite progress inspection.

shows that below the collateral threshold, they nearly do. Loss amounts and loan amounts have a Pearson correlation of $\rho = 0.87$ below the threshold. Above the threshold, loan amounts diverge from the 45-degree line (as borrowers adjust to avoid collateral) but continue to increase in the loss amount ($\rho = 0.70$).

Panel A of Figure 3 also includes the density of the amount that borrowers originally requested on their loan applications. The summary sheet given to households by FEMA lists the collateral requirements (Online Appendix A), and some households appear cognizant of this requirement when making an original request. However, the majority of bunching occurs afterwards, suggesting that the collateral requirement becomes more salient to consumers as the borrowing process progresses. In one of our alternative bunching approaches below, we use the household's originally requested loan amount as a proxy for the loan they would have requested in the absence of collateral requirements.

Figure 3: Loss Amounts and Loan Amounts



Note: This figure shows damages, originally requested loan amounts, and final loan amounts. The loss amount is based on an onsite loss inspection. Values are centered based on the prevailing collateral threshold: $10,000 from 2005-2007, $14,000 from 2008-2013, and $25,000 from 2014-2018.

3 Bunching Estimation

3.1 Household Problem and Assumptions

We assume that household i selects a loan amount z_i by solving the following problem. The household experiences disaster damages, represented by random variable ν_i. The household's ideal loan amount $\hat{z}_i$ depends on these damages $\hat{z}_i(\nu_i)$. Household utility is increasing in z_i up to $\hat{z}_i$. The household dislikes posting collateral, but can avoid doing so by selecting a loan no greater than z^*, the collateral threshold. The household has a private value of collateral x_i, which is measured as the maximum loan amount that the household would give up to avoid posting collateral. Thus, the household will bunch at the collateral threshold if and only if its ideal loan amount is above the threshold but not by more than its private collateral value. These conditions will lead the household to choose the following loan amounts:

$$z_i = \begin{cases} z^* & \text{if } z^* < \hat{z}_i(\nu_i) < z^* + x_i, \\ \hat{z}_i(\nu_i) & \text{otherwise.} \end{cases} \tag{1}$$

The variable of interest is the household's private collateral value x_i. This collateral value is unobserved and, for bunchers, so is the ideal loan amount. However, the distribution of ideal loan amounts $h(\hat{z})$ can be estimated in several ways. Our first estimation method is based on the excess mass at the bunch point and the distribution of selected loan amounts $h(z)$. The counterfactual distribution $h(\hat{z})$ is first estimated by fitting an approximation on the portion of the density either not subject to collateral requirements (where $\hat{z}_i < z^*$) or sufficiently far away (where $\hat{z}_i > z^* + max(x_i)$) and then extrapolating the approximation over the portion of the density that is subject to the requirements.[10] Our other estimation methods make use of additional borrower data that we observe – loss amounts and original requests – as well as time variation in the bunch point to estimate $h(\hat{z})$ at the individual borrower level. With an estimate of $h(\hat{z})$, we can then estimate the distribution of households' value of collateral x based on the difference between the distributions of ideal loan amounts $h(\hat{z})$ and selected loan amounts $h(z)$. Specifically, we can estimate $P(x_i < \hat{z}_i(\nu_i) - z^*)$, the probability that a randomly chosen household's value of collateral x_i is smaller than the difference between its ideal loan amount and the collateral threshold.

Translating bunching behavior into the collateral aversion distribution requires two assumptions. First, we assume that there are no frictions in adjusting loan amounts. In the presence of

[10] This methodology was developed, across different applications, by Saez (2010), Chetty et al. (2011), and Kleven and Waseem (2013). For an excellent review, see Kleven (2016).

adjustment frictions, the observed loan amount might not reflect the borrower's fully-informed preference. The assumption appears to hold in our setting, as all borrowers are given the opportunity to costlessly change their loan amount up until the loan disbursement.[11] Second, we assume that, within the bunching region, a household's ideal loan amount $\hat{z}_i$ is independent of its private value of collateral x_i. If households' ideal loan amounts and collateral values are correlated, then the model would suffer from a form of selection bias, undermining identification of households' private collateral values. This is a reasonable assumption to hold in our setting. As described in Section 2.3, households' ideal loan amounts appear to depend on the size of their loss resulting from a natural disaster, modeled as $\hat{z}_i(\nu_i)$ above, and the size of disaster damages is plausibly randomly assigned in the region around the collateral threshold. We conduct additional analyses below that support this assumption, including comparing borrowers with the same size damages across changes in the collateral threshold and allowing for the inclusion of covariates.

3.2 Estimation

We follow the notation of Kleven and Waseem (2013) and model the density of observed household borrowing amounts z_i as a binned histogram, which approximates the distribution of loan amounts $h(z_i)$. Define c_j as the number of borrowers in bin j and $\overline{z_j}$ as the median amount borrowed by households in bin j. Let

$$\begin{aligned} c_j &\approx h(z_i; \beta_p, \gamma_m, \rho_r, \theta_k) \\ &= \sum_{p=0}^{P} \beta_p (\overline{z_j})^p + \sum_{m=z^*}^{\overline{z_U}} \gamma_i \mathbb{1}[\overline{z_j} = m] + \sum_{r \in R} \rho_r \mathbb{1}\left[\frac{\overline{z_j}}{r} \in \mathbb{N}\right] + \sum_{k \in K} \theta_k \mathbb{1}\left[\overline{z_j} \in K \wedge \overline{z_j} \notin [z^*, \overline{z_U}]\right] + \varepsilon_j \quad (2) \end{aligned}$$

The first term is an order P polynomial approximation of the density in the absence of bunching due to collateral or round numbers.[12] This polynomial is parameterized by β_p. The second term is the alteration of the density in the bunching region $[z^*, \overline{z_U}]$ induced by the collateral requirements. z^* is the bunch point and $\overline{z_U}$ is the maximum loan amount from which borrowers move to instead borrow at the bunch point. This is parameterized by γ_i where $\gamma_{m=z^*}$ represents the excess mass at the bunch point and $\gamma_{m \in (z^*, \overline{z_U}]}$ represents the deficient mass in the bins where the bunchers came from. The third term controls for the tendency of borrowers to bunch at round numbers R, such as every $5,000, where we observe a partial set before the bunching region. Their impact is

[11] As noted by Kleven (2016), this assumption is extremely strong in the original income elasticity case, but is much weaker in many recent bunching settings.

[12] We use a polynomial of order 9, as is common in the literature. Our results are robust to a wide range of polynomial orders.

parameterized by ρ_r. The final term represents the set of numbers K, such as \$50,000, where there may be additional bunching due either to rounding or other program features that we cannot control for using the pre-threshold data. Their impact is parameterized by θ_k. We denote the binned histogram approximation of the distribution of ideal loan amounts as $\hat{c}_j$, which is the predicted value of Equation (2) setting $\gamma_i = 0$.

To estimate Equation (2), we first determine the upper end of the bunching region $\overline{z_U}$, following the iterative procedure of Kleven and Waseem (2013). We increase $\overline{z_U}$ until the estimated excess mass of bunchers is equal to the missing mass between the observed and counterfactual distributions. This allocation process begins just to the right of the bunch point and continues until all bunchers are allocated. The iterative procedure ends when the upper end of the bunching region $\overline{z_U}$ is located at the point where the excess mass of bunchers equals the missing mass. Following the determination of $\overline{z_U}$, we estimate Equation (2) via OLS.

The percentage of households who do not bunch in each bin after the bunch point $(1 - \frac{\hat{c}_j - c_j}{\hat{c}_j} = 1 - P(Bunch_j))$ is equivalent to $P(x_i < \hat{z}_i(\nu_i) - z^*)$ above, the CDF for the underlying distribution of households' collateral aversion at ideal loan amount $\hat{z}_i$. Following the identifying assumptions described above, the ability to identify collateral aversion comes from the plausibly random assignment of disaster damages in the bunching region. Damages differ in their distance to the collateral threshold, creating variation in the amount that a consumer would be required to give up to avoid posting collateral.[13]

Kleven (2016) raises two technical issues regarding the amount that bunchers move to locate at the bunch point that merit specific consideration in our setting. First, the counterfactual distribution may be mis-specified. The estimated shape relies on the polynomial approximation (the first term in Equation 2) to project over a potentially large range of loan amounts. Mis-estimation of the counterfactual distribution would affect our estimates of how much borrowers move (Blomquist et al., 2021). The second issue is whether the program's collateral requirements elicit an extensive margin response: Potential borrowers may choose to forego the loan altogether instead of choosing a lower loan amount to avoid posting collateral. Extensive margin responses would also contribute to the missing mass between the observed and counterfactual distributions, biasing downward our estimates of the amount that bunchers move. The effects of both technical challenges on the counterfactual distribution are likely small near the bunch point, but may become

[13]Collateral aversion may vary with observable characteristics of the consumer (e.g., credit score), which we explore below. If disaster damages are randomly assigned, then these characteristics add noise, but not bias to the estimates.

more meaningful when estimating the upper end of the bunching region $\overline{z_U}$.[14] Because of these technical issues, we use two alternative measures of the bunching behavior, which are not prone to the same challenges, and compare the results with the traditional method (Section 3.4).

3.3 Results

Table 2 describes the results from traditional bunching estimation. We report standard errors, derived from block bootstrapping at the disaster level. The first column describes bunching when the threshold is set at $10,000. For this threshold, the bunching region ranges from $10,000 to $21,000, and in this range, 70% of borrowers move to the bunch point. On average, borrowers in the bunching region are willing to give up 44% ($7,900) of their ideal loan value due to the collateral requirement. The results are qualitatively consistent across the collateral thresholds: the share of borrowers who move to the bunch point ranges from 73 to 78%, and the median amount that borrowers in the bunching region give up is between 39% and 47% of their ideal loan amount.

Table 2: Traditional Bunching Estimation

	(1)	(2)	(3)
Collateral Threshold	10,000	14,000	25,000
Bunching Region	10,000 - 20,700	14,000 - 24,500	25,000 - 49,900
Private Value of Collateral			
Mean	7,944	8,227	18,268
	(278)	(746)	(562)
Mean (%)	44.31	37.02	42.25
	(0.84)	(2.12)	(0.74)
Median (%)	47.37	39.39	45.65
	(0.98)	(2.48)	(0.74)
25th Percentile (%)	33.33	30.69	31.51
	(1.07)	(1.21)	(3.81)
75th Percentile (%)	52.15	43.32	49.70
	(1.09)	(2.64)	(0.50)
% in Bunching Region who Bunch	73.40	78.27	75.81

Note: This table presents the results of our bunching estimation using the traditional bunching estimator. Columns are separated by different collateral thresholds. Standard errors, in parentheses, are block bootstrapped at the disaster level.

[14] Kleven and Waseem (2013) show that extensive margin effects are less likely near the bunch point. For example, a collateral-averse consumer with an ideal loan of $25,500 would likely prefer a collateral-free, $25,000 loan over not taking the loan; however, a collateral-averse consumer with an ideal loan of $50,000 might not.

Graphical displays of our traditional bunching estimation are shown in Figure 4, with each sub-figure representing a different bunching regime. The y-axis for all of the figures is in log scale. The black lines are the observed distribution (c_j). The red lines represent our estimated counterfactual distribution ($\hat{c_j}$) using the traditional methodology described above. The spikes in the red lines are points where we allow for rounding (R) and separate bunching (K). The largest spike in the black line is the bunch point (z^*) and the shaded gray area represents the bunching region. The end point of the bunching region occurs where the sum of the "missing" borrowers ($\hat{c_j}$ - c_j) equals the excess mass at the bunch point.

Figure 4 highlights two features of the estimation. First, in each panel, the counterfactual distribution closely fits consumers' selected loan amounts below the collateral threshold. This close fit shows that the estimation successfully approximates consumers' selected loan amounts with the counterfactual distribution in a range of values for which they are expected to match. Second, for Panels A and B, the figure shows that the (shaded) bunching region ends before the distributions of consumers' selected and ideal loan amounts fully converge. This missing mass beyond the estimated bunching region may be explained by mis-estimation of the counterfactual distribution (shifting the red line lower would extend the bunching region to larger loan amounts), by extensive-margin responses (consumers who forgo the loan contribute to the missing mass), or both.

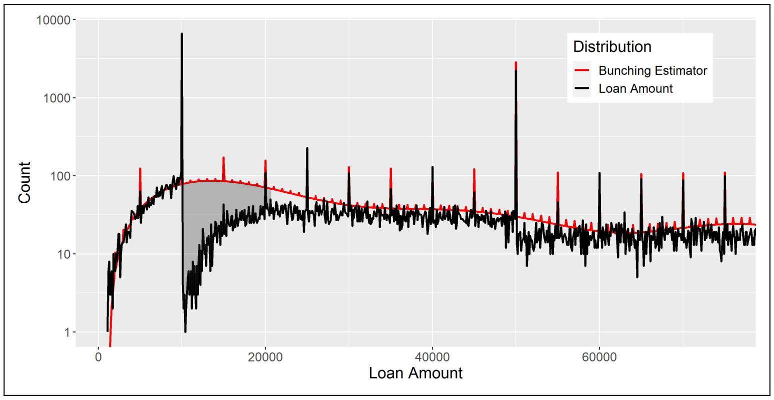
3.4 Alternative Bunching Estimators

Our data offer more information regarding the counterfactual distribution relative to other settings examining bunching behavior. Using two additional approaches, we estimate households' responses to the collateral threshold with this additional information for comparison with the traditional bunching estimation methods. The first alternative method uses variation in the collateral threshold over time: For a range of loan amounts, the change in the collateral threshold creates a counterfactual in which consumers' loan amounts can be observed in the absence of the requirement to post collateral. The second method uses consumers' originally requested loan amounts, which provide insight into their ideal loan amounts.

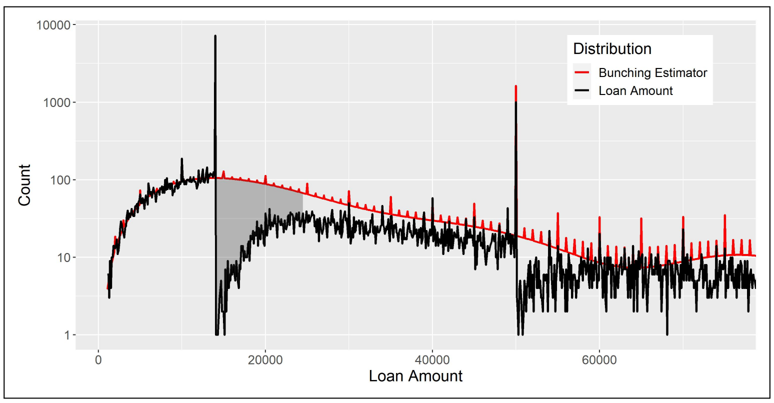
In contrast to standard bunching estimation methods, which measure bunching using the count of consumers in binned histograms, our alternative bunching approaches are estimated at the consumer level, which offers several additional advantages. First, these models include covariates to control for features of the consumer and setting that might correlate with collateral aversion. Second, these alternative methods are less prone to the limitations of traditional bunch-

Figure 4: Bunching Estimation, Traditional Method

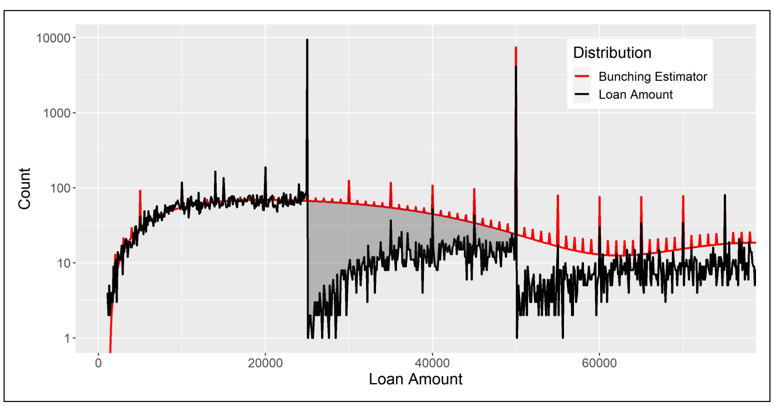
Panel A: \$10,000 Threshold (2005-2007)



Panel B: \$14,000 Threshold (2008-2013)



Panel C: \$25,000 Threshold (2014-2018)



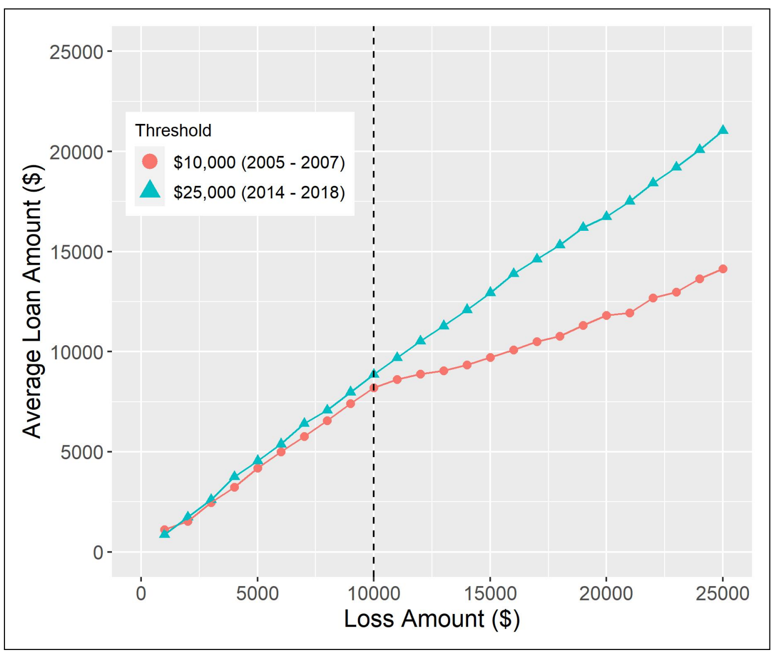
Note: This figure represents our bunching estimation, with each sub-figure representing a different bunching regime. The black lines are the observed distribution (c_j). The red lines represent our counterfactual distribution ($\hat{c_j}$). The spikes in the red lines are points where we allow for rounding (R) and additional bunching (K). The shaded area represents the bunching region. The end point of the bunching region occurs where the sum of the "missing" borrowers ($\hat{c_j}$ - c_j) equals the excess mass at the bunch point.

ing methods documented by Kleven (2016) and discussed in Section 3.2, such as how extensive margin responses may influence measurement of the bunching region. We compare the collateral aversion estimates across methods at the end of this subsection.

3.4.1 Difference-in-Bunching Counterfactual

The first alternative method uses the time variation in the collateral threshold to estimate counterfactual ideal loan amounts. Figure 5 illustrates the identification graphically, comparing the relationship between loss amount and loan amount in two different regimes, one with the \$10,000 threshold (shown in red circles), and one with a collateral threshold of \$25,000 (blue triangles). Regardless of threshold, households with losses below \$10,000 tend to borrow very close to, but slightly below, their loss amounts. However, immediately after the loss amount crosses \$10,000 (the dashed vertical line), the two lines sharply diverge. While the relationship continues linearly for consumers in the \$25,000 threshold regime, the relationship flattens immediately for the \$10,000 threshold regime. This divergence is due to the frequency of bunching when the collateral threshold is set at \$10,000 for loss amounts in the range of \$10,000 to \$25,000.

Figure 5: Difference-in-Bunching Method, Parallel Trends



Note: This figure shows the relationship between losses and loan amounts for the \$10,000 and \$25,000 thresholds.

We exploit this identification across threshold regimes in an estimation that is similar to a traditional difference-in-differences design using individual-level data, including covariates. For this method, we restrict the data to households in either the \$10,000 or \$25,000 collateral threshold who have losses below \$25,000. Because households cannot borrow more than their losses, households who borrow when the threshold is set at \$25,000 cannot bunch and thus represent the control group. Households who borrow when the threshold is set at \$10,000 can only bunch when their loss is above \$10,000. An additional group is those with losses above \$10,000 but who borrow less than \$10,000. These borrowers are not subject to bunching under either threshold and thus represent an additional comparison group for testing parallel trends. We separate this group by assigning borrowers with losses above \$10,000 who borrow less than \$10,000, regardless of threshold, into their own separate bin, which we index as $LossBin_{-1}$.

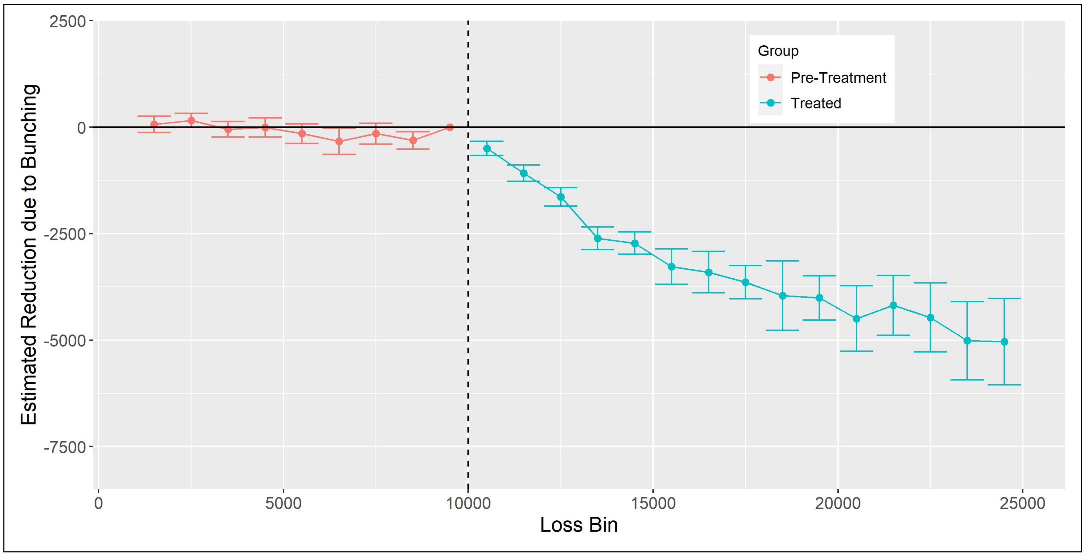
The "treatment effect" for this method thus measures how the collateral requirement affects consumers' loan amounts by comparing consumers with the same loss amount. Specifically, with loss amounts binned into J bins, we estimate the following event-study style equation, with the \$9,000 - \$10,000 loss bin as the omitted reference category, for household i:

$$\begin{aligned} LoanAmount_i =& \sum_{j}^{J} \alpha_j * LossBin_j + \sum_{j}^{J} \beta_j * LossBin_j * 1(Threshold = \$10,000) \\ &+ \gamma * X_i + \varepsilon_i \\ LossBin_j \in& \{\$1K - \$2K, \$2K - \$3K, ..., \$24K - \$25K, -1\} \end{aligned} \tag{3}$$

Where α_j represents the average amount borrowed by households when the collateral threshold is set at \$25,000 (the control group) who suffer losses in loss bin j. Coefficients β_j capture the treatment effects: the additional reduction in borrowing by households who suffer the same size losses, but do so during the \$10,000 collateral regime and are therefore subject to the collateral requirement. X_i represents a set of demeaned, borrower-level control variables which include credit score, monthly income (logged), home value, interest rate, debt-to-income ratio, and LTV ratio for the home. In contrast to the traditional bunching estimation strategy in Section 3.2, which relies on the assumption that the marginal buncher is defined by the equality of the excess and missing masses, the difference-in-bunching method employs a much weaker assumption. Specifically, we assume that the relationship between loss amounts and ideal loan amounts is consistent under both the \$10,000 and \$25,000 collateral regimes.

Figure 6 shows the treatment effects from this difference-in-bunching estimation. Each point represents an estimated coefficient (β_j), and the associated 95% confidence interval, of the difference in the final loan amounts for borrowers in each loss bin. Points to the left of the vertical dashed line (shown in red) assess for pre-trends in our setting: The loan amounts of borrowers with predicted ideal loan amounts below $10,000 would not be expected to be affected by the collateral requirement, and we are able to precisely estimate no response.

Figure 6: Difference-in-Bunching Estimation Results



Note: This figure shows the difference-in-bunching estimation results. Each point represents an estimated coefficient, and associated 95% confidence interval, of the impact of the collateral requirement on loan amounts.

In contrast, points to the right of the threshold are affected by the collateral requirement. The figure shows that, for example, consumers with losses of $16,000 reduce their loan amount by an average of $3,000 because of the collateral requirement. The slope of the treatment effect is steeper near the threshold and then flattens for larger amounts, reflecting that a smaller share of borrowers bunch as the distance between the threshold and their ideal loan amount grows.[15]

The primary limitation of this estimation method is that it is limited to examining consumers with losses below $25,000. Thus the largest ideal loan amount we can predict is roughly $23,000, where we find that collateral requirements induce a reduction of $5,000 in loan amounts on average.

[15]The coefficient on our additional control group, those with losses above $10,000 but loan amounts strictly less than the bunch point, is $133 with a 95% confidence interval of [-124, 390]. Thus, these borrowers whose ideal loan amounts are below $10,000 would not be expected to be affected the collateral requirement, and we find no response to the change in collateral regime.

3.4.2 Original Request Counterfactual

Our second alternative method exploits that consumers request a loan amount on their initial application, before reviewing the program requirements with a loan officer. We use the consumer's originally requested loan amount as a proxy for the loan they would have taken in the absence of collateral requirements. This original request approach allows for examining bunching behavior beyond the $25,000 threshold that limits the difference-in-bunching method.

Typically, a borrower's original request is informative of its ideal loan amount as the vast majority of bunching occurs after the original request is submitted (Panel A of Figure 3). However, for those who bunch in their original request, about 30% of bunchers, the request is not informative about their ideal loan amount as they have already adjusted based on collateral rules. We estimate the ideal loan amount for bunchers with "uninformative" original requests using observably similar bunchers whose requests are "informative." We use a nearest neighbor matching approach, which involves pairing uninformative bunchers with the closest eligible informative buncher. We then use the matched informative buncher's original request as our prediction for the uninformative buncher (described in detail in Online Appendix C).

Similar to the difference-in-bunching method, an advantage of this second method is that we observe an estimate of the ideal loan amount at the individual borrower level. Using a linear probability model, we estimate the probability of bunching as a function of the (binned) percentage of a borrower's originally requested loan that they would have to give up to bunch:

$$P(Bunch_i) = \sum_j^J \beta_j DistanceBin_j + \gamma * X_i + \varepsilon_i \tag{4}$$

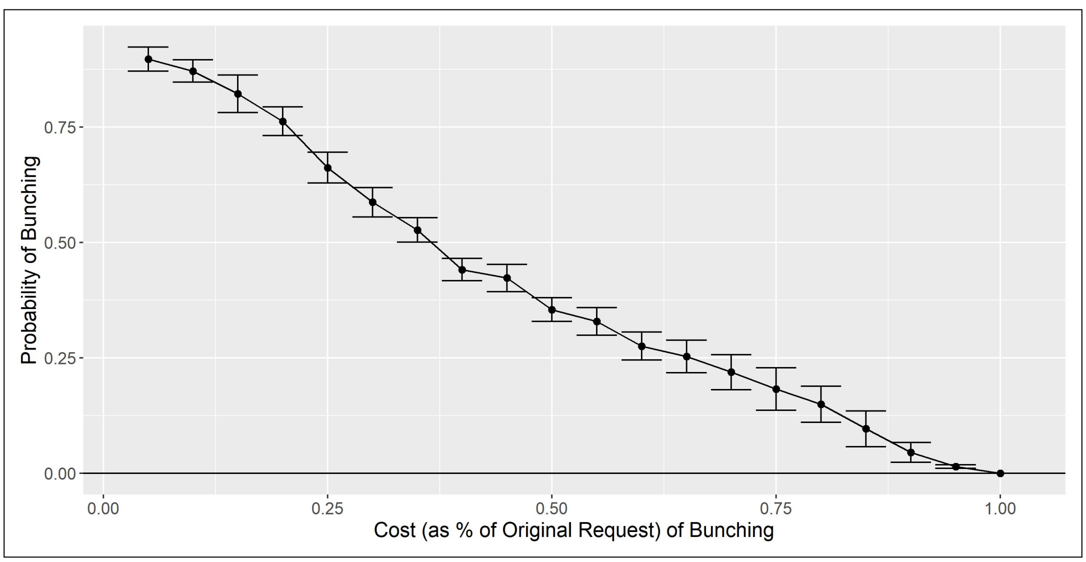
$$DistanceBin_j \in \{0\% - 5\%, 5\% - 10\%, ..., 95\% - 100\%\}$$

$DistanceBin$ describes the difference in percentage terms between the borrower's original request and the collateral threshold. For example, when the collateral threshold is $10,000, a consumer with an original request of $20,000 would have a distance of 50%. Distances are binned in 5 percentage point (pp) intervals. X_i is the same set of demeaned, borrower-level control variables used in Equation 3.

This estimation method requires an alternative assumption than the difference-in-bunching method, namely, that the originally requested loan amount is a good proxy for the borrower's ideal loan amount. We find support for this interpretation of original requests based on patterns in the data and our discussions with the program directors: While certain circumstances may motivate borrowers to adjust their loan amounts in either direction, overall, borrowers who do not bunch tend to borrow an amount very close to their original request. For instance, among borrowers with initial requests and final loans below the collateral threshold, where there is no saliency of the collateral requirements, the average initial request is $115 larger than the average final loan amount.

Figure 7 shows the results of our alternative bunching estimation (described in Equation 4) using original requests. Each point represents an estimated coefficient, with an associated 95% confidence interval, of the probability of bunching at different costs of bunching. Cost is measured as the share of a borrower's ideal loan amount that they would have to forego to avoid posting collateral. In the smallest cost bin, where borrowers have to give up less than 5% of their ideal loan amount to avoid collateral, nearly 80% of borrowers bunch at the threshold. As the cost of bunching increases, the probability of doing so strictly decreases. Nonetheless, we find that 50% of borrowers will give up at least 40% of their ideal loan to avoid collateral (i.e., 50% of borrowers are willing to give up at least $6,700 when the collateral threshold is $10,000). Around 15% will give up 75% of their ideal loan (i.e., give up $30,000 when the threshold is $10,000) to avoid posting collateral.

Figure 7: Original Request Approach Estimation Results



Note: This figure shows the original request approach estimation results. Each point represents an estimated coefficient, with an associated 95% confidence interval, of the probability of bunching at different "costs" of bunching.

3.4.3 Comparison Across Methods

Each of the three methods – traditional bunching estimators, difference-in-bunching, and original requests – uses a distinct group to estimate consumers' ideal loan amounts and relies on different information about the borrower's decision. The estimated coefficients for each method can be transformed to describe the underlying distribution of collateral aversion. Recall from above that this CDF can be drawn from the proportion of households who do not bunch at a specific ideal loan amount. Regarding the difference-in-bunching estimation, the ratio of consumers' predicted loan amounts with versus without the collateral requirement can be used to estimate this proportion. For example, suppose the average borrowing for households with losses of $20,000 is $15,000 when the collateral threshold is $25,000, but only $12,500 when the threshold is $10,000. Since the bunching decision is binary – borrowers will select either their ideal loan amount of $15,000 or will bunch at the threshold of $10,000 – we can calculate the share of households who do not bunch from the ratio of distances of the expected loan amounts from $10,000.

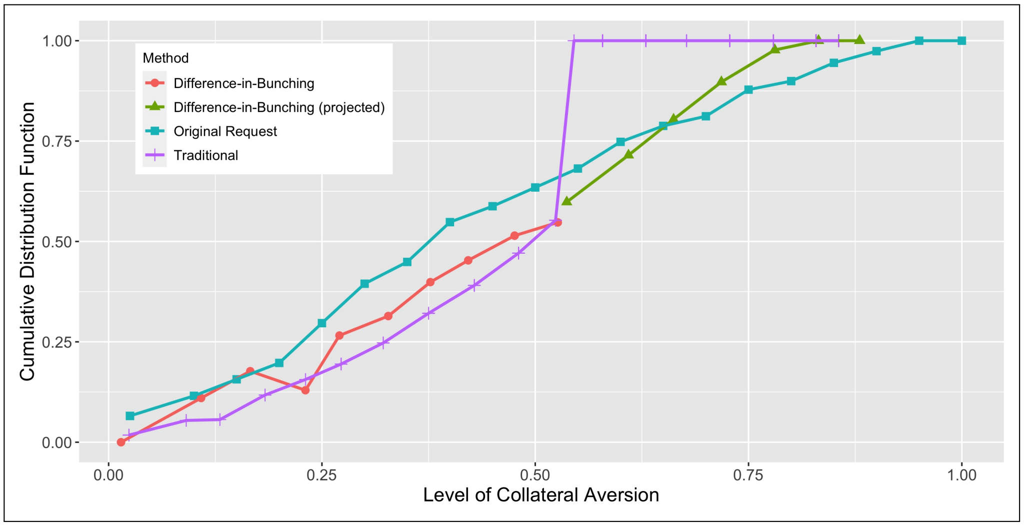
$$1 - P(Bunch) = \frac{E[LoanAmount|LossBin = j; Threshold = \$10,000] - 10,000}{E[LoanAmount|LossBin = j; Threshold = \$25,000] - 10,000}$$

In this example, the probability of not bunching would be 0.5. Thus $5,000 would represent the median level of collateral aversion: Half of the households value avoiding collateral less than $5,000 of credit, do not bunch, and thus borrow $15,000. The other half value avoiding collateral greater than $5,000 of credit, bunch, and thus borrow $10,000, giving an average loan of $12,500. We can then calculate the marginal effect of bunching on loan amounts for each loss bin to recover the partial distribution of collateral aversion, up to the expected loan amount for a household with $25,000 in losses.

Regarding the original request method, estimating the distribution of collateral aversion is straightforward. This method predicts the probability of bunching for a given distance bin j. Thus, the CDF of collateral aversion for the average borrower is captured by the inverse of the regression coefficients, $1 - \beta_j$, across the J bins in Equation (4).

Figure 8 shows the CDF of collateral aversion estimated by each of the three approaches when the collateral threshold is set at $10,000. The horizontal axis measures collateral aversion as the percent of the household's ideal loan amount that it would be willing to give up to avoid posting collateral. Since the difference-in-bunching estimation is limited to households with losses up to $25,000, we project the CDF beyond $25,000 using an isotonic regression.

Figure 8: Implied CDFs of Collateral Aversion for Different Methods



Note: This figure shows the implied CDFs for each of the three bunching methods for the $10,000 threshold. The traditional method uses a graphical approach while the Difference-in-Bunching and Original Request methods use an equation approach. The latter half of the Difference-in-Bunching CDF is projected by an isotonic regression. The level of collateral aversion represents the maximum percentage of a borrower's ideal loan amount that it would be willing to give up to avoid collateral.

One noteworthy aspect of the distributions in Figure 8 is the differing estimates of the endpoint of the bunching region between the traditional method and the alternative approaches. A known difficulty for traditional bunching methods is estimating this endpoint as the estimate is highly sensitive to extensive margin responses and is furthest from the primary data used to project the distribution (Kleven, 2016). The estimates of the alternative methods are less sensitive to these concerns, and we find a much wider distribution of collateral aversion using these methods. The traditional method estimates that the most collateral averse borrowers would only be willing to give up around 55% of their ideal loan to avoid posting collateral; the alternative method estimates are in the range of 80 to 90%.

Despite large differences in estimating the endpoint of the bunching region, each method produces a similar collateral aversion result at the median. The traditional approach and the difference-in-bunching approach each estimate that the median household would forgo around 47% of its ideal loan amount to avoid posting collateral (i.e., they would rather borrow $10,000 uncollateralized vs. $19,000 collateralized); the original request approach estimates a median of 42%. Online Appendix D additionally reports the median collateral aversion for the $14,000 and $25,000 thresholds for the traditional and original request approaches and provides a summary of the different methods and their assumptions. Across all methods and thresholds, we find consistent estimates: The median household is generally willing to give up between 40% to 50% of its ideal loan to avoid posting collateral.

3.5 Mechanisms and Heterogeneity

Having established that many borrowers are averse to posting collateral, and in doing so give up substantial amounts of subsidized loans at a time of need, we next turn to better understanding the drivers of collateral aversion. With the richness of our data and setting, we can examine selection into who bunches and evaluate a number of specific hypotheses that unpack the mechanisms underlying this bunching behavior.

We divide this discussion into three parts, covering adverse selection, financial tradeoffs, and behavioral considerations. These considered factors are not necessarily mutually exclusive, and the borrower characteristics described below (e.g., credit score and income) may be correlated. In addition to the univariate results, we conducted multivariate analyses, which we briefly describe at the end of the section, to ensure that the observed relationships hold in models with controls.

3.5.1 Adverse vs. Advantageous Selection

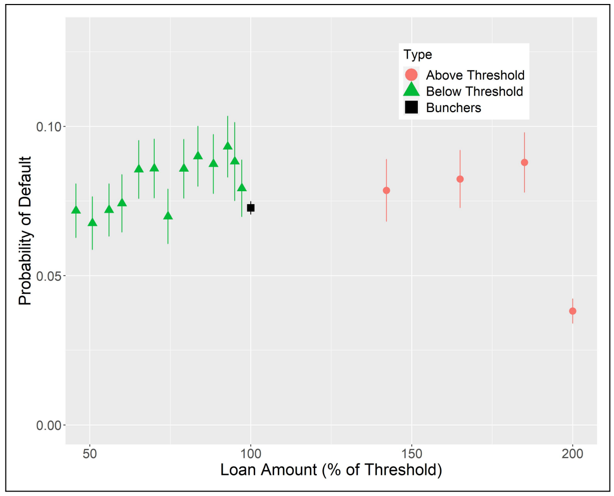
Posting collateral is particularly costly for those who have a high expectation that they will subsequently default. A standard adverse selection explanation for the bunching behavior we observe would be that individuals with private information regarding their propensity to default would be more likely to avoid posting their primary residence as collateral.

In Figure 9 Panel A, we present the relationship between default rates and loan amounts. We measure the default rate as the share of loans that have been charged off by the program. Realized default rates incorporate the consequences of both observable and unobservable borrower characteristics. The comparison of interest is borrowers who bunch at the threshold (marked with a black square) versus those taking slightly smaller loans (just to the left of bunchers, marked with green triangles). These two groups have similar loan amounts and identical repayment incentives (neither group is collateralized) and so any differences in realized defaults can be attributed to selection effects.

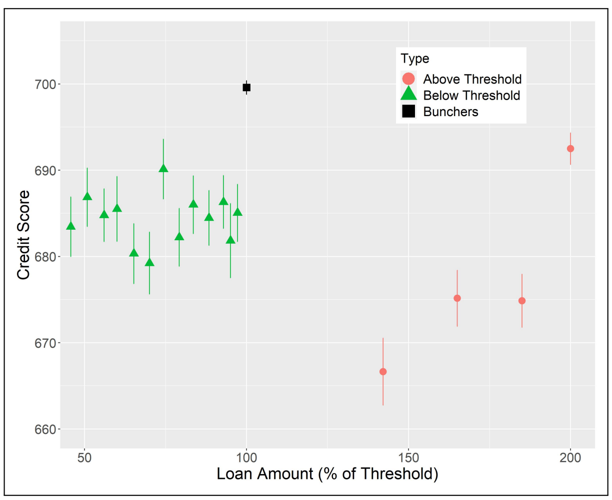
The pattern in realized defaults suggests *advantageous selection*: Bunchers are less risky than borrowers taking smaller loans. Below in Section 4 we examine default behavior in general, and moral hazard in particular, in more detail.

Figure 9: Advantageous Selection at the Collateral Threshold

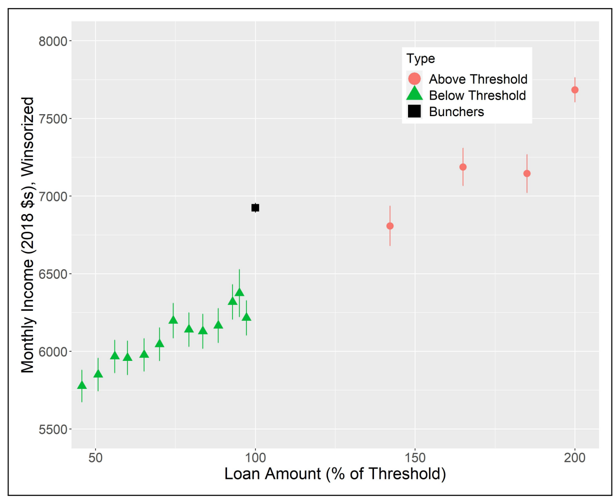
Panel A: Default Rate



Panel B: Credit Score



Panel C: Income



Note: This figure shows the percent of borrowers who default (Panel A), the average credit score (Panel B), and the average monthly income (in 2018$s) by loan amount as a percent of the collateral threshold.

In Figure 9, we additionally examine selection along observable dimensions. In Panel B, we show the relationship between credit scores and the propensity to bunch at the uncollateralized threshold. In this case, the comparison of interest is borrowers who bunch versus those who elect to take a larger, collateralized loan (those to the right of bunchers, marked with red circles in the figure).[16] We again find evidence of advantageous selection: Bunchers have credit scores that are

[16]In contrast to the *ex post* comparison of loan defaults, the comparison here is *ex ante*, examining how the characteristics of borrowers who bunch differ from those who do not bunch.

over 20 points higher than borrowers above the loan amount threshold. Panel C shows a similar pattern for income, with bunchers having higher incomes on average.

In sum, these figures suggest that, in the bunching region, borrowers who choose to bunch are lower risk as measured both *ex ante* and *ex post* than those who do not.

3.5.2 Financial Tradeoffs

Financial tradeoffs may contribute to borrowers' decisions to bunch. An optimizing time-consistent consumer would compare the costs of taking a collateralized loan relative to taking a smaller loan, which they might combine with outside financing (e.g., personal savings). If consumers are indeed optimizing in the choice to avoid collateral, then the cost of the subsidized loan should influence the decision to bunch. We consider two potential costs: interest rates and hassle costs.

We examine consumers' responses to borrowing costs by leveraging discrete jumps in the interest rate offered on disaster loans over time. The applicant's rate depends on the disaster declaration date. Most borrowers pay an interest rate that is about half of the prevailing 30-year mortgage market rate when their disaster occurred. The program's offered rate is adjusted quarterly based on movements in private market rates. We examine a narrow window around rate changes when the timing of loan applications (based on a specific disaster) is exogenous to the prevailing interest rate. We can thus identify the sensitivity of bunching with respect to interest rates based on these exogenous rate changes.[17]

We find that the propensity to bunch is highly sensitive to the offered interest rate, with a 100 bps change in interest rates associated with a 9 pp change in the likelihood of bunching. For example, increasing the program's average interest rate from 2.5% to 3.5% would be expected to increase the share of borrowers who bunch from 30% to 39%. Thus, prospective borrowers, who are offered a subsidized interest rate after suffering a natural disaster, nonetheless respond strongly to the cost of credit in their decision to collateralize the loan.

Another element of the financial tradeoff is the hassle cost of origination. Collateralizing a loan requires additional documentation that adds to the incentive to bunch at the collateral threshold. The hassle costs of taking a collateralized federal disaster loan appear similar to those of taking a private-sector, collateralized home loan such as a second lien or home equity line of credit

[17]This approach is developed by Collier and Ellis (2021) who examine extensive margin responses to the program's offered interest rates. We describe additional details of the estimation strategy in Online Appendix E.

(HELOC).[18] Overall, we anticipate that if consumers were deterred from taking a collateralized disaster loan due to hassle costs, they would not tend to substitute it with a private home loan because the hassle costs are so similar. Rather, for consumers with sufficient means, hassle costs might motivate supplementing an uncollateralized disaster loan with other (non-credit) outside options such as personal savings. As in other settings with prominent search or hassle costs, such as mortgage refinancing, we find that the most responsive households are those with higher incomes, likely greater outside resources, and likely to have less time to deal with hassle costs (e.g., see Andersen et al., 2020).[19]

3.5.3 Behavioral Considerations

Finally, preferences (rational or otherwise) toward debt and risk may also contribute to the decision to avoid collateral. While the previous subsection notes that consumers' decisions on whether to bunch depend on financial tradeoffs, it remains surprising that so many consumers prefer to borrow at the threshold rather than receiving a large, very low-interest collateralized loan. Previous research in uncollateralized settings has shown that some consumers appear to be "debt averse," even when the terms of the debt are subsidized or otherwise quite favorable (Cadena and Keys, 2013; Field, 2009). Debt aversion may be even more extreme when attached to a collateral requirement, as some homeowners may be particularly afraid of losing their home due to a failure to repay.

An examination of consumers' bunching decisions given their existing home equity appears to highlight the importance of such behavioral factors. Homeowners with substantial equity in the home have more to lose if they default on the disaster loan than consumers whose collateral is already fully committed. Based on this logic, we would expect to find a strong, negative relationship between bunching and the loan-to-value (LTV) ratio on a consumer's existing home loans.

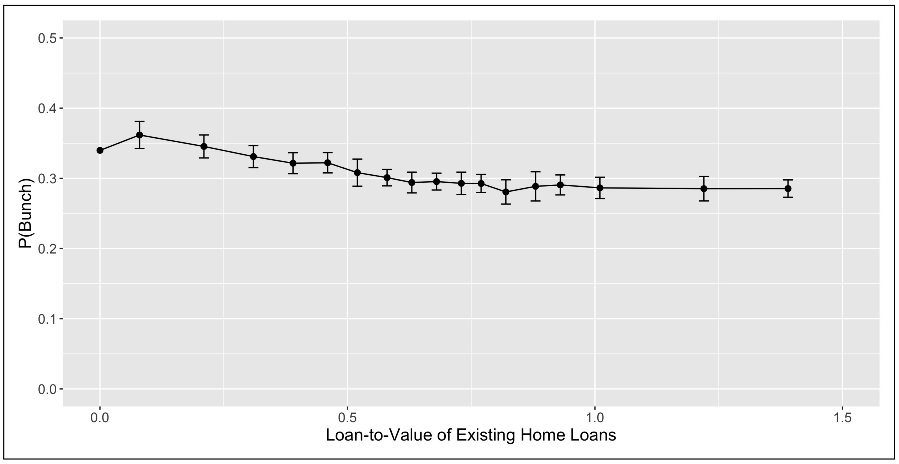
Figure 10 shows the share of borrowers who bunch and their existing LTVs. Borrowers *without* a mortgage (LTV = 0) are around 5 pp more likely to bunch than those with an LTV above 0.5, providing some support for the financial incentives created by existing debt. However, a marked

[18] Both disaster loans and private home loans require a title check and assessment of the property's value. A private loan may potentially be disbursed in less time than a disaster loan (see Section 2 on disaster loan disbursements); unlike private loans, federal disaster loans do not include closing costs or other origination fees.

[19] A further financial consideration is that accepting a larger subordinated loan may make it more difficult to refinance a first lien on the property. Some particularly savvy households may want to protect their option value to refinance at a later date. For this consideration to take precedent over the more immediate needs of rebuilding after a disaster, a household would need to anticipate a sharp decline in interest rates that would make the future refinancing option more valuable than these short-term repairs.

feature of the figure is how little a borrower's LTV matters in the decision to bunch. Almost 30% of consumers with LTVs above 1 (i.e., consumers who are already underwater on their home loans) reduce their loan amount to avoid posting collateral. The response of these borrowers, who appear to have negative equity and thus no immediate financial incentive to bunch, additionally suggests that behavioral factors influence bunching decisions.

Figure 10: LTV on Existing Home Loans and Probability of Bunching



Note: This figure shows the share of households who bunch based on the loan-to-value of their existing home loans. The figure is based on a regression of the likelihood of bunching on LTV bins, loss amount bins, and disaster fixed effects. Standard errors are clustered by disaster. Consumers with an LTV = 0 do not have a mortgage (n = 43,000) and serve as the reference group. Each additional point represents around 6,700 borrowers. The sample is restricted to borrowers with loss amounts of at least the collateral threshold.

As a robustness test, we conduct a multivariate analysis using the covariates discussed in this section (e.g., credit score, LTV, etc.), reported in Online Appendix F. The multivariate regressions yield qualitatively similar results to the presented univariate analyses. Namely, the likelihood of bunching increases in a borrower's credit score and in the offered interest rate. Also, the borrower's existing LTV has a statistically significant, but economically small negative association with bunching.

In summary, these results regarding posting collateral echo the mortgage refinancing literature, which finds both puzzling failures to exercise valuable options, but also predictably greater responsiveness when the financial benefits increase (Andersen et al., 2020; Keys et al., 2016). With observed heterogeneity in bunching suggestive of advantageous selection, we next turn to questions related to collateral's role in default and moral hazard.

Table 3: Default Summary Statistics

	Mean	SD	Percentiles p10	p50	p90
Default Rate (%)	10.7				
Time to Default (Years)	4.9	2.9	1.7	4.2	9.2
Amount ($) | Default	20,050	12,535	7,029	15,827	38,678
Amount (% of Loan) | Default	79.3	22.0	45.7	86.9	100.0

Note: Monetary values in 2018$. This table, and all estimation for this section, uses a sample limited to borrowers with losses below $50,000 who either bunch or borrow above the threshold.

4 Collateral and Loan Defaults

In this section, we examine the causal effect of collateral on borrowers' default rates. A key consideration regarding collateral requirements is whether consumers have discretion over the decision to default. While collateral has traditionally been viewed as reducing defaults by aligning the borrower's incentives with the lender's, recent evidence suggests that mortgage defaults are largely driven by adverse life events, events over which consumers may have little control (e.g., Ganong and Noel, 2020b). If posting collateral has no bearing on consumer default rates, collateral requirements may provide fewer benefits to lenders – and create more harm to consumers, who are already in difficult circumstances – than traditionally assumed. Ultimately, the effect of collateral is an empirical question, but isolating the causal influence of collateral on loan default is challenging.

Table 3 provides summary statistics on program loan defaults. Almost 11% of all borrowers default on their loan. The median borrower who defaults does so 4 years after being approved for the loan, resulting in a charge-off amount of $16,000, which represents 87% of the original loan principal. To better identify the effect of collateral through the borrower's choice to bunch, we limit our sample for this section to borrowers in the bunching region: those with losses below $50,000 who either bunch or borrow above the threshold.

4.1 Methods

Posting collateral may affect default rates through three channels. First, collateral increases the consequences of defaulting and so may induce the household to take additional actions to avoid default. We are interested in measuring this moral hazard effect, the reduction in default likelihood from collateralizing the loan. Second, the collateral requirement may affect default rates by (mechanically) reducing the size of loan that a household takes. A household who chooses a smaller loan over a larger one will owe less in principal and have smaller monthly payments, both of which can reduce default risk. This loan-size channel is also a form of moral hazard, but has the opposite predicted effect of the collateral channel since uncollateralized loans are smaller. Finally, selection may influence default rates as consumers who choose to use collateral may differ from those who do not. For example, in Section 3.5 we show that borrowers who bunch tend to be more creditworthy than borrowers who choose slightly larger loan amounts. Here, we describe how our identification strategy can disentangle the effect of collateralizing consumers' loans on default rates from the loan size and selection effects.

We model the relationship between collateral and loan default with a linear discrete survival function:

$$\begin{aligned} P(Default_{i,t}) &= X_{i,t}\beta' + \varepsilon_{i,t} \\ X_{i,t} &= (\mathbf{Collateral_i}; \tau_t, LossBin_i, log(LoanAmount_i), Disaster_i) \end{aligned} \tag{5}$$

where $P(Default_{i,t})$ is the probability that household i either defaults on the loan in year t or has already defaulted on its loan in a year prior to t. $\mathbf{Collateral_i}$ is a binary indicator for whether borrower i's loan is collateralized. τ_t is a series of fixed effects representing the years since loan origination. To account for the impact of loss size on default rates and ensure that we are comparing households with similar size losses, we bin losses into $1,000 bins and include $LossBin_i$ as a series of fixed effects. $LoanAmount_i$ is the final loan amount for household i. $Disaster_i$ is a series of disaster fixed effects and controls for any disaster-specific effects on default risk, such as local labor market impacts, as well as time-specific events. All standard errors for this section are clustered at the $Disaster_i$ level, since this is the source of our random variation in the collateral threshold (Abadie et al., 2017). Like other survival models, this estimation relies on the proportional hazard assumption, that the explanatory variables impact the default rate equally across periods.

In this reduced-form regression, the coefficient on $\mathbf{Collateral_{i,t}}$ represents the combined effect of collateralization (the first channel) and selection (the third channel). We measure the loan size effect (the second channel) by including the logged loan amount as a control. The logged loan amount may not fully capture the relationship between loan size and default risk so we also model loan amounts more flexibly in robustness tests (described below). To separate the collateralization and selection effects, we need an instrument that influences the decision to collateralize, but does not affect the default risk except through the collateral channel.

Our instrument is derived from variation in the collateral threshold over time. Because loss timing due to natural disasters is plausibly exogenous, we can compare households who had the same size loss yet were different distances away from the bunch point. Figure 11 illustrates the identifying variation, showing how bunching behavior changes with the thresholds. Panel A shows the stark increase in bunching probability for borrowers with loss amounts slightly above the threshold. As loss amounts grow further from the threshold, the bunching probability decreases. Panel B shows how this propensity to bunch impacts the rate of loan collateralization. Borrowers with loss amounts below the threshold never have to post collateral, with the probability increasing as the losses grow. Our instrument exploits the vertical distance between the lines in Panel B. Borrowers on the same vertical line have the same loss amount (by experiencing disasters at different points in time), yet can have very different probabilities of collateralization based on their distance from the bunch point.

We thus define our instrument $\overline{\mathbf{Distance_i}}$ as the distance (in percentage terms) between the loss of household i and the bunch point.[20] Because we are controlling for loss size through binned fixed effects, and the bins do not move over time, the only within-bin variation in $\overline{\mathbf{Distance_i}}$ is from the collateral threshold moving over time. Thus, we recover the local average treatment effect (LATE) for borrowers who would bunch under a higher collateral threshold but not the lower threshold.

To isolate the causal impact of collateral on default risk, we use two-stage least squares. Our 2SLS model is

First Stage:

$$P(Collateral_i) = Z_i\gamma' + v_i \tag{6}$$

$$Z_i = (\overline{\mathbf{Distance_i}}; \tau_t, LossBin_i, log(LoanAmount_i), Disaster_i)$$

Second Stage:

$$P(Default_{i,t}) = \widehat{X_i}\beta' + e_{i,t} \tag{7}$$

$$\widehat{X_{i,t}} = (\widehat{\mathbf{Collateral_i}}; \tau_t, LossBin_i, log(LoanAmount_i), Disaster_i).$$

where the first stage estimates the impact of distance to the bunch point on the probability that the household collateralizes. The second stage (Equation (7)) is the same as Equation (5) except

[20] Thus, for the example above of a \$30,000 loss, the distance measure would be 17% if the collateral threshold were \$25,000 and 67% if the threshold were \$10,000. In measuring the distance for household i, we proxy for the household's actual loss with the median loss amount in its bin. This is to ensure that we are avoiding any within-bin variation in loss amounts inducing an effect through a separate causal pathway. The correlation with our measure and the actual distance is greater than 0.99.

for $\widehat{\textbf{Collateral}_i}$, which instruments for the presence of collateral with the predicted values from the first stage (Equation (6)).

Table 4: Moral Hazard Estimation: First Stage

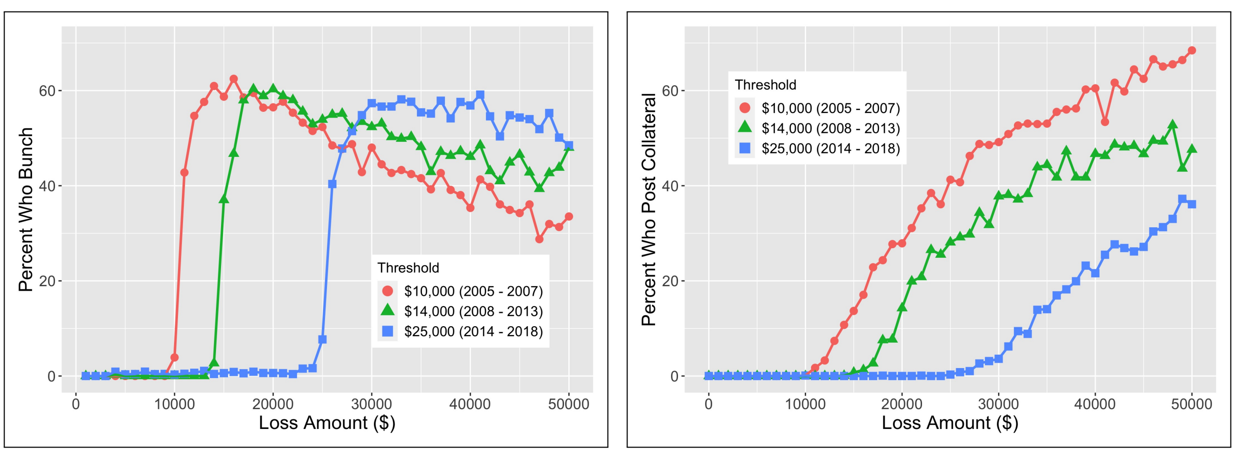
	Dependent variable:
	Collateral
Distance IV	1.036***
	(0.031)
ln(Loan Amount)	1.535***
	(0.149)
Dependent Var. Mean:	0.39
Instrument F-Stat:	1,086
Disaster Fixed Effects?	Yes
Time Since Origination Fixed Effects?	Yes
Loss Size Fixed Effects?	Yes
Data Level?	Household - Loan Year
Observations	592,214
Residual Std. Error	0.213

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents the results of the first stage of our two stage least squares moral hazard estimation (Equation 6). Standard errors, clustered at the disaster level, are in parenthesis.

Figure 11: Bunching and Collateral by Loss Amount

Panel A: Bunching

Panel B: Collateral



Note: This figure shows the percent of borrowers who bunch at the collateral threshold (Panel A) and the percent who post collateral (Panel B) by loss amount and collateral threshold regime.

As shown in Table 4, the instrument is strong and the first stage coefficient is in the anticipated direction. Borrowers who must give up a larger amount of their loan (due only to the time variation in the bunch point) in order to avoid collateral are significantly less likely to bunch and therefore much more likely to have collateralized loans. For a borrower whose ideal loan amount is equal to their loss amount, the coefficient implies an almost one-to-one trade-off – for every additional 1% of their ideal loan the borrower must give up to avoid collateral, they are 1 pp less likely to bunch. The second stage then allows us to separately identify the causal effect of collateral on default.

The interpretation of the coefficient on $\mathbf{Collateral_{i,t}}$ as only the effect of collateral on default risk depends on the assumption that the direct effect of loan size on default risk (the second channel described above) is being effectively controlled for via the additively separable log term. In Online Appendix G, we explore a (nearly) exhaustive way to account for non-linearity in our control variables: a Lasso regression. Rather than including only a logged representation of the amount the household borrows, we allow log and linear terms for the nominal loss amount. Additionally, we include polynomial terms through the fifth power for both variables and then let the algorithm pick the functional form with the best predictive properties. When allowing for this flexible non-linearity, we obtain qualitatively similar results.

4.2 Reduced Form and 2SLS Results

The first column of Table 5 shows the average impact of collateral on the likelihood of default. Column (1) is the reduced form estimate and so does not account for potential selection effects. In this estimate, collateral reduces the default hazard rate by around 1 pp, an estimated 16% reduction from the estimated counterfactual default rate with no collateral rules. However, when we account for selection in Column (2) by instrumenting for the use of collateral with the distance from the threshold, we find that the causal effect of collateral reduces the hazard rate by 3 pp. This response is equivalent to a 34% reduction in the default hazard rate and is more than double the raw correlation. This difference highlights the need to account for the advantageous selection documented above – better quality borrowers are more willing to reduce their loans to avoid collateral.

In Column (3) of Table 5 we add other observable borrower characteristics – credit score, monthly income, and debt-to-income ratio – that are correlated with both default risk and bunching likelihood. If our instrument is effectively controlling for selection, then the inclusion of the controls should not change our coefficient estimate, only the standard errors. Indeed, we find that the coefficient on collateral remains almost identical. We take this as strong evidence of our ability to isolate the causal effect of collateral from changing bunch points.

The results also highlight that collateral may serve as a substitute for credit score and income from an underwriting standpoint. For example, posting collateral reduces the default hazard by approximately the same amount as a 100-point increase in the borrower's credit score. The findings suggest support for theoretical predictions that collateral requirements may facilitate lending to lower income and credit score populations who might otherwise be credit rationed.

Column (4) shows results from a linear probability model, instead of a hazard model, of the likelihood that the borrower ever defaults.[21] While this alternative specification does not account for the influence of time in the way that a hazard model does, it offers two benefits. First, it does not require the proportional hazard assumption. Second, the coefficient for the linear probability model is more easily interpreted as the direct impact of collateral on ever defaulting. From these results, we estimate a counterfactual, uncollateralized loan default rate of 14% and that collateral reduces the default rate by 6 pp. This 39% reduction in default rates is very similar to the hazard model estimate.

In Online Appendix H, we test the robustness of our estimation to various model design choices with a specification curve (Simonsohn et al., 2020). We assess the modeling choices of (1) the size of the loss size bins; (2) how to control for loan size; (3) data restrictions on loss size (e.g., limiting the sample to borrowers with losses below $50,000); (4) the use of additional controls that are not used in the lending decision but are correlated with default rates; and (5) the inclusion of "non-informative borrowers" who borrow below the bunch point. We run different regressions across the various combinations of our modeling choices and find our estimates are remarkably consistent. Out of the 240 different regressions, every point estimate on the (instrumented) effect of collateral on the default hazard is less than zero, with 99% statistically different from zero. The 95th percentile of our estimates is -0.056 and the 5th percentile is -0.024.

Our setting, which features two changes of the collateral threshold, allows us to isolate the causal effect of posting one's primary residence as loan collateral on loan default. This setting is unique: The vast majority of prior research on the relationship between collateral and moral hazard focuses on firms rather than individuals, and uses observational data rather than a well-identified environment. We find that collateral provision causally reduces defaults by 35%, suggesting that the possibility of losing one's home provides a strong countervailing force to moral hazard.

[21] Because we observe borrowers for different amounts of time, we weight this regression by the number of loan years for which we observe each borrower.

Table 5: Moral Hazard Estimation: All Measures

	Dependent variable:			
	Default Hazard			Default Rate
	(1)	(2)	(3)	(4)
Collateral	-0.015^{**}			
	(0.006)			
Collateral (instrumented)		-0.031^{*}	-0.030^{**}	-0.058^{**}
		(0.017)	(0.015)	(0.025)
ln(Loan Amount)	0.053^{***}	0.070^{***}	0.060^{***}	0.132^{***}
	(0.007)	(0.018)	(0.016)	(0.026)
Credit Score (00s)			-0.034^{***}	
			(0.002)	
ln(Monthly Income)			-0.022^{***}	
			(0.003)	
Debt-to-Income Ratio			-0.000^{***}	
			(0.000)	
Method:	OLS	2SLS	2SLS	2SLS
Implied Percentage Change:	-0.18	-0.34	-0.34	-0.39
Disaster Fixed Effects?	Yes	Yes	Yes	Yes
Time Since Origination Fixed Effects?	Yes	Yes	Yes	No
Loss Size Fixed Effects?	Yes	Yes	Yes	Yes
Data Level?	Household - Loan Year	Household - Loan Year	Household - Loan Year	Household
Observations	592,214	592,214	592,214	54,123
Residual Std. Error	0.263	0.263	0.260	19.223

Notes: *p<0.1; **p<0.05; ***p<0.01. The first column shows the estimation using regular OLS (Equation 5). The second column shows the results from the second stage of the two-stage least squares estimation (Equation 7). The third column shows the same two-stage least squares estimation with additional controls for default risk. The final column shows, instead of a hazard model, a linear probability model for the borrower ever defaulting, weighted by the number of observed loan years. Standard errors, clustered at the disaster level, are in parentheses.

5 Conclusion

In this paper, we examine the impact of collateral requirements on consumer borrowing behavior. While the provision of collateral is usually an endogenous equilibrium outcome after a negotiation between borrowers and lenders, our setting is free from such endogeneity concerns. With Federal Disaster Loans, borrowers select whether or not to post their primary residence as collateral when they choose the size of the loan, but this choice has no impact on loan approval or any other loan terms. Thus, we can isolate both *ex ante* collateral aversion and the *ex post* consequences of posting collateral independent from all other loan features and the extensive margin of approval.

Collateral provision in the form of one's primary residence appears to be perceived as very costly, consistent with the literature on consumers' high perceived default costs associated with mortgage delinquency (Bhutta et al., 2017) and reluctance to borrow against home equity through reverse mortgages (Nakajima and Telyukova, 2017). Using a variety of bunching techniques that validate and extend traditional methods, we estimate that the median borrower is willing to give up about 40% of their ideal loan amount to avoid collateral. That this loan is provided at a long-term, low fixed interest rate and intended to repair property damages makes the degree of collateral aversion even more striking. In addition, the fear of losing one's home appears to causally reduce loan default rates. We find that collateral induces a decline in defaults comparable to increasing credit scores by 100 points.

These findings suggest an interesting new dimension of heterogeneity in credit markets based on responsiveness to collateral requirements that deserves further examination. Our work represents the first estimates of how sensitive *ex ante* consumer demand and *ex post* loan performance are to collateral requirements. Whether these findings generalize to other consumer or business lending settings remain questions for additional research.

Our results ultimately demonstrate that housing collateral is a key factor in the actions of consumers, even during a period of acute need and even when homeowners may have no equity at stake. One potential implication of our findings is that collateral requirements in private markets might be too rigorously enforced relative to the deterrent effect of collateral provision. Lenders often limit credit access at an LTV ratio below 1 out of concern that borrowers will not repay if their debts exceed their collateral. However, we find that borrowers appear to place a value on collateral beyond this financial consideration. When borrowers treat an underwater property as if they have equity at stake, then lenders may find new opportunities to extend credit to households in need.

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Online Appendix A Example Forms

Hurricane Harvey Loan Fact Sheet

Date: 11/07/2017

U.S. Small Business Administration

U.S. SMALL BUSINESS ADMINISTRATION
FACT SHEET - DISASTER LOANS

TEXAS Declaration #15274 & #15275
(Disaster: TX-00487)
Incident: HURRICANE HARVEY

occurring: *August 23 through September 15, 2017*

in the ***Texas*** *counties of:* ***Aransas, Austin, Bastrop, Bee, Brazoria, Caldwell, Calhoun, Chambers, Colorado, DeWitt, Fayette, Fort Bend, Galveston, Goliad, Gonzales, Grimes, Hardin, Harris, Jackson, Jasper, Jefferson, Karnes, Kleberg, Lavaca, Lee, Liberty, Matagorda, Montgomery, Newton, Nueces, Orange, Polk, Refugio, Sabine, San Jacinto, San Patricio, Tyler, Victoria, Walker, Waller & Wharton;***
for economic injury only in the contiguous ***Texas*** *counties of:* ***Angelina, Atascosa, Brazos, Brooks, Burleson, Guadalupe, Hays, Houston, Jim Wells, Kenedy, Live Oak, Madison, Milam, San Augustine, Shelby, Travis, Trinity, Washington, Williamson & Wilson;***
and for economic injury only in the contiguous ***Louisiana*** *parishes of:* ***Beauregard, Calcasieu, Cameron, Sabine & Vernon***

Application Filing Deadlines:
Physical Damage: *November 30, 2017* **Economic Injury: *May 25, 2018***

If you are located in a declared disaster area, you may be eligible for financial assistance from the U.S. Small Business Administration (SBA).

What Types of Disaster Loans are Available?

- Business Physical Disaster Loans – Loans to businesses to repair or replace disaster-damaged property owned by the business, including real estate, inventories, supplies, machinery and equipment. Businesses of any size are eligible. Private, non-profit organizations such as charities, churches, private universities, etc., are also eligible.
- Economic Injury Disaster Loans (EIDL) – Working capital loans to help small businesses, small agricultural cooperatives, small businesses engaged in aquaculture, and most private, non-profit organizations of all sizes meet their ordinary and necessary financial obligations that cannot be met as a direct result of the disaster. These loans are intended to assist through the disaster recovery period.
- Home Disaster Loans – Loans to homeowners or renters to repair or replace disaster-damaged real estate and personal property, including automobiles.

What are the Credit Requirements?

- Credit History – Applicants must have a credit history acceptable to SBA.
- Repayment – Applicants must show the ability to repay all loans.
- Collateral – Collateral is required for physical loss loans over $25,000 and all EIDL loans over $25,000. SBA takes real estate as collateral when it is available. SBA will not decline a loan for lack of collateral, but requires you to pledge what is available.

What are the Interest Rates?

By law, the interest rates depend on whether each applicant has Credit Available Elsewhere. An applicant does not have Credit Available Elsewhere when SBA determines the applicant does not have sufficient funds or other resources, or the ability to borrow from non-government sources, to provide for its own disaster recovery. An applicant, which SBA determines to have the ability to provide for his or her own recovery is deemed to have Credit Available Elsewhere. Interest rates are fixed for the term of the loan. The interest rates applicable for this disaster are:

	No Credit Available Elsewhere	Credit Available Elsewhere
Business Loans	3.305%	6.610%
Non-Profit Organization Loans	2.500%	2.500%
Economic Injury Loans		
Businesses and Small Agricultural Cooperatives	3.305%	N/A
Non-Profit Organizations	2.500%	N/A
Home Loans	1.750%	3.500%

Amendment #8

What are Loan Terms?

The law authorizes loan terms up to a maximum of 30 years. However, the law restricts businesses with credit available elsewhere to a maximum 7-year term. SBA sets the installment payment amount and corresponding maturity based upon each borrower's ability to repay.

What are the Loan Amount Limits?

- Business Loans – The law limits business loans to $2,000,000 for the repair or replacement of real estate, inventories, machinery, equipment and all other physical losses. Subject to this maximum, loan amounts cannot exceed the verified uninsured disaster loss.
- Economic Injury Disaster Loans (EIDL) – The law limits EIDLs to $2,000,000 for alleviating economic injury caused by the disaster. The actual amount of each loan is limited to the economic injury determined by SBA, less business interruption insurance and other recoveries up to the administrative lending limit. EIDL assistance is available only to entities and their owners who cannot provide for their own recovery from non-government sources, as determined by the U.S. Small Business Administration.
- Business Loan Ceiling – The $2,000,000 statutory limit for business loans applies to the combination of physical, economic injury, mitigation and refinancing, and applies to all disaster loans to a business and its affiliates for each disaster. If a business is a major source of employment, SBA has the authority to waive the $2,000,000 statutory limit.
- Home Loans – SBA regulations limit home loans to $200,000 for the repair or replacement of real estate and $40,000 to repair or replace personal property. Subject to these maximums, loan amounts cannot exceed the verified uninsured disaster loss.

What Restrictions are there on Loan Eligibility?

- Uninsured Losses – Only uninsured or otherwise uncompensated disaster losses are eligible. Any insurance proceeds which are required to be applied against outstanding mortgages are not available to fund disaster repairs and do not reduce loan eligibility. However, any insurance proceeds voluntarily applied to any outstanding mortgages do reduce loan eligibility.
- Ineligible Property – Secondary homes, personal pleasure boats, airplanes, recreational vehicles and similar property are not eligible, unless used for business purposes. Property such as antiques and collections are eligible only to the extent of their functional value. Amounts for landscaping, swimming pools, etc., are limited.
- Noncompliance – Applicants who have not complied with the terms of previous SBA loans may not be eligible. This includes borrowers who did not maintain flood and/or hazard insurance on previous SBA loans.

Note: Loan applicants should check with agencies / organizations administering any grant or other assistance program under this declaration to determine how an approval of SBA disaster loan might affect their eligibility.

Is There Help with Funding Mitigation Improvements?

If your loan application is approved, you may be eligible for additional funds to cover the cost of improvements that will protect your property against future damage. Examples of improvements include retaining walls, seawalls, sump pumps, etc. Mitigation loan money would be in addition to the amount of the approved loan, but may not exceed 20 percent of total amount of physical damage to real property, including leasehold improvements, and personal property as verified by SBA to a maximum of $200,000 for home loans. It is not necessary for the description of improvements and cost estimates to be submitted with the application. SBA approval of the mitigating measures will be required before any loan increase.

Is There Help Available for Refinancing?

- SBA can refinance all or part of prior mortgages that are evidenced by a recorded lien, when the applicant (1) does not have credit available elsewhere, (2) has suffered substantial uncompensated disaster damage (40 percent or more of the value of the property or 50% or more of the value of the structure), and (3) intends to repair the damage.
- Businesses – Business owners may be eligible for the refinancing of existing mortgages or liens on real estate, machinery and equipment, up to the amount of the loan for the repair or replacement of real estate, machinery, and equipment.
- Homes – Homeowners may be eligible for the refinancing of existing liens or mortgages on homes, up to the amount of the loan for real estate repair or replacement.

What if I Decide to Relocate?

You may use your SBA disaster loan to relocate. The amount of the relocation loan depends on whether you relocate voluntarily or involuntarily. If you are interested in relocation, an SBA representative can provide you with more details on your specific situation.

Are There Insurance Requirements for Loans?

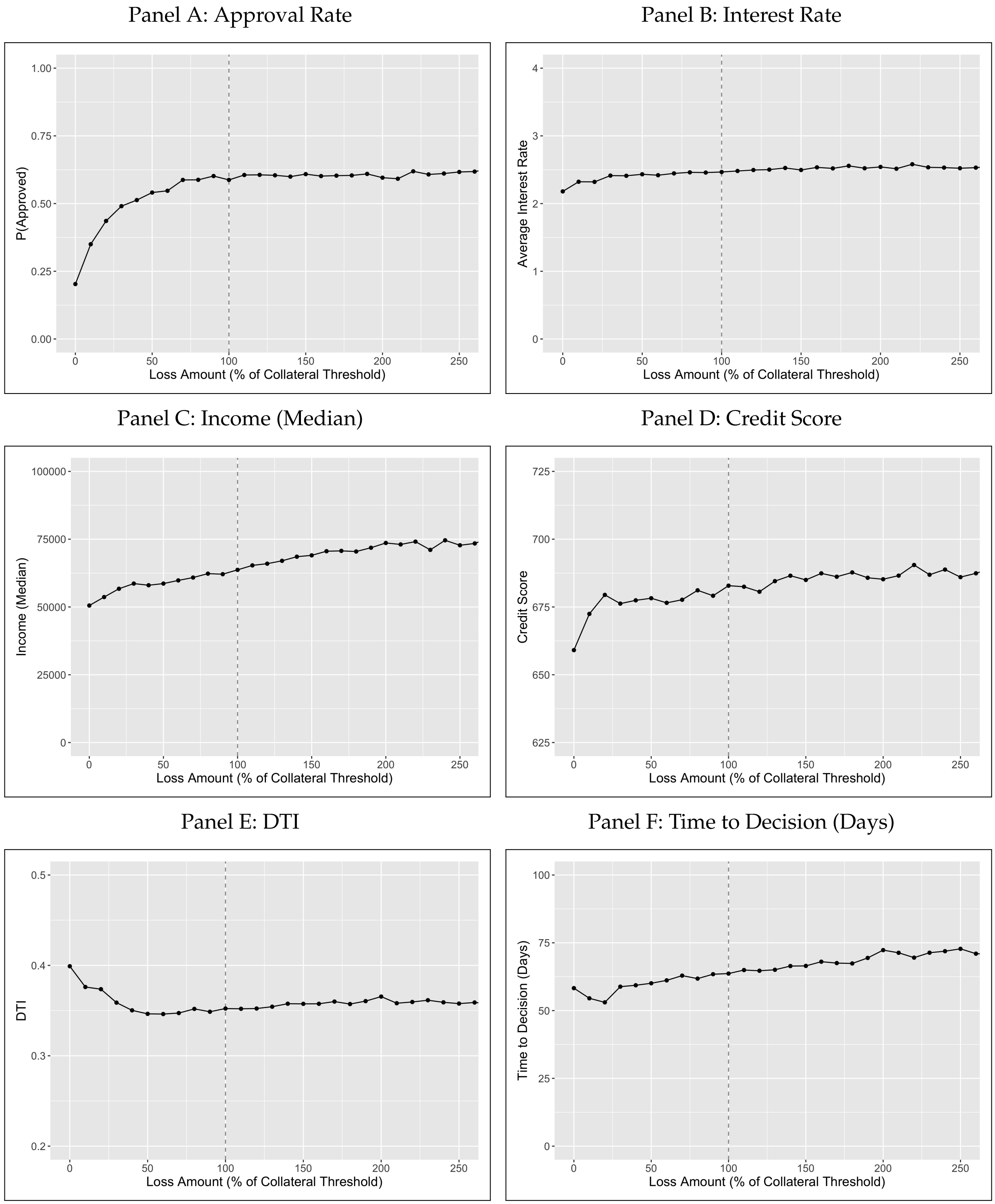
To protect each borrower and the Agency, SBA may require you to obtain and maintain appropriate insurance. By law, borrowers whose damaged or collateral property is located in a special flood hazard area must purchase and maintain flood insurance. SBA requires that flood insurance coverage be the lesser of 1) the total of the disaster loan, 2) the insurable value of the property, or 3) the maximum insurance available.

For more information, contact SBA's Disaster Assistance Customer Service Center by calling (800) 659-2955, emailing *disastercustomerservice@sba.gov*, or visiting SBA's Web site at *https://www.sba.gov/disaster*. Deaf and hard-of-hearing individuals may call (800) 877-8339. Applicants may also apply online using the Electronic Loan Application (ELA) via SBA's secure Web site at *https://disasterloan.sba.gov/ela*.

Online Appendix B Additional Variables and the Collateral Threshold

Figure 12 shows that approval rates, interest rates, income, credit score, debt-to-income (DTI), and the time to render a lending decision are smooth in the loss amount around the collateral threshold. The lending decision time is the duration in days from the disaster declaration to the date when the program renders an underwriting decision. We also examined the duration the application date to the decision date and the application date to the final disbursement date, and in each case, the duration is smooth around the collateral threshold.

Figure 12: Smoothness of Variables Around the Collateral Threshold



Note: This figure shows that household and loan characteristics are smooth around the collateral threshold. The horizontal axis is the loss amount as a percent of the collateral threshold. The time to decision is the duration in days from the disaster declaration to the date when program approves or declines the loan.

Online Appendix C Matching Method For Original Requests

Before meeting with a loan officer, borrowers are given an information sheet that lists the collateral threshold. While most bunchers (70%) seem to overlook this information, some borrowers choose to bunch in their initial request. For these "uninformative" bunchers, the original request does not represent a proxy for their ideal loan amounts as it already reflects their attitudes toward posting collateral. To run our original request method of bunching estimation, we need a proxy for the ideal loan amount of every buncher, including these uninformative bunchers. We estimate the ideal loan amount for the uninformative bunchers, where we do not observe a meaningful original request, by matching them with "informative" bunchers, where we do observe a meaningful original request. We use a nearest neighbor matching approach, which involves pairing uninformative bunchers with the closest eligible informative buncher. We then use the matched informative buncher's original request as our prediction for the uninformative buncher.

Nearest neighbor matching is one of the most common forms of matching used in the social sciences (Thoemmes and Kim, 2011). This matching technique requires a measure of "distance" between units.[22] We use the popular Mahalanobis distance measure. Specifically, we define the distance $\delta_{MD}(\mathbf{x}_i, \mathbf{x}_j)$ between uninformative buncher i and informative buncher j as

$$\delta_{MD}(\mathbf{x}_i, \mathbf{x}_j) = \sqrt{(\mathbf{x}_i - \mathbf{x}_j)' S^{-1} (\mathbf{x}_i - \mathbf{x}_j)}$$

where x is a standardized vector of each covariate for that buncher and S is the covariance matrix calculated for all of the covariates. x includes credit score, monthly income (logged), debt-to-income ratio, home value, interest rate, year, and LTV ratio for the home. After calculating this distance, the pair match for each uninformative buncher is the informative buncher with the smallest distance who has the same collateral threshold.[23] We then use the original request of the matched informative buncher as our prediction for the ideal loan amount for the uninformative buncher. As a robustness check on the procedure, we also perform a cross-validation check by re-running the matching procedure with one covariate left out. We can then use the matched value for this unused covariate as a test of how well the procedure is able to match other unused variables.

Table C1 summarizes the effectiveness of the matching procedure. The first column shows the average value for our matching covariates for the uninformative bunchers. The second column shows the average value of the original request and covariates for our matched sample of informative bunchers. The third column shows the average value of the original request and covariates for the full sample of informative bunchers. The final column shows results for our "leave one out" cross-validation procedure and represents the average value of the covariate for the matched borrowers when that covariate is not used in the matching procedure. The differences between the first column and the third column are stark. Across all of the covariates, the only one where the matching procedure fails is the debt-to-income ratio. Average losses, the most important covariate in predicting loans, for all informative bunchers was over $70,000 while the average for uninformative bunchers was only $30,000. This difference can perhaps be explained

[22] The most common distance measure is the propensity score, which does not apply in our setting as we do not have a "treatment" variable.

[23] We allow "replacement" matching: Multiple uninformative bunchers may be matched with a single informative buncher.

by the salience of the threshold listed on the information sheet. The matching procedure virtually eliminates the difference and ensures that we are predicting ideal loan amounts using borrowers with very similar loan amounts and the result of this can be seen in the average original request distance, which captures the difference in dollars between the original request and the collateral threshold. The average informative buncher would have to give up over half of their ideal loan amount to avoid collateral while, for the matched sample, the distance drops to 32%. Finally, the values from our cross-validation check, Column (4), are typically much closer to the values in the second column than the third, which indicates our matching method is able to match on unused covariates nearly as well as the ones used directly. There is one notable exception: we are unable to match the buncher's total loss well unless actively matching on it. This is due to the inherent randomness in loss size and is encouraging for our other methods which rely on loss size being plausibly exogenous.

Table C1: Impact of Matching

	Average Values			
	(1) Uninformative Bunchers	(2) Informative Bunchers Post-Match	(3) Informative Bunchers Pre-Match	(4) Informative Bunchers Leave-Out
Original Request Distance (%)	–	32.22	53.91	–
Total Loss	30,213	31,034	70,545	61,883
Home Value	184,888	185,230	225,736	202,077
LTV Ratio (%)	58.58	57.36	51.23	57.36
Interest Rate	2.63	2.54	2.37	2.54
Credit Score	687	687	696	680
ln(Monthly Income + 1)	8.51	8.51	8.60	8.51
Debt-to-Income Ratio (%)	45.83	60.43	52.49	60.43
Year	2011	2011	2012	2011

Note: This table summarizes the impact of the matching procedure. Column (1) shows the average value for our matching covariates for the uninformative bunchers. Column (2) shows the average value of the original request and covariates for our matched sample of informative bunchers. Column (3) shows the average value of the original request and covariates for the full sample of informative bunchers. Column (4) shows results for our "leave one out" procedure and represents the average value of the covariate for the matched borrowers when that covariate is not used in the matching procedure.

Online Appendix D Comparison of Bunching Estimation Results

Table D1 provides a summary of the methods and limitations of each of our three methods. Table D2 provides the estimated median collateral aversion for all three methods across the different thresholds.

Table D1: Summary of Methods

	Method	Information Used to Estimate Ideal Loan Amount	Limitations
(1)	Traditional Bunching Estimator	Distribution of borrowers outside of bunching region but same collateral requirements	- Difficult to determine marginal buncher - Extensive margin problems - Cannot include covariates
(2)	Difference-in-Bunching	Borrowers with the same loss amounts, but different collateral requirements	- Distributions may not be consistent over time (inflation, etc.) - Can only estimate for losses below $25,000
(3)	Original Request	Borrowers' initially requested loan amounts	- Must estimate ideal loan for borrowers who bunch in original request (30%) - Original request may not be perfect proxy for ideal loan amount.

Table D2: Alternative Bunching Estimators, Median Collateral Aversion

	Median Collateral Aversion (%)			
	(1)	(2)	(3)	(4)
Collateral Threshold	10,000	14,000	25,000	All
Traditional Bunching Estimator	47.37	39.39	45.65	–
	(0.98)	(2.48)	(0.74)	–
Original Request Approach:				
- No Covariates	40.50	41.90	40.40	40.70
	(1.10)	(1.40)	(3.65)	(1.18)
- Covariates	41.50	44.30	44.50	42.20
	(1.10)	(1.83)	(4.78)	(1.36)
Difference-in-Bunching Approach:				
- No Covariates	47.64	–	–	–
	(2.53)	–	–	–
- Covariates	46.81	–	–	–
	(2.88)	–	–	–

Note: This table presents the median collateral aversion for estimation method, delineated by rows. Columns are separated by different collateral thresholds. Standard errors, in parentheses, are block bootstrapped at the disaster level.

Online Appendix E Instrument for Interest Rates

The program's quarterly interest rate adjustment provides a source of identification for the impact of interest rates on bunching behavior.[24] Figure 13, Panel A plots the two rates offered by the program over time against the rate for a 30-year fixed-rate mortgage (Federal Reserve Bank of St. Louis, 2020). The program's market interest rate is meant to reflect the prevailing interest rate; however, the program only adjusts the rate quarterly. Within a short window on either side of the quarterly change, unobserved conditions affecting bunching behavior, such as alternative credit options, should be stable while the program rate changes discretely. Panel B of Figure 13 shows an example window around the rate change on December 29, 2008. In this example, a household who qualified for the below-market rate would receive a rate of 2.69% if it was affected by an event that was declared a disaster on December 28, but would receive a rate of 2.19% if it experienced an event that was declared a disaster on December 30, regardless of when the household applied or was approved.

Figure 13: Interest Rates Over Time

Panel A: Full Time Series

Panel B: One Window

Note: This figure plots the two interest rates offered by the FDL program over time plotted against the average private market interest rate for a 30-year fixed mortgage. Panel A shows the full time series from 2005 through May 2018. Panel B shows an illustrative window, which includes two-weeks before and two weeks after Dec. 29th, 2008, a date when the FDL program adjusted its rates.

To isolate the impact of interest rates on bunching, we subset the data into those borrowers whose disasters occur withing two weeks (before or after) a rate change.[25] We then use which side of the rate change (lower rate side vs. higher rate side) the borrower's disaster falls on as an instrument. Formally, we estimate

$$Rate_{i,t} = \alpha_0 + \alpha 1\{\text{Lower Rate Side}_{i,t}\} + X_{i,t}\gamma + \nu_{i,t}$$

[24]This identification was developed by Collier and Ellis (2021) and much of this description is drawn from their paper.

[25]To improve the strength of our instrument, we also limit to only borrowers who receive the below-market rate.

Table E1: Impact of Interest Rates

	Dependent variable:	
	P(Bunch)	Interest Rate
	(1)	(2)
Interest Rate (fitted)	0.089^{**}	
	(0.044)	
Low Rate Side		-0.180^{***}
		(0.031)
Additional Controls:	Yes	Yes
Original Request Bin FEs:	Yes	Yes
Year FEs:	Yes	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents the coefficients on the stacked RD. The first column represents the second stage and shows the causal effect of the interest rate on bunching behavior. The second column shows the results from the first stage. The F stat for the instrument in the first stage is 32. Additional controls are debt-to-income ratio, credit score, monthly income (logged), home value, total loss, and LTV ratio.

$$P(Bunch_{i,t}) = \beta_0 + \beta \widehat{Rate_{i,t}} + X_{i,t}\theta + \varepsilon_{i,t} \tag{A1}$$

where $1\{\text{Lower Rate Side}_{i,t}\}$, our instrument, is a binary indicator for borrower i being on the low side of a rate change; $X_{i,t}$ is the same vector of control variables and fixed effects, including binned original requests, as in Equation (4); and β then gives the causal impact of interest rates on bunching behavior. Table E1 provides the results of the estimation.

Online Appendix F Mechanisms and Heterogeneity: Multivariate Regression

Table F1 examines the likelihood that a borrower bunches in a multivariate regression using a set of covariates (e.g., credit score, borrower income, and the loan-to-value ratio of borrowers' existing home loans). The table shows how specific features of the borrower and setting correlate with bunching while controlling for other factors. Column (4) regresses the borrower's originally requested loan amount – a proxy for the borrower's ideal loan amount – on these covariates in a model with disaster-specific fixed effects. Many of these covariates are strongly related to borrowers' original requests. For example, borrowers with higher incomes and more valuable homes have larger original requests. The first three columns regress the likelihood of bunching on the same covariates. Column (3) omits fixed effects, Column (2) includes disaster fixed effects, and Column (1) additionally includes binned original request fixed effects. Column (1) is our preferred model and can be interpreted as examining the bunching probability and its correlates while holding a borrower's ideal loan amount constant. For example, Column (1) indicates that for a given ideal loan amount, higher interest rates increase the likelihood that a borrowing household reduces its loan to bunch at the collateral threshold. A comparison of the variance explained (R^2) across the models in Columns (1) to (3) shows that the borrower's original request is especially important in predicting whether a borrower bunches. The covariates are most useful for explaining borrower's original request (Column 4), though the covariates offer some additional insights regarding the decision to bunch, conditioning on the original request.

Table F1: Covariate Analysis

	Dependent variable:			
	P(Bunch)			Original Request ($000s)
	(1)	(2)	(3)	(4)
Interest Rate	0.018***	0.021***	−0.013	−3.900***
	(0.002)	(0.004)	(0.011)	(1.200)
Debt-to-Income Ratio (%)	−0.000	−0.000**	−0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Credit Score (00s)	0.021***	0.019***	0.027***	1.100**
	(0.003)	(0.003)	(0.003)	(0.460)
ln(Monthly Income + 1)	−0.017***	−0.027***	−0.008	7.800***
	(0.003)	(0.004)	(0.006)	(1.300)
Home Value ($0,000s)	0.000	−0.000	0.000	0.180**
	(0.000)	(0.000)	(0.000)	(0.070)
Total Loss ($000s)	0.005	0.002	0.003	0.830**
	(0.004)	(0.004)	(0.004)	(0.360)
LTV 70-90	−0.013***	0.000	0.010	−7.100***
	(0.003)	(0.005)	(0.009)	(1.400)
LTV 90-100	−0.008*	0.004	0.024*	−9.000***
	(0.005)	(0.008)	(0.014)	(1.700)
Negative Equity	−0.010**	−0.005	0.018**	−6.500***
	(0.004)	(0.005)	(0.009)	(1.700)
No Mortgage	0.007**	−0.012**	−0.020***	5.500***
	(0.003)	(0.006)	(0.007)	(1.300)
Constant			0.200***	
			(0.023)	
Original Request Bin FEs:	Yes	No	No	-
Disaster FEs:	Yes	Yes	No	Yes
Within R^2	0.007	0.005	0.007	0.025
R^2	0.311	0.046	0.007	0.259

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents the coefficients on covariates that may affect bunching decisions. The first column shows the estimation using all covariates and both disaster and original request bin fixed effects. The second and third column omit combinations of fixed effects. The fourth column regresses borrowers' original requests on the same covariates. Standard errors, clustered at the disaster level, are in parenthesis. LTV 0 - 70 is the left out category. Negative Equity implies an LTV > 100 and No Mortgage implies an LTV = 0.

Online Appendix G Lasso

The interpretation of the coefficient on $\mathbf{Collateral_{i,t}}$ in Equation (7) as only the effect of collateral on default risk depends vitally on the implicit assumption that the effect of loan size on default risk is being effectively controlled for via the additively separable log term. This assumption may not hold. For a (nearly) exhaustive way to account for non-linearity in our control variables, we turn to the Lasso.

The least absolute shrinkage and selection operator (Lasso) is a model selection technique originally developed by Tibshirani (1996) as an improvement on step-wise regression. The technique is currently popular in the machine learning literature and has recently entered the econometrics literature.[26] The Lasso is a form of penalized OLS where the sum of the absolute value of the coefficients is limited. The Lasso is beneficial here because it allows us to account for (nearly) arbitrary non-linearity in our control variables via polynomial approximation. Rather than including only a logged representation of the amount the household borrows, we allow log and linear terms for the nominal loss amount. Additionally, we include polynomial terms through the fifth power for both variables. We then allow the Lasso to select the ones that are most important. Importantly, this method of approximating non-linearity in control variables preserves the linear nature of the treatment variables allowing for instrumentation. Formally, our final model is

$$\begin{aligned}
&\textbf{First Stage:} \\
P(Collateral_i) &= Z_{i,t}\gamma'_{Lasso} + v_{i,t} && \text{(A2)} \\
\text{where } \gamma'_{Lasso} &= \underset{\gamma}{\text{argmin}} \left\{ \sum (P(Collateral_i) - \hat{Z}_{i,t}\gamma')^2 \right\} \text{ subject to } \|\gamma\|_1 \leq \lambda_1 \\
&\textbf{Second Stage:} \\
P(Defaulted_{i,t}) &= \hat{L}_{i,t}\beta'_{Lasso} + e_{i,t} && \text{(A3)} \\
\text{where } \beta'_{Lasso} &= \underset{\beta}{\text{argmin}} \left\{ \sum (P(Defaulted_{i,t}) - \hat{L}_{i,t}\beta')^2 \right\} \text{ subject to } \|\beta\|_1 \leq \lambda_2 \\
&\textbf{Third Stage:} \\
P(Collateral_i) &= Z^P_{i,t}\gamma' + v_{i,t} && \text{(A4)} \\
Z^L_{i,t} &= (\overline{\textbf{Distance}_\textbf{i}}; \hat{Z}_{i,t} \text{ such that } \gamma_{Lasso} \neq 0 \text{ or } \beta_{Lasso} \neq 0) \\
&\textbf{Fourth Stage:} \\
P(Defaulted_{i,t}) &= \hat{L}^p_{i,t}\beta' + e_i && \text{(A5)} \\
\hat{L}^p_{i,t} &= (\widehat{\textbf{Collateral}_\textbf{i}};; \hat{L}_{i,t} \text{ such that } \gamma_{Lasso} \neq 0 \text{ or } \beta_{Lasso} \neq 0). \\
&\textbf{Controls:} \\
\hat{X}_i &= (log(LoanAmount_i), LoanAmount_i) \\
\hat{F}_{i,t} &= (\tau_t, LossBin_i, Disaster_i) \\
\hat{Z}_{i,t} &= (\overline{\textbf{Distance}_\textbf{i}}; \hat{X}_i, \hat{F}_{i,t}, \hat{X}^2_i, \hat{X}^3_i, \hat{X}^4_i, \hat{X}^5_i) \\
\hat{L}_{i,t} &= (\textbf{Collateral}_\textbf{i}; \hat{X}_i, \hat{F}_{i,t}, \hat{X}^2_i, \hat{X}^3_i, \hat{X}^4_i, \hat{X}^5_i)
\end{aligned}$$

Where $\hat{L}_{i,t}$ and $\hat{Z}_{i,t}$ are the collection of our variables of interest; our 10 loss control variables; and all fixed effects. We run the Lasso on both stages of the 2SLS approach (Equations (A2) and (A3)) to make sure we incorporate the proper control variables for both models.[27] In Equations (A4) and (A5) we then estimate an unpenalized version of the full model using all of the control variables whose coefficients were non-zero in the either the first or second stage (Belloni et al., 2016). The included variables and combinations of variables in $\hat{L}^p_i$ can be interpreted as the optimal polynomial form of the control variables that can be represented in a limited (via the choice of

[26] See Bai and Ng (2008), Caner (2009), Belloni et al. (2012), Belloni et al. (2014b), Belloni et al. (2014a), Belloni et al. (2016), and Chernozhukov et al. (2015) among others for general usage. See Carson et al. (2020) for a similar usage in separating selection from causal effects while accounting for non-linear controls.

[27] In Equations (A2) and (A3), only the coefficients on loan amount variables are penalized. λ_1 and λ_2 are determined via 5-fold cross-validation separately for Equations (A2) and (A3).

Table G1: Moral Hazard Estimation

	Dependent variable:		
	Default Hazard		
	(1)	(2)	(3)
Collateral	-0.015^{**}		
	(0.006)		
Collateral (fit)		-0.031^{*}	-0.026^{*}
		(0.017)	(0.016)
ln(Loan Amount)	0.053^{***}	0.070^{***}	0.066^{***}
	(0.007)	(0.018)	(0.018)
Loan Amount^2			-0.008^{**}
			(0.004)
Loan Amount^3			0.003^{*}
			(0.002)
Loan Amount^4			-0.000
			(0.000)
Implied Percentage Change:	−0.18	−0.34	−0.29
Lasso Loan Size Controls?	No	No	Yes
Disaster Fixed Effects?	Yes	Yes	Yes
Time Since Origination Fixed Effects?	Yes	Yes	Yes
Loss Size Fixed Effects?	Yes	Yes	Yes
Data Level?	Household - Loan Year	Household - Loan Year	Household - Loan Year
Observations	592,214	592,214	593,857
Residual Std. Error	0.263	0.263	0.263

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents the results of the first stage of our two stage least squares moral hazard estimation (Equation 6). The final column includes our Lasso-selected controls for loan size. Standard errors, clustered at the disaster level, are in parenthesis.

l_1) number of terms. This isolates the interpretation of $\widehat{\mathbf{Collateral_i}}$ as the causal effect of only collateral on loan default risk.

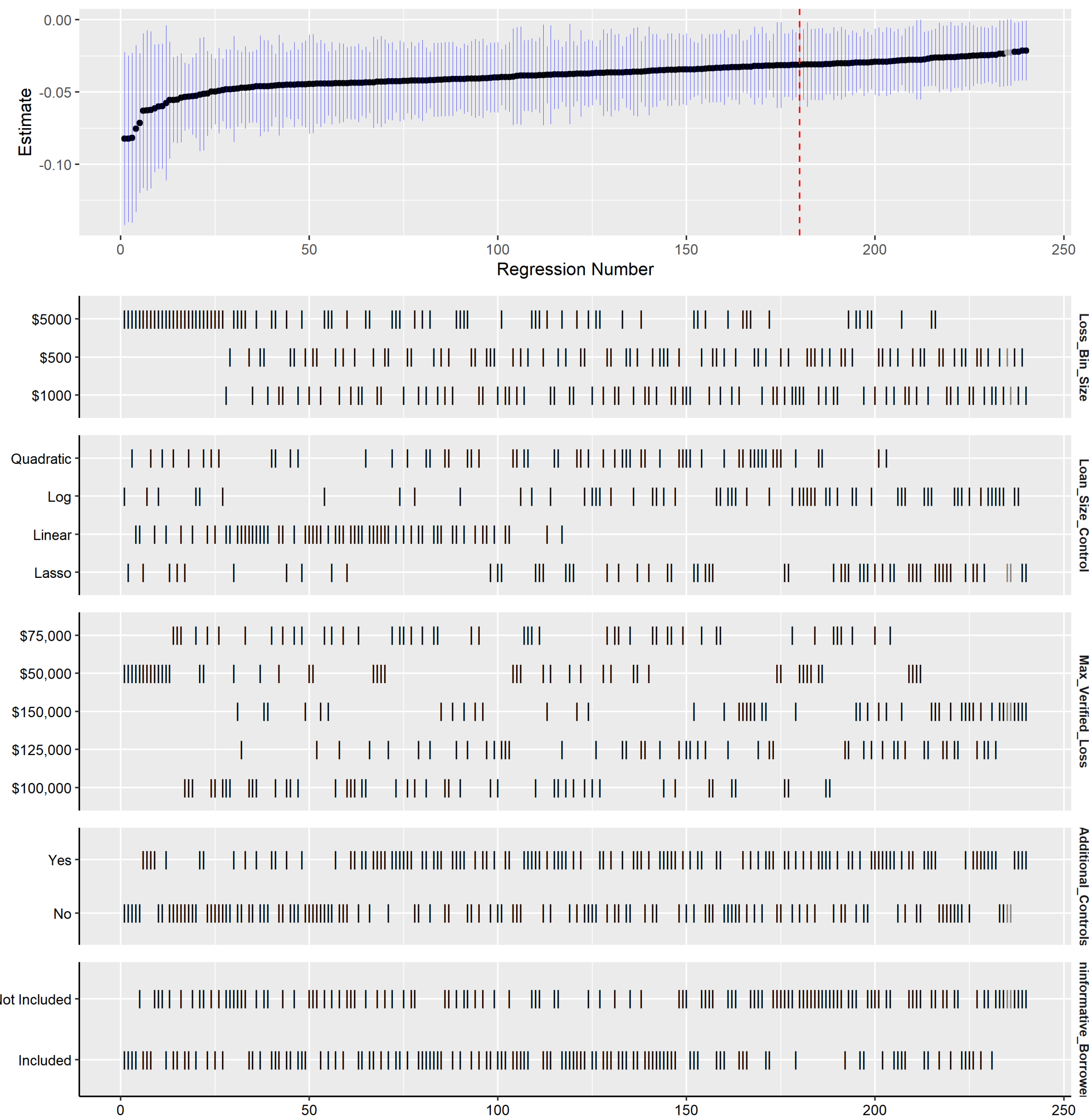
The results of our Lasso estimation are presented in the third column of Table G1. Of the 10 potential combinations of loan size, the Lasso procedure "selected" to include a squared, cubic, and quadratic term for loss size in addition to the logged version included in our main analysis. Inclusion of these controls does slightly reduce our point estimate, however the statistical significance is unaltered and the two coefficients are not statistically different from each other. We take this as evidence that our main analysis does not suffer from over-reliance on the additively separable logged control.

Online Appendix H Specification Curve

One may worry about the robustness of our moral hazard results based on various specifications. To address this, we estimate what is known as a specification curve (Simonsohn et al., 2020). The purpose of a specification curve is to graphically summarize how the estimates from the model change based on various potential modeling choices made by the researcher. Figure 14 plots our estimated moral hazard effect, with 90% confidence intervals, from 120 different regressions, which are the result of different combinations of our modeling choices. We had modeling control over (1) the size of the loss size bin; (2) how to control for loan size; (3) what subsample (based on loss size) to subsample to; (4) the use of additional controls that are not used in the lending decision but are correlated with default rates; and (5) the use of "uninformative borrowers" who borrow below the bunch point. Model options shaded black are statistically significant at the 10% level; whereas model options shaded grey are not. The red, dashed vertical line shows the estimation using our preferred specification. The visual patterns in the bottom half of Figure 14 show how each choice impacts the estimate of moral hazard. Options that appear more often on the left of the figure tend to drive the estimate away from zero and options that are more on the right tend to drive the estimate toward zero.

This first takeaway from Figure 14 is the remarkable consistency of our estimate with regards to modeling choices. Every point estimate is below zero with 99% of the 240 regressions significantly below zero. The 95th percentile of our estimates is -0.056 and the 5th percentile is -0.025 and our preferred specification sits in the middle. Our choice of a $1000 bin size does not lead to different estimates than using a smaller bin such as $500, but is more conservative than a larger bin size like $5000. Our inclusion of a non-linear control for loan size also appears to be a conservative approach. Our sample selection based on loss size also has an impact. As the limit moves away from our preferred max of $50,000, the estimate moves toward zero. This is due to the inclusion borrowers who are very unlikely to move to the bunch point given how far away they are, which reduces the power of our instrument. Finally, the inclusion of additional controls has no observable impact on our moral hazard estimate. We take this as evidence that our instrument satisfies the exclusion restriction and is not merely acting as a proxy for other, unobserved, covariates with default rates.

Figure 14: Specification Curve



Note: This figure plots the estimated moral hazard effect of collateralizing the loan, with 90% confidence intervals, from 240 different regressions. The numbering on the x-axis indicates the regression number. The red, dashed vertical line shows the estimation using our preferred specification. The panels below the primary curve indicate the modeling options that can be varied for the specification curve. The options include (1) the size of the loss size bin; (2) how to control for loan size; (3) what subsample (based on loss size) to subsample to; (4) the use of additional controls that are not used in the lending decision but are correlated with default rates; and (5) the use of "uninformative borrowers" who borrow below the bunch point. Options shaded black are statistically significant at the 10% level; options shaded grey are not. The visual patterns in the bottom half of Figure 14 show how each choice impacts the estimate of moral hazard. Options that appear more often on the left of the figure tend to drive the estimate away from zero and options that are more on the right tend to drive the estimate toward zero. Additional control variables are monthly fixed debt, monthly income, and credit score.