The Cost of Consumer Collateral: Evidence from Bunching*

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Abstract

How do collateral requirements impact consumer borrowing behavior? 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. Our bunching estimates suggest that the median borrower is willing to give up 40% of their loan amount to avoid posting collateral. Exploiting time variation in the threshold, we estimate collateral causally reduces default rates by 36%. Finally, we structurally estimate households' non-financial attachment to their homes and find a median value of $11,000, creating a wedge between lender and borrower valuation of collateral of 15%. Our results explain high perceived default costs in the mortgage market, and document the importance of collateral for reducing moral hazard in consumer credit markets.

JEL Codes: D14, D82, G23, G28

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1 Introduction

The world runs on collateral. In the United States, household debt comprises $15 trillion, and the vast majority of this debt (80%) is secured with collateral, most commonly by the pledge of the borrower's home (Federal Reserve Bank of New York, 2021). This housing collateral is central to the resilience of the banking system and the economy (e.g., Bernanke et al., 1999; Kiyotaki and Moore, 1997). 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.

Recent research challenges conventional notions regarding the role of collateral in lending markets. Collateral has been traditionally viewed as a mechanism to encourage repayment by increasing consumers' "skin in the game" and reducing moral hazard (e.g., Bester, 1985; Chan and Thakor, 1987). However, research on mortgage defaults during the Great Recession and thereafter finds that collateral values have little bearing on repayment (Bhutta et al., 2017), with Ganong and Noel (2023) estimating that 94% of defaults are associated with 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 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. These disasters produce large, exogenous shocks: The median homeowner applying to this program has incurred $50,000 in uninsured damages.

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. No other loan terms change around the collateral threshold. We can thus exploit this discontinuity to identify the effect of collateral on borrower decisions.

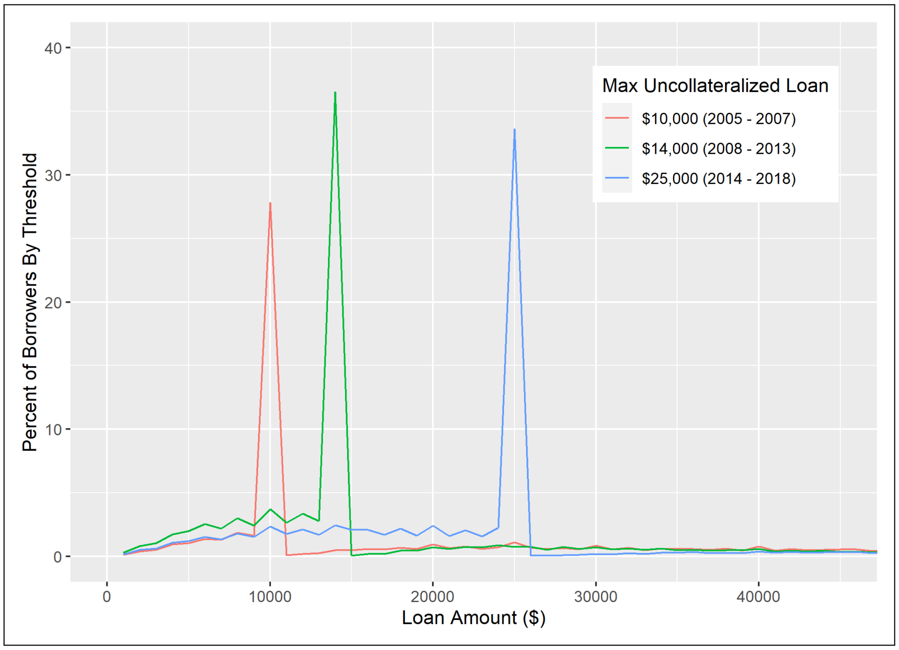
We speak to three pressing questions in the literature regarding consumer collateral. First, do consumers value collateral? Findings that home equity is insufficient to explain mortgage repayment call into question whether pledging one's home influences borrowing decisions at origination. We leverage our setting to examine how collateral requirements affect credit demand. Second, does collateral affect consumer defaults? Evidence that adverse life events are central to mortgage default raise questions regarding the extent to which collateral affects repayment. We develop an instrument for whether consumers supply collateral to examine the causal effect of collateral on repayment. Third, what drives consumers' collateral concerns? Mortgage default imposes a set of penalties on consumers: home equity losses but also moral/stigma effects, credit score reductions, and relocation requirements (Guiso et al., 2013). While the literature shows that consumers' borrowing behavior reflects concerns beyond home equity, it has been unable to disentangle the effects of these additional factors. Using a structural model, we separate the effects of collateral-related incentives (home equity and relocation requirements) from the broader set of repayment concerns (stigma and credit score effects) on borrowing decisions.

Do consumers value collateral? Figure 1 shows the distribution of loan amounts under each of the three collateral threshold regimes used by the program. From 2005 to 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.

We can infer households' private value of collateral by measuring how much they deviate 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 this counterfactual, we first employ a difference-in-bunching estimator, which leverages variation in the collateral threshold over time. To identify the impact of collateral, we compare the loan amounts for individuals with the same amount of disaster-related damages, but under different collateral threshold regimes. The method generates individual estimates of the amount given up to avoid posting collateral.

We find that households are highly sensitive to collateral rules: The median borrower is willing to give up about 40% of their ideal loan to avoid collateral. Using a back-of-the-envelope calcula-

Figure 1: Bunching in Loan Amounts



Note: This figure plots the distribution of loan amounts for borrowers who own their home. 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.

tion, we translate households' collateral aversion into a net present value: The median household is willing to forgo a benefit of $26,000 to avoid securing the loan with their home.[1]

We use two other approaches to estimate households' ideal loan amounts for comparison with the difference-in-bunching results. Our first alternative approach uses a traditional bunching estimator that extrapolates from 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. Our second alternative approach leverages the fact that households report the amount that they would like to borrow on the initial loan application, which appears to be a strong proxy for their ideal loan amount. Despite using different sources of identifying variation, our alternative methods reach similar estimates of the extent of collateral aversion — the median borrower is willing to give up between 40 and 50 percent of their loan to avoid posting collateral.

[1]Using the interest rate demand curve for the loan program estimated by Collier and Ellis (2022), we also estimate that 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%).

Does collateral affect consumer defaults? We examine the causal impact of collateral on defaults by exploiting the same time variation in the collateral threshold as the difference-in-bunching estimation above. Consumers are more likely to bunch if the threshold is near their original loss amount. For example, a consumer with a loss amount of $30,000 would be more likely to bunch if the collateral threshold were $25,000 than if it were $10,000. We use changes in the collateral threshold as an instrument for whether the borrower's loan is collateralized in a 2SLS estimation.

We find that collateral causally reduces default rates by about 35%. For context, a reduction of this large 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 commitment of a primary residence as collateral, indicating the important role that collateral plays in addressing moral hazard in household lending.

What drives consumers' collateral concerns? For insights into the mechanisms underlying collateral aversion, we turn to heterogeneity in bunching behavior across borrowers. We find that collateral decisions reflect a combination of financial and non-financial considerations. More creditworthy borrowers (based on *ex ante* credit score and income) are more likely to bunch, supporting an *advantageous selection* interpretation of bunching behavior. The decision of these better-off borrowers to avoid supplying collateral may result from their access to low-cost alternatives (e.g., private credit) that are unavailable to less creditworthy borrowers. Similarly, consumers are more likely to bunch when disaster loan interest rates increase relative to private market rates. Regarding non-financial considerations, we find that among borrowers who are already underwater on their existing home loans (i.e., their LTV ratios exceed 1) and so have no equity at stake, around 30% still bunch at the threshold to avoid posting their homes as collateral. This bunching behavior seems to reflect consumers' attachment to their homes.

We develop a structural model to assess the weight that consumers place on attachment to the home when making collateral decisions. In this model, households can borrow at low interest rates when providing collateral, but doing so risks home equity and would require households to relocate from a home to which they may be attached if they default. Alternatively, households can borrow at a higher interest rate on an unsecured loan in the private market. We estimate the model using our reduced form findings of households' ideal loan amounts and the influence of collateral on default risk. We observe each borrower's home equity and so can separately identify how attachment to the home affects their decision to supply collateral. We find that the median household has a home attachment of $11,000, which represents the value that the consumer places on losing the home. For comparison, as the median borrower has $78,000 in home equity, this home attachment increases the perceived penalty of collateralized default by around 15% if the borrower loses all home equity in the process. Thus, consumers' collateral aversion suggests an important wedge between how borrowers and lenders evaluate collateral.

We provide some of the first evidence of the impact of collateral requirements on household borrowing and repayment behavior. A large literature examines the central role of collateral in the financial system and macroeconomy. Collateral values amplify business cycles, influence the transmission of monetary policy, and appear to be an important driver in the Great Depression and Great Recession (Bernanke, 1983; Gertler and Bernanke, 1989; Gan, 2007; Mian and Sufi, 2014). Prior research on collateral decisions has almost exclusively focused on corporate borrowing (e.g., Jimenez et al., 2006; Benmelech and Bergman, 2009; Chaney et al., 2012; Calomiris et al., 2017; Luck and Santos, 2019), with recent papers exploring how legal changes affect the relative value of collateral or creditor rights (Cerqueiro et al., 2016; Ersahin et al., 2019; Costello, 2019; Zevelev, 2020). While this literature has focused on the market value of collateral, our analyses show that consumers' valuation comprises a mixture of financial and non-financial components such as attachment to the home. These non-financial components suggest a type of friction and can rationalize prior research showing 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, 2020).

By estimating the causal effect of collateral on the likelihood of default, we also inform an extensive loan contracting literature on the role of collateral in mitigating moral hazard in credit markets (Berger and Udell, 1990; Boot and Thakor, 1994; Coco, 2000; Jiménez and Saurina, 2004; Berger et al., 2011; Ioannidou et al., 2019). Recent work in this area has sought well-identified settings to disentangle causal channels (O'Malley, 2020; Gertler et al., 2021). Our results offer new empirical support for the important role that collateral can play in mitigating asymmetric information to expand access to consumer credit (Bester, 1985; Chan and Thakor, 1987).

We find 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; Gupta and Hansman, 2022). The existing literature emphasizes homeowners' considerations, such as home equity and the option value of potential changes in house prices, as well as the consequences of default, including moral considerations and direct financial costs. In contrast to prior work, we are able to isolate the threat of forced relocation from other motivations. Although the Federal Disaster Loan program's contract design would not be provided in a competitive private market, it nonetheless preserves the core economic trade-off that borrowers face: Securing a loan with one's home expands credit access but comes at the risk of losing the house. As a result, we expect consumers to carry the attitudes toward collateral that we document into other borrowing and repayment decisions.[2]

Finally, we add to a growing literature assessing how consumers manage climate risks (e.g., Gallagher and Hartley, 2017; Bakkensen and Barrage, 2022; Bernstein et al., 2019; Keys and Mulder, 2020; Deryugina et al., 2018; del Valle et al., 2022). The costs of severe climate events are growing. For example in the U.S., an average of 3 disasters each year exceeded $1 billion in damages in the 1980s; that number has grown to 15 in the last decade (USD 2022, NOAA, 2022). These trends underscore the importance of effective government climate policies to help households and their communities recover. Our analysis is one of the first investigations of a key federal recovery program (Begley et al., 2020; Billings et al., 2022; Collier and Ellis, 2022). By channeling low-interest loans into affected communities, the program intends to facilitate reinvestment. Our findings show that households' reluctance to pledge their homes limits this reinvestment channel.

2 Data and Setting

This section describes the Federal Disaster Loan (FDL) program and our data, drawing on 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.

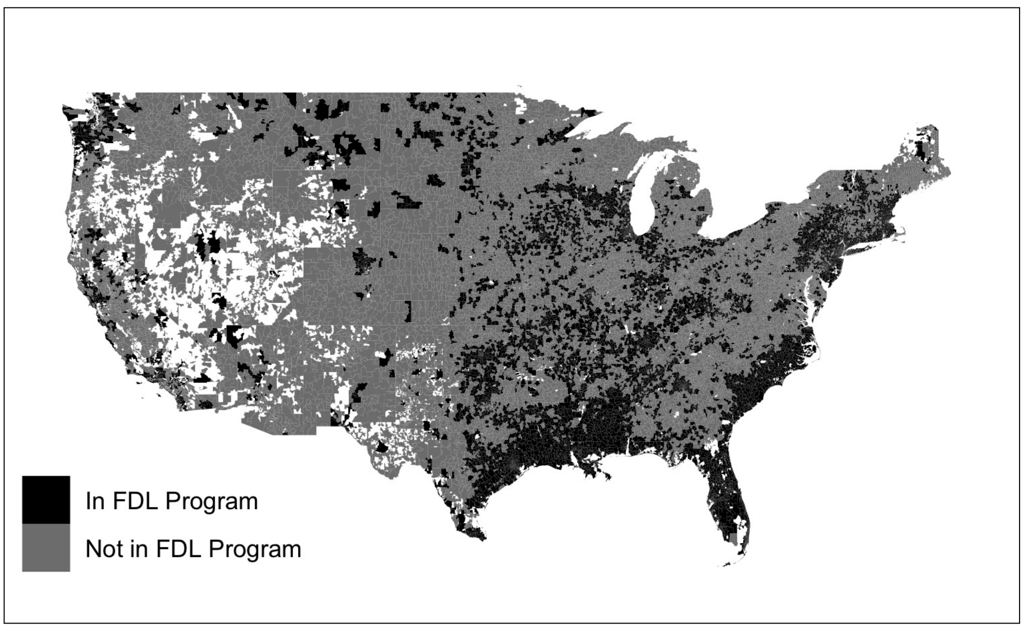
Effectively all (98%) of household FDL applications are associated with a presidential disaster declaration. For these declarations, FEMA coordinates the local response, establishing temporary offices in affected neighborhoods. Households harmed by the disaster are encouraged to register with these FEMA 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

[2] The existing literature emphasizes that consumer credit behavior is often influenced by characteristics of the setting (e.g., motivation for borrowing, recovery process, see Karlan and Zinman, 2019; Gross et al., 2021), and we expect that these characteristics similarly may influence the specific magnitude of consumer collateral aversion in other contexts.

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: 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. This onsite inspection also assesses the value of the home once it has been repaired. Lending decisions largely depend on the interaction of the applicant's credit score and *existing* debt-service-to-income (DTI) ratio (excluding 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 33, which is similar to GSE mortgage borrowers.[3] Around 70% of borrowers have a mortgage; they have a median loan-to-value (LTV) ratio of 0.7 on their existing home loans.

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 $52,816 (median of $25,609) with a 2.47% interest rate, 22 year maturity, and $261 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.[4] 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

[3]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 99th percentile borrower has a DTI of 50 for Fannie Mae, versus a DTI of 79 for the FDL program. Similarly, the 1st percentile borrower has a credit score of 632 for Fannie Mae, compared to 531 in the FDL program.

[4]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	34,802	72,787	148,751
Credit Score	695	76	593	693	798
DTI (%)	33	22	9	32	55
Home Equity	117,689	159,569	81	77,622	285,532
Mortgage LTV (%)	70	40	24	69	108
Loss Amount	101,697	118,478	13,263	50,844	270,396
Insurance Claims	30,838	67,726	0	1,137	112,590
Loan Amount	52,816	66,880	10,025	25,610	144,927
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 on 197,470 borrowers. Income, DTI, Equity, LTV, Loss Amount, and Insurance Claims are winsorized at the 0.5% and 99.5% levels. "Income" is annual adjusted gross income. "Credit Score" is the FICO score of the primary applicant. "DTI" is the household's existing total monthly debt service payments as a percent of monthly income. "Mortgage LTV" only includes households with mortgages and is the combined loan-to-value ratio on their existing home loans. "Loss Amount" is the program's onsite assessment of property losses.

home debt. As a result, the program's claim on the home may not fully collateralize the disaster loan.[5]

For a collateralized home loan in any credit market, including this one, posting collateral contributes to the hassle costs of borrowing as it requires additional documentation and may delay loan disbursement. For disaster recovery loans, the incremental documentation for collateralizing the loan is small: The loan is already underwritten and the property assessed in-person regardless of securing the loan. The additional documentation entails an agreement allowing the lender to place a lien on the property. We return to the discussion of hassle costs in Section 5.1.

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 due, in part, 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.

Regarding disbursement delays from collateralizing, the program secures the loan when total disbursements exceed the collateral threshold. The program provides an initial disbursement amount up to the collateral threshold; the second disbursement pushes the loan balance above the

[5]Pan et al. (2023) examine how the program's collateral rules affect small business borrowers' loan amounts.

threshold, which adds to disbursement times.[6] 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). The program takes the following actions if the borrower defaults, which are described in publicly available program documentation. 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). In addition to the program's documents, legal blogs describe the risks of securing a disaster recovery loan with one's home, e.g., "If you put up real estate as collateral for the loan and later default, like by failing to make the payments, the lender might foreclose" (Loftsgordon, 2022).

In summary, the program uses similar mechanisms to the private sector, as private lenders may also adjust loan terms due to hardship and use a combination of credit reporting, garnishment, and collateral seizure in response to nonrepayment. While each of these tools incentivizes repayment, it is possible that consumers have a different perception of the likelihood that the government will collect on collateral relative to a private lender. Similar to private markets, securing a loan with one's home in our setting expands access to low-cost credit but comes at the risk of losing the home. As a result, we expect that consumers would approach other borrowing decisions with the attitudes reflected in our findings. We further discuss the potential external validity of our findings in the conclusion.

2.3 Loss Amounts and Loan Amounts

The application process offers additional insights on households' borrowing needs and proceeds as follows. Households first allow the program to verify their income, examine their credit report, and conduct an onsite loss inspection to determine the amount of property damages. The loss amount caps the applicant's eligible loan amount. After the loss inspection, the applicant meets with a loan officer to finalize the application. The applicant then requests a loan amount, which

[6] The timing of disbursements below the threshold is the same for borrowers who ultimately collateralize their loans and those who do not. The first disbursement (up to the collateral threshold) arrives a median of 51 days after the decision date. The second disbursement (above the threshold) arrives a median of 82 days after the first disbursement. The data do not clarify if the delay in disbursements is due to securing the loan or at the behest of the borrower because of contractor workflow.

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 exactly the collateral threshold. Among borrowers whose losses exceed the collateral threshold, 38% choose a loan amount at the threshold.[7]

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 shows that below the collateral threshold, they nearly do. Borrowers choose loan amounts that are slightly smaller than their loss amounts, suggesting that they may supplement the loan with some out-of-pocket funds such that their ideal loan amount is not necessarily the full loss amount. 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, suggest-

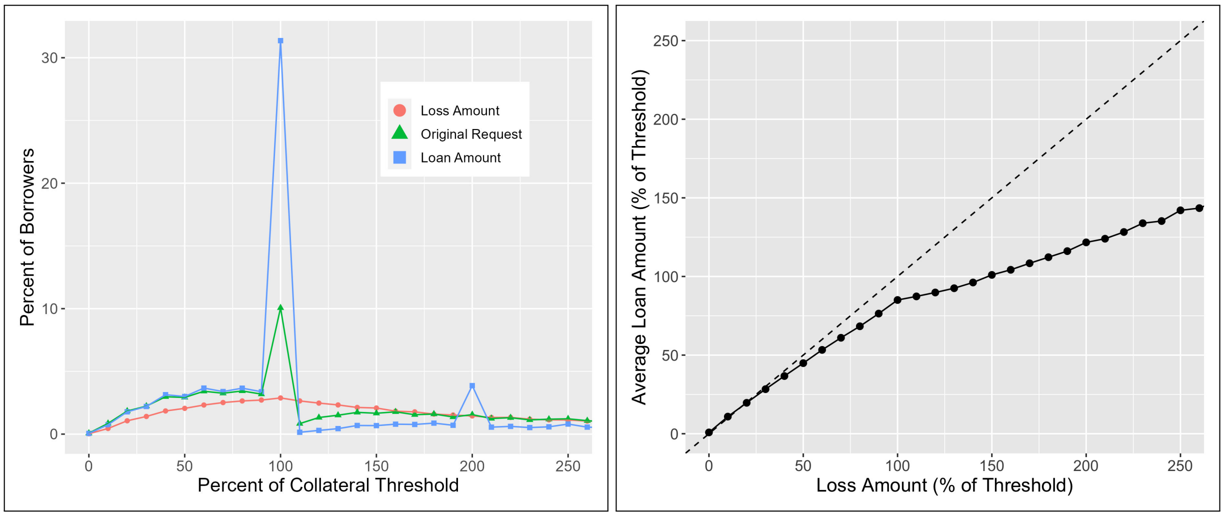
[7]We also observe some bunching at 200% (which represents $50,000 in 2014-2018). This bunching is likely due to additional requirements on loan disbursements exceeding $50,000: The applicant must acquire a building permit, document the total estimated cost of the project, account for all financing for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

ing 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

Panel A: Distributions

Panel B: Relationship of Final Loans and Losses



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 Do Consumers Value Collateral?

3.1 Household Problem

We formalize the household's problem of whether to collateralize its loan in a stylized model. The model illustrates the setting's connection to a more general household problem in consumer credit markets. In the general problem, households needing to finance an expense may choose between an unsecured loan or a secured loan offered at a lower interest rate. Our setting mirrors this problem. We take as given that households will fund repairs up to the collateral threshold with an unsecured disaster loan. The stylized problem focuses on whether to fund the incremental costs of repairs above the threshold through a secured or unsecured loan. We extend this model, adding richness and estimating it structurally, in Section 5.2.

A representative household experiences disaster damages, represented by random variable ν. The damages create a mandatory expenditure $\hat{l}(\nu)$. In our setting, the household is offered an uncollateralized loan up to an amount c with $c < \hat{l}$ at a low interest rate. It has two options to fund the remaining damages $l \equiv \hat{l} - c$: (1) borrow l using an unsecured but higher-interest-rate loan or (2) borrow l at the low interest rate using a loan secured with the consumer's home. Let r represent the gross interest rate on the collateralized loan, and r_u the rate on the uncollateralized loan with $r_u > r$.[8]

The household either repays the loan in full or defaults and pays none of the principal and interest. If the household defaults on an uncollateralized loan, it incurs penalty ψ, representing a reduction in its credit score and the stigma of defaulting. If the household defaults on a collateralized loan, it incurs penalty ψ and an additional penalty ϕ, which represents the possible loss of home equity in the foreclosure process and the non-financial cost of having to leave a home to which the consumer is attached. Collateral reduces the likelihood of default such that the household defaults on a collateralized loan at rate γ and an uncollateralized loan at rate γ_u. Because the collateralized loan has additional penalties in default, if consumers have discretion we would expect providing collateral to endogenously affect the default rate, leading to $\gamma(\phi, \psi) < \gamma_u(\psi)$. To simplify the model, we treat γ and γ_u as given, but in Section 4 we directly estimate the causal effect of collateral provision on loan default.

The household's value functions for the uncollateralized and collateralized loans are, respectively

$$V_u = (1 - \gamma_u)U(w - r_u l) + \gamma_u U(w - \psi) \tag{1}$$

$$V = (1 - \gamma)U(w - rl) + \gamma U(w - \psi - \phi) \tag{2}$$

where U is household utility over lifetime wealth w.

The household only chooses to collateralize its loan if

$$\begin{aligned} V &\geq V_u \\ (1 - \gamma)U(w - rl) - (1 - \gamma_u)U(w - r_u l) &\geq \gamma_u U(w - \psi) - \gamma U(w - \psi - \phi). \end{aligned} \tag{3}$$

[8]We focus on a private, uncollateralized loan as the most relevant outside option for disaster loan applicants. In practice, households may have a range of additional strategies to fund disaster repairs (e.g., withdrawing retirement savings, borrowing from family).

Equation 3 offers two intuitive insights. First, it shows that the household only prefers to collateralize the loan if it values the reduction in interest that must be paid more than its expected utility cost of losing the collateral. Second, since the difference in repayment amounts is larger for larger loans, the likelihood that the consumer chooses the collateralized loan increases in the loan size ($\partial(V - V_u)/\partial l > 0$).

Measuring Collateral Aversion. The model offers a straightforward way to quantify collateral aversion: the maximum loan amount that the household is willing to forgo to avoid supplying collateral. We define collateral aversion x as the loan value at which the consumer is indifferent between a collateralized and uncollateralized loan, $x \equiv l | V = V_u$. The funding need is a function of two variables: (1) the damages imposed by the disaster, which is random variable ν, and (2) the collateral threshold c. As a result, the decision is stochastic such that the household will prefer the collateralized loan with probability $P(x < l(\nu, c))$.

We leverage this framing in our empirical approach. We assume that each household i has a private value of collateral x_i. At the time of application, the household is only willing to provide collateral at this reservation price. The distribution of private values across households can be conceptualized as a "collateral supply curve." An ideal experiment would uncover this aggregate supply curve by randomly varying prices and observing the share of households willing to provide collateral at each price.

Our setting approximates this experiment through two sources of plausibly exogenous variation in the funding need that affect the likelihood that the household supplies collateral (i.e., $P(x_i < l(\nu_i, c))$). The first is the size of disaster damages: Households with larger realized damages are more likely to exceed their reservation price and supply collateral. The size of damages ν_i uncovers collateral aversion as long as it is exogenous to the household's collateral aversion x_i, a consideration that we explore empirically below. Our preferred estimation strategy leverages an additional source of variation: changes in the collateral threshold c over time. Thus, households who experience a disaster when the collateral threshold is set at a lower value are more likely to exceed their reservation price and supply collateral than those experiencing a disaster when the collateral threshold is higher.

To provide a more general measure in the empirical results, we also transform our estimates of collateral aversion from forgone low-interest loan dollars to a net present value. Consider a counterfactual in which the household could borrow $\tilde{z}$ at rate r from the disaster loan program *without* collateralizing the loan, resulting in

$$V_u^+ = (1 - \gamma_u)U(w - rl) + \gamma_u U(w - \psi). \tag{4}$$

For a risk-neutral consumer, we can translate this difference ($V_u - V_u^+$) into the net present value of the change in T amortized payments over the life of the loan

$$NPV = (1 - \gamma_u) \sum_{t=1}^{T} \beta^{(t-1)} l \left(\frac{(r-1)r^t}{r^t - 1} - \frac{(r_u - 1)r_u^t}{r_u^t - 1} \right) \tag{5}$$

where β is the household's discount rate.[9] In the structural estimation in Section 5.2, we allow for risk aversion and decompose consumers' collateral aversion into equity losses and attachment to the home.

3.2 Difference-in-Bunching Estimation

Uncovering households' collateral aversion first requires estimating their ideal loan amounts, the amount that households would have borrowed in disaster loans absent collateral requirements. Ideal loan amounts can be estimated in several ways. Our preferred method uses time variation in the collateral threshold. Figure 4 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.

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.[10]

[9] We assume that the household is patient, $\beta = 1/r_s$ where r_s is the gross, risk-free return on household savings.

[10] 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 $LossBin_{-1}$.

Figure 4: 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.

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:

$$LoanAmount_i = \sum_j^J \alpha_j LossBin_j + \sum_j^J \beta_j LossBin_j \times 1(Threshold = \$10,000) + \gamma X_i + \varepsilon_i \quad (6)$$

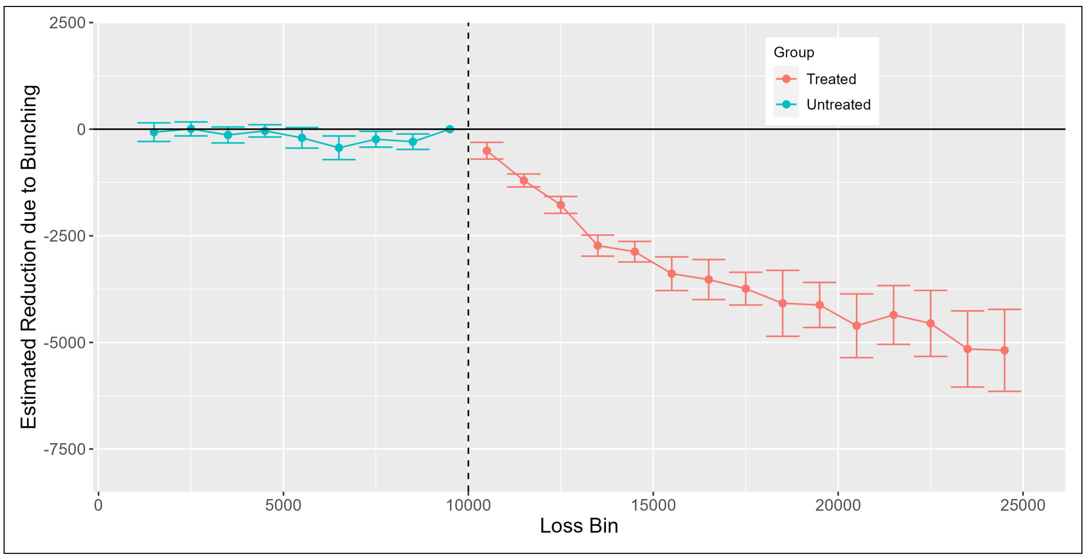
$$LossBin_j \in \{\$1K - \$2K, \$2K - \$3K, ..., \$24K - \$25K, -1\}$$

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 reduction in borrowing by households who suffer the same losses, but do so subject to the $10,000 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. Following Abadie et al. (2023), we cluster our standard errors, via block-bootstrapping, at the disaster level, which is our unit of randomization. As an additional assessment, we similarly estimate the model comparing households with the

$14,000 threshold (instead of $10,000) to those with the $25,000 threshold and present the results across approaches in Section 3.5.

Figure 5 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 blue) assess for the equivalent of placebo-style "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 5: 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. Loans smaller than the $10,000 are untreated in that they are never subject to collateral requirements. Loans above $10,000 require collateral provision when the threshold is $10,000, but do not when the threshold is $25,000.

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.

The primary limitation of this estimation method is that it is constrained 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.

3.3 Estimating the Collateral Aversion Distribution

The difference-in-bunching results can be used to estimate the distribution of collateral aversion. Since the bunching decision is binary, we can calculate the share of households who do not bunch from the ratio of distances of the expected loan amounts from $10,000:

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

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. In this example, the probability of not bunching would be 0.5.[11] 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; the average loan across the two groups is $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.

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 adjustment frictions, the observed loan amount might not reflect the borrower's fully-informed preference. However, in our setting borrowers are given the opportunity to costlessly change their loan amount up until the loan disbursement. Second, we assume that, within the bunching region, a household's ideal loan amount $\hat{l}_i$ is independent of its private value of collateral x_i, conditional on observed covariates. If households' ideal loan amounts and collateral values are correlated, then the model would suffer from a form of selection bias, undermining the direct translation of bunching behavior into a distribution of households' private collateral values.

As described in Section 2.3, households' ideal loan amounts depend on the size of their loss resulting from a natural disaster, modeled as $\hat{l}_i(\nu_i)$ above: The size of disaster damages is plausibly randomly assigned in the region around the collateral threshold. To explore this assumption further, we regress the distance between the homeowner's losses and the collateral threshold on

[11] ($12,500 - $10,000)/($15,000 - $10,000) = 0.5.

observable characteristics of the homeowner (e.g., credit score, income, mortgage LTV, see Appendix C.1). We find no evidence that household characteristics relate to this distance measure, providing support for the assumption that households' loss amounts are plausibly randomly assigned in the bunching region.

Using this approach, we estimate that the median borrower is willing to forgo 47% of their ideal loan amount to avoid supplying collateral. We present and discuss the full distribution of collateral aversion in Section 3.5.

3.4 Alternative Bunching Estimators

We use two additional approaches to estimate households' responses to the collateral threshold for comparison with the difference-in-bunching estimation methods. Complete details of these approaches can be found in the appendix. As in the difference-in-bunching method, each alternative method follows similar steps. We first estimate a counterfactual to determine the amount that consumers would have borrowed absent the collateral requirement. From that counterfactual, we then determine the amount that consumers are willing to give up to avoid supplying collateral. Finally, we describe the distribution of collateral aversion across borrowers. We compare the collateral aversion estimates across methods in the next subsection.

3.4.1 Traditional Bunching Methodology

The traditional bunching method constructs a counterfactual based on the distribution of selected loan amounts. Specifically, this method bins borrowers by their selected loan amounts. Using a count regression, we model the number of borrowers in each loan amount bin using a flexible polynomial approximation on the range of loan amounts that are unaffected by the collateral requirement (e.g., amounts below the threshold). The polynomial is projected as a counterfactual over the range of loan amounts that are affected by the collateral rules. The count regression also includes an indicator for loan amounts at the collateral threshold to measure the "excess mass," the number of borrowers who select this loan amount beyond the counterfactual estimate. Similarly, indicator variables for loan amounts that are larger than the threshold are expected to reflect the "missing mass," the reduction in borrowers selecting these loan amounts because they instead choose a loan equal to the collateral threshold.

To determine the distance that borrowers move to locate at the threshold, we assign borrowers in the excess mass to the missing mass, starting with loan amounts just larger than the threshold. Once all borrowers in the excess mass have been assigned to a counterfactual ideal loan amount, the maximum loan amount represents the upper end of the bunching region, the maximum amount that borrowers moved to locate at the collateral threshold. Thus, this two-step method provides an estimate of households' ideal loan amounts from the polynomial approximation, the magnitude of bunching at the threshold (the excess mass), and the number of borrowers who relocated from specific loan bins to borrow at the threshold (the missing mass).[12]

With these estimates, we can determine the distribution of collateral aversion, measured in the amount of subsidized loan dollars that consumers would be willing to forgo to avoid supplying collateral. Let n_j represent the number of borrowers for loan amount bin j and $\hat{n}_j$ represent the count of ideal loan amounts at amount j estimated by the polynomial approximation. The share of households who bunch at each loan amount j in the bunching region, $P(Bunch_j) = \frac{\hat{n}_j - n_j}{\hat{n}_j}$, allows us to trace out the distribution of collateral aversion. We report the technical details of this estimation, required assumptions, and full results in Appendix C.2 in the interest of space.

3.4.2 Original Request Counterfactual

For additional comparison, we also examine the loan amount that consumers requested on their initial application, before meeting with a loan officer. The original request appears to be a good proxy for most borrowers' ideal loan amounts.[13] About 10% of consumers bunch in their original requests, so the request is not informative of their ideal loan amount as they have already adjusted based on collateral rules. Therefore, we impute their ideal loan amounts based on the original requests of observationally similar consumers who bunch later in the application process (described in detail in Online Appendix C.3). This required imputation is a limitation of this approach: Consumers who bunch in their original requests may differ from other bunchers in unobservable ways (e.g., sophistication) that correlate with their collateral aversion. The primary benefit of this original request approach is that it allows for examining bunching behavior beyond the $25,000 threshold that limits the difference-in-bunching method.

Using a linear probability model, we estimate the probability of supplying collateral as a function of the (binned) percentage of a borrower's originally requested loan that they would have to

[12] 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).

[13] Consumers who never bunch typically borrow an amount near their original request. The majority of consumers who bunch do so after submitting their original request (See Panel A of Figure 3).

give up to bunch:

$$P(Collateral_i) = \sum_{j}^{J} \beta_j Distance_j + \gamma X_i + \varepsilon_i \quad (7)$$

where $Distance_j$ describes the difference in percentage terms between the borrower's original request and the collateral threshold. For example, when the collateral threshold is \$25,000, a consumer with an original request of \$50,000 would have a distance of 50%. Distances are binned in 5 percentage point intervals. X_i is the same set of demeaned, borrower-level control variables used in the difference-in-bunching estimation. Since the estimation predicts the probability that a consumer selects a collateralized loan for a given distance bin j, the distribution of collateral aversion for the average borrower is captured by the regression coefficients, β_j, across the J bins in Equation (7). We discuss the results in the next section (full results in Appendix C.4).

3.5 Comparing Estimates of Collateral Aversion

Here, we compare and discuss the estimates of collateral aversion across the three approaches. Each of the three methods — difference-in-bunching, traditional bunching estimators, and original requests — uses a distinct group to estimate consumers' ideal loan amounts and relies on different information about the borrower's decision.

Despite these differences, each method produces a similar collateral aversion estimate at the median (Table 2). The difference-in-bunching approach and traditional approach each estimate that the median household would forgo around 50% of its ideal loan amount to avoid supplying collateral (i.e., they would rather borrow \$10,000 uncollateralized vs. \$20,000 collateralized); the original request approach estimates a slightly lower median of around 40%.

We can translate the estimates into a back-of-the-envelope net present value using Equation (5). To do so, we assume that households are able to access unsecured credit at an interest rate of 4 pp above the concurrent 30-year mortgage rate, save at a risk-free interest rate of 1%, and default at the program's average default rate of 12%. We find that by bunching at the threshold, the median household forgoes a benefit of \$26,000 in net present value. We are also able to measure dispersion in borrowers' collateral aversion, with the 25th percentile willing to give up \$14,000 in NPV and the 75th percentile willing to give up \$30,000.[14]

[14] This specific estimate uses the traditional bunching estimation result for the \$25,000 threshold, which is the current collateral threshold.

Table 2: Median Collateral Aversion

	Median Collateral Aversion (%)			
	(1)	(2)	(3)	(4)
Collateral Threshold	10,000	14,000	25,000	All
Difference-in-Bunching Approach:				
- No Covariates	47.64	39.13	–	–
	(2.89)	(1.45)	–	–
- Covariates	46.81	38.60	–	–
	(3.16)	(1.67)	–	–
Traditional Bunching Estimator	47.37	39.39	45.65	–
	(0.98)	(2.48)	(0.74)	–
Original Request Approach:				
- No Covariates	39.40	37.00	37.10	37.90
	(0.76)	(0.86)	(3.23)	(0.77)
- Covariates	38.80	36.70	38.30	37.80
	(0.72)	(0.87)	(3.49)	(0.79)

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 (Abadie et al., 2023).

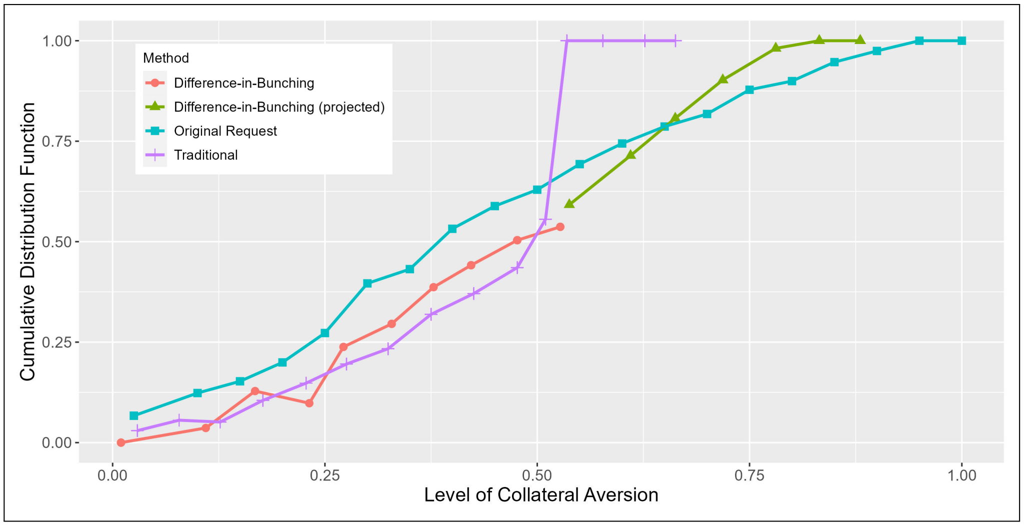
Figure 6 shows the CDF of collateral aversion estimated by each of the three approaches when the collateral threshold is set at $10,000. The horizontal axis measures collateral aversion as the share of the household's ideal loan amount that it would be willing to give up to avoid supplying collateral. The approaches differ in their estimates of the upper end of the collateral aversion distribution. 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. The traditional bunching method is conservative by construction, allocating bunchers starting with the missing mass just above the bunch point. The assumed maximum collateral aversion for this method occurs at the upper end of the bunching region (which is at 52% in this estimation, see Section C.2 for additional technical details). The difference-in-bunching and original request methods take additional information into account and suggest a wider distribution of collateral aversion, such that the 90th percentile consumer would be willing to forgo at least 70% of their ideal loan to avoid posting collateral.[15]

In summary, in this section we examine the extent to which collateral requirements affect consumers' borrowing decisions. We find that borrowers are highly sensitive to collateral rules. The

[15]Online Appendix C.5 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.

median borrower is willing to forgo 40 to 50% of their ideal loan amount to avoid supplying collateral, an amount which represents $26,000 in NPV terms. These estimates reflect consumers' decisions at the time of origination; in the next section, we assess how collateral concerns affect loan repayment.

Figure 6: 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 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. The sharp increase in the traditional bunching method after 0.50 is due to the assumption that missing mass is equal to excess mass.

4 Does Collateral Affect Consumer 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. If posting collateral has little bearing on consumer default rates, collateral requirements may provide fewer benefits to lenders — and create more harm to consumers, who may already be experiencing difficult circumstances — than traditionally assumed.[16] Ultimately, the effect of collateral on loan default is an empirical question, but isolating its causal influence is challenging.

[16]Collateral provides an additional benefit to lenders as acquiring the asset securing the loan reduces their losses from default. Thus, collateralized lending may be optimal even if collateral does not directly affect default rates.

Table 3 provides summary statistics on program loan defaults. Almost 10% of 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 $24,000, which represents 88% of the original loan principal.

Table 3: Default Summary Statistics

			Percentiles		
	Mean	SD	p10	p50	p90
Default Rate (%)	9.9				
Time to Default (Years)	5.0	3.0	1.7	4.3	9.5
Amount ($) | Default	28,950	23,577	7,828	23,754	61,054
Amount (% of Loan) | Default	80.3	21.7	47.2	87.9	100.0

Note: Monetary values in 2018$. This table, and all estimation for this section, uses a sample limited to borrowers with losses up to $100,000.

4.1 Identification and Estimation

A central challenge to assessing the causal effect of collateral on defaults is potential selection bias. Consumers who choose to supply collateral may differ from those who do not, confounding direct comparisons of the default rates on secured and unsecured loans. For example, in Section 5.1, we show that borrowers who bunch tend to be more creditworthy than borrowers who choose slightly larger loan amounts.

To separate the effects of collateralization and selection, we leverage changes in the collateral threshold as an instrument. As discussed in Section 3.2, the threshold changes induce variation in the cost of collateralizing over time. Panel (A) in Figure 7 illustrates this identifying variation in the decision to bunch, showing how bunching behavior changes starkly with the thresholds for households with the same size losses. Panel (B) translates this behavior into our first stage difference-in-bunching instrument for whether or not the loan is collateralized.

We implement two-stage least squares estimations using changes in the collateral threshold as an instrument,

First Stage:

$$P(Collateral_i) = \sum_{j}^{J} \alpha_j LossBin_j \times Threshold_i + \sum_{j}^{J} \beta_j LossBin_j + \gamma log(LoanAmount_i) + \delta X_i + \tau_t + Disaster_i + \varepsilon_i$$

$LossBin_j \in \{\$10K - \$11K, \$11K - \$12K, ..., \$99K - \$100K\}$

Second Stage:

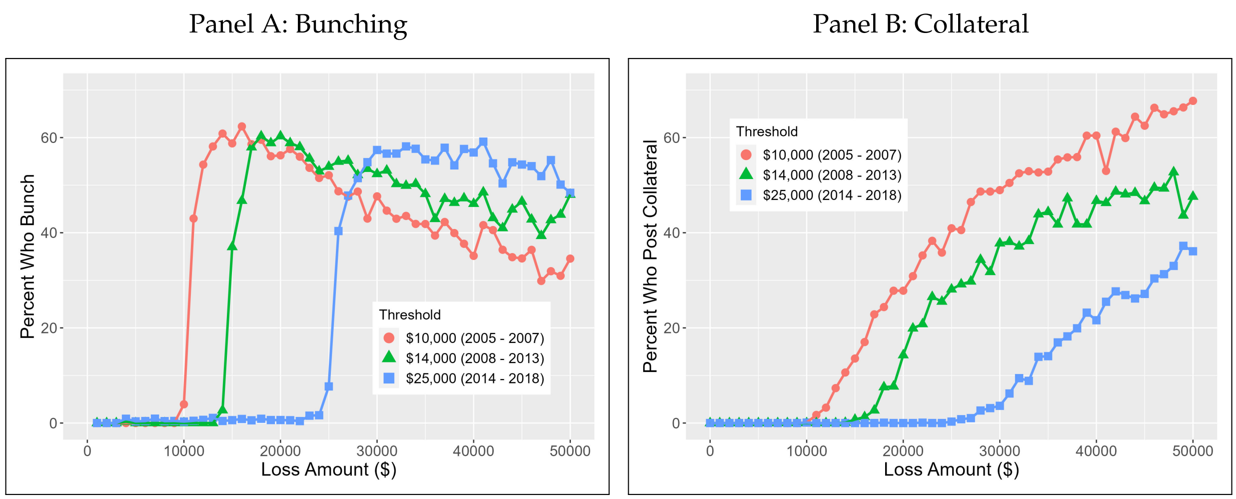
$$P(Default_{i,t}) = \theta \widehat{Collateral_i} + \sum_{j}^{J} \eta_j LossBin_j + \psi log(LoanAmount_i) + \pi X_i + \tau_t + Disaster_i + e_{i,t} \quad (8)$$

The first stage estimates the likelihood that the household collateralizes the loan. The instruments are the interaction terms between the household's losses ($LossBin_j$) and the collateral threshold, which is a set of indicators for whether the household's threshold was set at \$14,000 or \$25,000. The reference group for the threshold indicators is the \$10,000 threshold. The model also includes the direct effect β_j of loss sizes $LossBin_j$ with losses binned in \$1,000 increments.[17] Thus, the instruments capture how, for a given level of disaster losses, increasing the threshold to \$14,000 or to \$25,000 affects the likelihood that the household provides collateral relative to when the threshold is set at \$10,000. The 2SLS equations also incorporate controls, including the household's loan amount (in logs), years since loan origination fixed effects τ_t, and disaster fixed effects $Disaster_i$.

In the second stage, we model the relationship between collateral and loan default with a linear discrete survival function where $P(Default_{i,t})$ is the probability that household i either defaults

[17] We limit our sample to those with losses above \$10,000 because our identifying variation in the first stage only applies to this group.

Figure 7: Bunching and Collateral by Loss Amount



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.

on the loan in year t or has already defaulted on its loan in a year prior to t.[18] $\widehat{Collateral}_i$ is the estimated likelihood of providing collateral based on the first stage equation.[19]

In addition to potential selection effects, it is possible that loan size influences the likelihood of default. The collateral requirement mechanically affects 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 has the opposite predicted effect of the collateral channel since uncollateralized loans are smaller and thus could attenuate our estimates. We assume that the impact of loan size on default rates can be captured by including a logged control variable and test the robustness of the results using other functional forms below (e.g., using a machine learning approach).

The core identifying assumption of this instrumental variables approach is that, given model controls, the instruments affect the likelihood of supplying collateral (the first stage outcome) but are otherwise unrelated to the likelihood of default (the second stage outcome). We conduct two assessments related to these assumptions. The first considers whether default rates differed for losses below the threshold across regimes. This type of placebo analysis helps assess for the possibility that the relationship between losses and default rates changes between collateral regimes, potentially violating the exclusion restriction. We find no evidence of "pre-trends," offering support for the assumption (Appendix F). Interpreting the 2SLS results as a local average treatment effect (LATE) also relies on a monotonicity assumption, that increasing the collateral threshold consistently reduces the likelihood of supplying collateral. Panel (B) of Figure 7 offers support for this assumption, showing that for a given level of losses, the probability of collateralizing declines as the threshold increases.

4.2 Results

The first column of Table 4 presents the average impact of collateral on the likelihood of default. Column (1) provides the reduced form estimate and so combines the effects of collateral on default and potential selection effects. In this estimate, collateral reduces the default hazard rate by

[18] We use a survival function because we do not observe every loan for the same period of time and many are still in force at the end of our observation window. See Tutz et al. (2016) for further information on discrete survival functions. We find similar results using a linear probability model of "ever default," described below. Like other survival models, this estimation relies on the proportional hazard assumption, that the explanatory variables impact the default rate equally across periods.

[19] All standard errors for this section are clustered at the disaster level, since this is the source of our random variation in the distance to the threshold (Abadie et al., 2023). All significant variables remain significant if we instead cluster by loss bin.

Table 4: Moral Hazard Estimation

	Dependent variable:				
	Default Hazard				Default Rate
	(1)	(2)	(3)	(4)	(5)
Collateral	-0.011^{*}				
	(0.006))				
Collateral (Instrumented)		-0.029^{**}	-0.031^{**}	-0.032^{**}	-0.052^{**}
		(0.012)	(0.012)	(0.013)	(0.019)
ln(Loan Amount)	0.038^{***}	0.051^{***}	0.042^{***}	0.042^{***}	0.081^{***}
	(0.006)	(0.01)	(0.009)	(0.01)	(0.016)
Credit Score (00s)			-0.031^{***}	-0.03^{***}	-0.045^{***}
			(0.002)	(0.002)	(0.002)
ln(Monthly Income)			-0.01^{***}	-0.014^{***}	-0.022^{***}
			(0.002)	(0.002)	(0.003)
Debt-to-Income Ratio			0.006	-0.013	-0.023^{*}
			(0.008)	(0.009)	(0.012)
Self Employed			0.007	0.011^{**}	0.012
			(0.005)	(0.005)	(0.008)
Age			-0.001^{***}	-0.001^{***}	-0.001^{***}
			(< 0.001)	(< 0.001)	(< 0.001)
LTV				0.026^{***}	0.037^{***}
				(0.005)	(0.007)
Home Equity ($00,000s)				-0.005^{**}	-0.01^{**}
				(0.002)	(0.004)
Method	OLS	2SLS	2SLS	2SLS	2SLS
Implied Percentage Change	-0.13	-0.33	-0.34	-0.36	-0.38
Disaster FEs	Yes	Yes	Yes	Yes	Yes
Time Since Origination FEs	Yes	Yes	Yes	Yes	No
Loss Size FEs	Yes	Yes	Yes	Yes	Yes
Data Level	Loan Year	Loan Year	Loan Year	Loan Year	Loan
Instrument F-Stat	–	186.00	178.60	167.10	155.10
Observations	864,057	864,057	864,057	864,057	83,256

Notes: *p<0.1; **p<0.05; ***p<0.01. The first column shows the estimation using regular OLS. The second column shows the results from the second stage of the two-stage least squares estimation (Equation 8). The third column shows the same two-stage least squares estimation with additional controls for default risk. The fourth column includes additional controls for home value and loan-to-value. 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 by disaster, are in parentheses (Abadie et al., 2023).

around 1.1 pp, an 13% reduction from the estimated counterfactual default rate with no collateral requirements.

Column (2) reports the results when instrumenting for the use of collateral with the distance from the threshold. The instrument is strong (F-stat $\geq$ 155) across all specifications. The Column (2) estimate reflects the causal effect of collateral: Collateralizing the loan reduces the default hazard rate by 3 pp. This response is equivalent to a 33% reduction in the default hazard and is nearly triple that of the naïve estimate in Column (1). The difference between the reduced form results in Column (1) and the causal estimate in Column (2) highlights the need to account for selection. Better quality borrowers are more willing to reduce their loans to avoid collateral (Section 5.1), and this advantageous selection partially attenuates the reduced form estimate of the effect of collateral requirements on defaults.

In Column (3) of Table 4 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. Column (4) adds the LTV on the borrower's existing home loans and their home equity, as these variables are of special interest in explaining the likelihood of default. 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 is nearly unaffected by including borrower characteristics. Column (4) is our preferred model because of the inclusion of additional controls and indicates that collateral reduces the default rate by 36%.

The results also highlight that collateral may serve as a substitute for creditworthiness 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 (5) shows results from a linear probability model, instead of a hazard model, of the likelihood that the borrower ever defaults.[20] 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 14.9% and that collateral reduces the default rate by 5.2 pp. This 38% reduction in default rates is very similar to the reduction generated by the hazard model in Column (4).

We conduct two sets of robustness tests, reported in Online Appendix F. First, we examine the extent to which changing the functional form approach of logging loan amounts affects our results. We use a Lasso regression to allow for a high degree of non-linearity in our control variables and find qualitatively similar results. Second, we test the robustness of our default hazard estimation to various model design choices with a specification curve (Simonsohn et al., 2020). Out of the 240

[20]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.

different regressions, every point estimate for 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 -0.047 and the 5th percentile is -0.025.

In summary, 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. We find that collateral provision causally reduces defaults by 36%, suggesting that the possibility of losing one's home provides a strong countervailing force to moral hazard.

5 What Drives Consumers' Collateral Concerns?

Having established that many borrowers are averse to posting collateral and that collateral commitments meaningfully influence loan repayment, we turn to examining potential drivers of collateral aversion. This section comprises two parts. The first uses variation in the cross section and over time, assessing how borrowers' *ex ante* credit score, income, and home equity and the program's interest rate relate to collateral decisions. The second part includes a structural model of borrowers' economic trade-off — collateral reduces borrowing costs but risks their home. We use this model to measure how, in addition to home equity, attachment to the home influences borrowers' decisions to supply collateral.

5.1 Descriptive Evidence

We first examine how the decision to supply collateral varies with borrower characteristics and the program's interest rate. We divide this brief discussion into financial considerations related to selection effects and borrowing costs, and non-financial considerations.[21]

5.1.1 Financial Considerations

Adverse vs. Advantageous Selection. Potential selection effects are ambiguous in our theoretical model. A standard adverse selection explanation is that individuals with greater default risk would avoid supplying collateral ($\partial(V - V_u)/\partial\gamma < 0$ in Equation 3). However, advantageous selection is also possible as default risk correlates with outside borrowing costs: low-risk borrowers

[21] 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 to ensure that the observed relationships hold in models with controls.

likely have lower-cost outside options, reducing the benefits of collateralizing the disaster loan ($\partial(V - V_u)/\partial r_u > 0$).

In Figure 8 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. Bunchers are less risky than borrowers taking smaller loans. Thus, the pattern in realized defaults suggests advantageous selection, which is consistent with our results in Section 4 becoming stronger when instrumented.

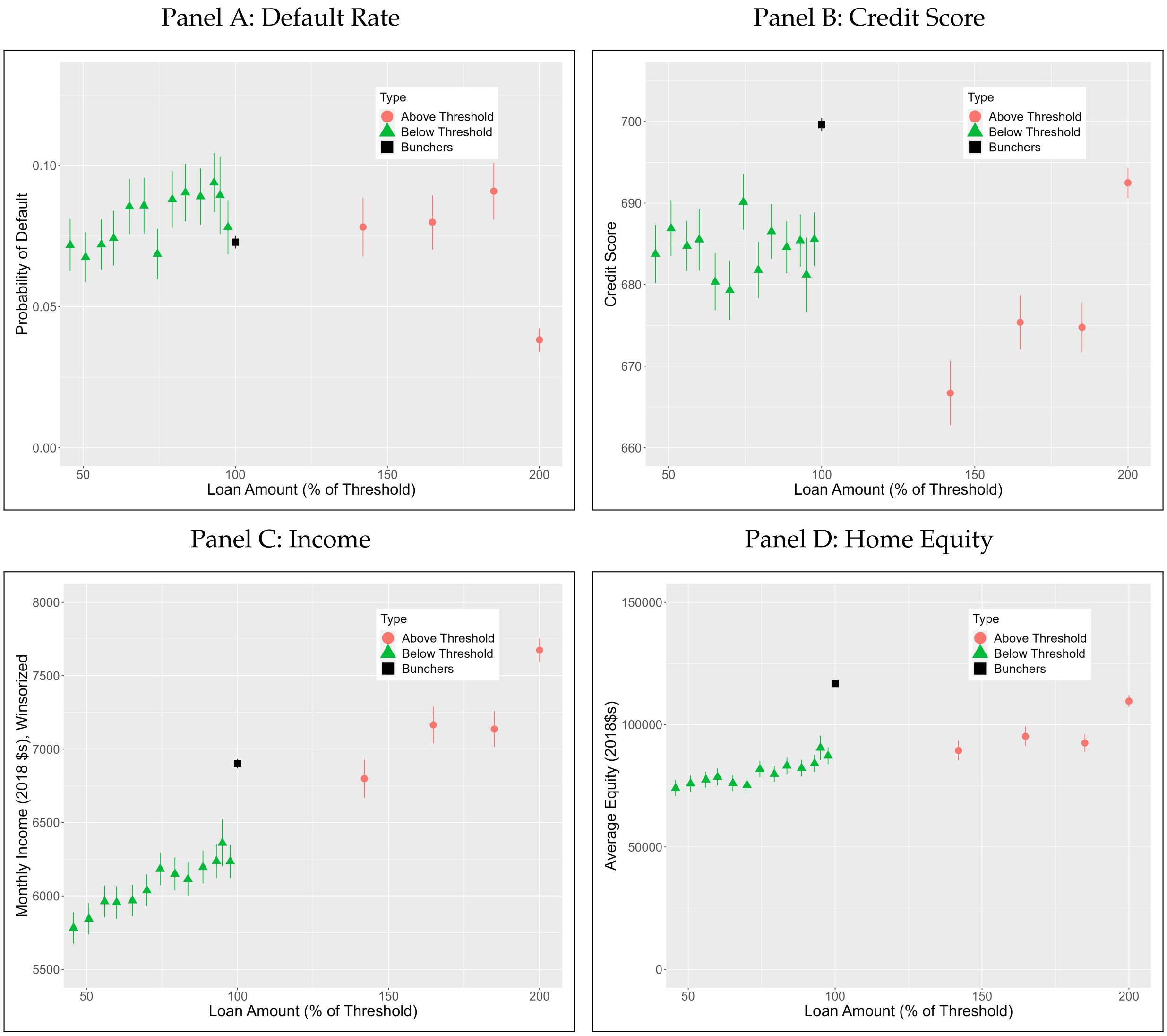
We additionally examine selection along observable dimensions in the remaining panels of Figure 8. In Panel B, we show the relationship between credit scores and the propensity to bunch at the uncollateralized threshold. In this case, the comparison of interest is borrowers who bunch versus those who elect to take a larger, collateralized loan (those to the right of bunchers, marked with red circles in the figure).[22] We again find evidence of advantageous selection: Bunchers have credit scores that are 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. Panel D shows that bunchers have more home equity, which aligns with borrowers' financial incentives as those with more equity have more to lose if defaulting on a collateralized loan ($\partial(V - V_u)/\partial\phi < 0$). 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.

Offered Interest Rates. We further explore the effects of borrowing costs on households' decisions to post collateral by using exogenous variation in the program's offered rate. We would expect an increase in the program's interest rate relative to outside options to reduce the likelihood that households take a collateralized loan ($\partial(V - V_u)/\partial r < 0$).

Indeed, we find that consumers' decisions to bunch depend on the offered interest rate. We examine bunching in response to exogenous variation in the interest rate. The applicant's rate is set based on the disaster declaration date and is fixed for the life of the loan. The program's offered rate is adjusted quarterly based on movements in private market rates. We compare consumers

[22]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.

Figure 8: Advantageous Selection at the Collateral Threshold



Note: This figure shows the percent of borrowers who default (Panel A), average credit score (Panel B), average monthly income (Panel C), and average home equity (Panel D) by loan amount as a percent of the collateral threshold. Monetary values are in 2018$ and winsorized at the 0.5% and 99.5% levels.

who experience a disaster just before versus just after the program's rate update. During this time, the program's rate jumps discretely while private market rates evolve smoothly.[23] We find that bunching is sensitive to the offered rate, with a 100 bps change in interest rates associated with a 9 pp change in the likelihood of bunching (see Appendix Table D1). For example, increasing

[23]This approach is developed by Collier and Ellis (2022) who examine extensive margin responses to the program's offered interest rates. We describe additional details of the estimation strategy in Online Appendix D.

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%.

Another element of the financial tradeoff is the hassle cost of origination. Recent research concludes that hassle costs play an important role in mortgage refinancing decisions, especially for better-off households (e.g., Andersen et al., 2020). In our setting, that higher-income households are slightly more likely to bunch (Figure 8) might signal the influence of hassle costs, though these costs seem insufficient to explain the magnitude of bunching. In particular, the additional documentation required to collateralize a disaster loan is small, as loan underwriting and an onsite inspection of the home occur regardless of whether the loan is collateralized (described in Section 2).[24]

5.1.2 Non-Financial Considerations

Non-financial considerations may also contribute to the collateral decision. Previous research in uncollateralized settings shows that some consumers appear to be "debt averse," even when the terms of the debt are subsidized or otherwise quite favorable (Field, 2009; Cadena and Keys, 2013). Debt aversion may reflect factors such as a dislike of borrowing or moral concerns regarding a possible default. These factors are continuous through the collateral threshold as bunchers and non-bunchers alike are taking on debt. However, supplying collateral increases the implications of default, potentially adding to debt aversion when the borrower's home is on the line.

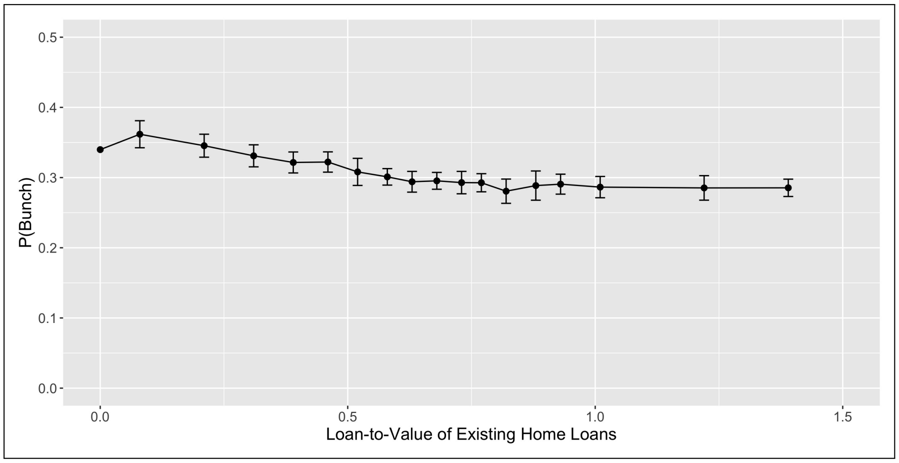
We highlight the importance of such non-financial factors by examining consumers' bunching decisions given their existing home equity. Homeowners with substantial equity in the home have more to lose if they default on the disaster loan than consumers whose collateral is already fully committed. Based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

Figure 9 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 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

[24] A further financial consideration is that accepting a larger subordinated loan may make it more difficult to refinance a first lien on the property. However, 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 uninsured short-term repairs.

appear to have negative equity and thus no immediate financial incentive to bunch, suggests that non-financial factors influence bunching decisions.

Figure 9: 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.

In summary, these results regarding posting collateral echo the mortgage refinancing literature: While consumers respond to financial incentives (e.g., interest rate changes), financial incentives alone are insufficient to explain borrowing decisions as consumers often fail to exercise financially beneficial options (Andersen et al., 2020; Keys et al., 2016).

5.2 Structural Estimation of Collateral Concerns

In this section, we add structure to the household's problem to assess how attachment to the home affects collateralized borrowing decisions. In general, concerns about default affect home borrowing choices through collateral-related channels — potential home equity losses and attachment to the collateral — and a broader set of consequences that are common across consumer credit products, regardless of collateral, including moral attitudes and effects on the consumers' credit score, which we refer to as "stigma." By studying households with underwater mortgages, recent research shows that the combined effect of attachment to the home and the stigma of default must be meaningful as consumers continue to pay their mortgages when no home equity is at stake

(Bhutta et al., 2017; Ganong and Noel, 2023). Our setting allows us to further disentangle these channels to estimate attachment to the home as we observe home equity and the stigma of default is continuous through the collateral threshold.

We extend the stylized model (Section 3.1) in recognition that households repay their loans over multiple years instead of repaying in a single period. We denote variables with an i subscript that are observed or estimated at the household level (e.g., the household's disaster loan interest rate r_i); the remaining variables rely on values from the existing literature and market data. Let p_i represent the amortized loan payment of a collateralized loan, which is a function of the needed loan amount l_i, the disaster loan interest rate r_i and maturity T_i. The amortized loan payment of an uncollateralized loan of the same size and maturity but at higher interest rate r_u is denoted p_{ui}. Household i values the uncollateralized and collateralized loan contracts respectively as

$$V_{ui} = (1-\gamma_{ui})U(w_i - \sum_{t=0}^{T_i-1}\left(\frac{1}{r_s}\right)^t p_{ui}) + \gamma_{ui}U(w_i - \psi) \tag{9}$$

$$V_i = (1-\gamma_i)U(w_i - \sum_{t=0}^{T_i-1}\left(\frac{1}{r_s}\right)^t p_i) + \gamma_i U(w_i - \psi - \phi_i). \tag{10}$$

As in Section 3.1, household utility U is a function of lifetime wealth, the household defaults with likelihoods γ_{ui} and γ_i on uncollateralized and collateralized loans respectively, and it incurs penalty ψ for any loan default and an additional penalty ϕ_i if defaulting on a collateralized loan. r_s is the gross, risk-free return on household savings, and its inclusion reflects that households can earn a return on funds needed to make future loan payments, which discounts the total cost of the loan over the household's lifetime. The household chooses a collateralized loan if and only if $V_i \geq V_{ui}$.

The collateralized default penalty ϕ_i comprises two components. The first is the loss of the household's financial equity ϕ_i^Q in foreclosure. The second is the household's attachment to the home ϕ_i^A, which is the variable of interest and must be estimated. ϕ_i^A captures the penalty of losing the home net of home equity losses (i.e., $\phi_i^A = \phi_i - \phi_i^Q$).[25] We employ a conservative assumption in assessing home attachment: We assume that all of the homeowners' equity would be lost in a default. While consumers generally have a right to any home equity left over after foreclosure, in practice all owner equity is typically eliminated when homes are sold at foreclosure sale prices

[25] We think of this attachment variable as primarily driven by fondness for a specific property, but it may also incorporate moving costs. The cost of a local move for a three-bedroom home averages $2,100 (see https://www.forbes.com/home-improvement/moving-services/movers-and-packers-cost/).

(see Goodman and Zhu, 2015; An and Cordell, 2021). This assumption is conservative because if homeowners expect to lose only a portion of their equity, the attachment value would be larger.[26]

We estimate the relevant default likelihoods (γ_{ui} and γ_i) through the methodology of Section 4. We estimate the needed loan amount l_i as the distance between the bunch point and the household's ideal loan amount using the original request approach, which provides ideal loan amount estimates for all borrowers (Section 3.4.2). While our data include proxies for household wealth, the estimation ultimately does not depend on wealth w_i.

Finally, we draw several model inputs from previous research and market data. An important literature estimates risk aversion from consumer choice data, including from health, auto, and homeowners insurance markets (e.g., Cohen and Einav, 2007; Handel, 2013; Sydnor, 2010). Following this literature which does not directly observe household wealth, we assume that households have CARA utility and risk aversion of $7.6 * 10^{-6}$ (Cohen and Einav, 2007). We additionally assume that the interest rate on the outside option r_u is 4 pp higher than the concurrent 30-year fixed rate mortgage, non-collateral costs of default ψ are $5,000, and the gross, risk-free return on savings is 1.01.[27] We also show how varying these model inputs affects the results.

We estimate attachment to the home as follows. Define ϕ_i^{A*} as the level of attachment to the home ϕ_i^A for which household i is indifferent between the lending contracts, $V_i = V_{ui}$. Following an approach used in the literature (e.g., Cohen and Einav, 2007), we solve for ϕ_i^{A*} through a second-order Taylor approximation of each instance of U, noting that $U(w_i + d) \approx U(w_i) + d * U'(w_i) + \frac{d^2}{2} * U''(w_i)$ where d captures deviations from lifetime wealth w_i. We next take the ϕ_i^{A*} estimates and construct a latent variable model to generate individual estimates of ϕ_i^A while controlling for covariates.[28] The intuition follows that of the bunching estimations (Section C.2): through the plausibly random assignment of disaster damages in the bunching region, we can uncover households' attachment by assessing the likelihood that a household bunches given an ideal loan amount. See Online Appendix G for full details.

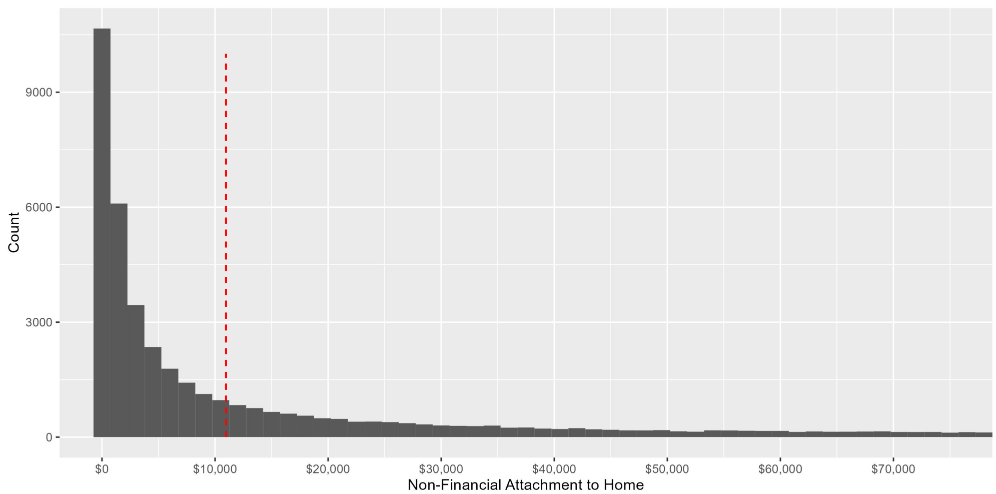
We find that the median household acts as if it has $89,000 at stake when pledging collateral. Recall that the median household has almost $78,000 in home equity (Table 1). Thus, using the

[26]Providing collateral might also deliver an amenity to homeowners in the case of default: The household could potentially live rent-free in the home for several months during the foreclosure process. We also employ a conservative assumption here, that households ignore this potential amenity when supplying collateral. Incorporating it would further increase our estimates of home attachment.

[27]Approximately, for the interest rate on the outside option r_u, we use the difference between the interest rate on a 2-year personal loan and the 30 year fixed-rate mortgage (FRED, 2020, 2023a). For the non-collateral costs of default ψ, we use the estimate from Liberman (2016) that borrowers are willing to pay the equivalent of 11% of their income for a good credit reputation. For the risk-free return on savings, we use the yield on a 1-year treasury (FRED, 2023b).

[28]To estimate the model, we assume $ln(\phi_i^A) = \beta X_i + \varepsilon_i$ where X_i is a vector of controls (including disaster fixed effects), and $\phi_i^A | X_i$ is distributed log-normal such that $\varepsilon_i \sim N(0, \sigma)$.

Figure 10: Distribution of Attachment to Home



Note: This figure shows the distribution of estimated attachment to the home (θ^A) using our base assumptions. The vertical, red dashed line shows the median estimate.

conservative assumption that all of this equity would be lost in a default, we estimate that the median household has a home attachment of $11,000. Our results suggest that attachment to one's home increases the perceived penalty of default by around 15%.

We also find substantial variation in home attachment. Figure 10 plots the distribution of individual estimates of ϕ_i^A. The median is marked with a red dashed line. Around 10% of our sample has an attachment to the home of no more than $0. However, many households would place an extremely large value on losing their home beyond the equity at stake, with 30% having an attachment greater than $50,000.

Table 5 shows our estimate's sensitivity to parameter values. Column (1) provides the estimated median attachment to the home (ϕ^A) for each set of assumptions, which are detailed in Columns (2)–(5). We find that doubling the level of risk aversion lowers the estimate to $8,000, while removing risk aversion increases it to $14,000. When the outside borrowing option is cheaper than the baseline (30-year fixed rate mortgage plus 3%), the estimated median non-financial attachment decreases to $6,000, while setting the outside cost of borrowing higher (30-year fixed rate plus 5%) increases the estimate to $16,000. Additionally, doubling the assumed risk-free return on savings, which determines discounting over time, reduces the estimate to $8,000; assuming that households only hold cash increases the estimate to $14,000. Our estimate is also relatively insensitive to the assumption of non-collateral default costs.[29]

Table 5: Structural Estimates of Home Attachment

	(1) Median Attachment ($)	(2) Risk Aversion	(3) Outside Option Interest Rate	(4) Risk-Free Savings Interest Rate	(5) Non-Collateral Default Cost
Base	10,978	$7.3 * 10^{-6}$	Mort. + 4	1%	5,000
2x Risk Aversion	8,083	$1.46 * 10^{-5}$	–	–	–
No Risk Aversion	14,292	0	–	–	–
Worse Outside Option	5,717	–	Mort. + 3	–	–
Better Outside Option	15,739	–	Mort. + 5	–	–
Higher Savings Interest Rate	7,945	–	–	2%	–
No Savings Interest Rate	13,463	–	–	0%	–
Zero Non-Collateral Default Costs	11,749	–	–	–	0
Higher Non-Collateral Default Costs	10,277	–	–	–	10,000

Notes: This table presents the median estimated level of attachment to the home (θ^A) under different parameter assumptions.

In summary, we isolate and quantify home attachment in our setting, showing that it adds a notable shadow cost to collateral. Households' borrowing decisions reflect an attachment to their home that is equivalent to $11,000 at the median. This value is net of any financial equity accrued in the home. One implication of this finding is that home attachment would operate as a type of friction relative to models of consumer borrowing and repayment behavior that focus solely on financial costs. This friction can help explain consumers' limited demand for financially attractive products that require pledging the home, such as reverse mortgages (e.g., Nakajima and Telyukova, 2017). Home attachment would also operate as a friction that reduces the likelihood of strategic default, influencing incentive compatibility conditions that affect credit supply and models of the economy.

6 Conclusion

In this paper, we examine the impact of collateral requirements on consumer borrowing behavior. By leveraging a discontinuity in collateral requirements for Federal Disaster Loans that changes

[29]Defaulting on either the collateralized or uncollateralized loan would induce default costs ϕ. The value of ϕ has a small effect on the median attachment values because taking the collateralized loan reduces the likelihood of default ($\mu_i < \mu_{ui}$) and so reduces the likelihood that the consumer incurs these costs.

over time, 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.

While canonical models of mortgage lending treat home equity as central to repayment decisions, a growing body of evidence shows that it is a secondary concern. What role, then, does collateral play in consumer decision-making? We first show that, at the time of loan origination, consumers perceive collateral provision in the form of one's primary residence as highly costly. Second, we find that committing one's home causally reduces loan default rates, addressing moral hazard concerns. Finally, we embed these *ex ante* and *ex post* responses to collateral in a structural model of borrowing and collateral provision, and provide new estimates of the influence of home attachment on borrowing decisions, which are substantial for many households.

Regarding whether the specific magnitudes of our estimates likely generalize, the existing literature highlights that consumer credit behavior is often influenced by the setting. For example, credit demand varies by product (e.g., first mortgage, credit card, etc., Karlan and Zinman, 2019) and repayment varies with default penalties (e.g., recourse laws and bankruptcy costs, Ghent and Kudlyak, 2011; Gross et al., 2021). We expect that the magnitude of collateral aversion may differ similarly across consumer credit markets based for example on loan terms and the expected recovery process.[30] Our results help reconcile findings from several strands of the literature in a single quasi-experimental context — consumers are averse to new collateral pledges, collateral reduces moral hazard concerns, but equity alone is insufficient to explain consumer borrowing behavior — which we take as evidence of the general nature of the collateral concerns that we document.

Our findings ultimately demonstrate that housing collateral is a key factor in the actions of consumers. The estimates suggest that borrowers' valuation of collateral blends both financial considerations and sizable non-financial attachment to the home. At the median, we estimate that non-financial home attachment increases the perceived penalty of collateralized default by around 15% if the borrower loses all home equity in the foreclosure process. This non-financial attachment creates a wedge between the value placed on collateral by borrowers relative to lenders. We conclude that consumers' previously puzzling borrowing and default decisions in collateralized markets should be re-examined with collateral aversion in mind.

[30] As an example in our setting, disasters vary in the type of destruction they create and the parts of the country they tend to affect, and these differences may influence consumers' borrowing decisions. In Appendix C.6, we subset the data by type and size of disaster. The resulting estimates of median collateral aversion range between 0.3 and 0.4. This range of aversion suggests substantially less heterogeneity than the effect of type and size of disaster on geographic mobility (see, e.g. Schultz and Elliott, 2013; Gallagher and Hartley, 2017; Deryugina et al., 2018; Behrer and Bolotnyy, 2023).

References

Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge (2023). When should you adjust standard errors for clustering? The Quarterly Journal of Economics 138(1), 1–35.

Agarwal, S., G. Amromin, I. Ben-David, S. Chomsisengphet, T. Piskorski, and A. Seru (2017). Policy intervention in debt renegotiation: Evidence from the home affordable modification program. Journal of Political Economy 125(3), 654–712.

An, X. and L. Cordell (2021). Mortgage loss severities: What keeps them so high? Real Estate Economics 49(3), 809–842.

Andersen, S., J. Y. Campbell, K. M. Nielsen, and T. Ramadorai (2020). Sources of inaction in household finance: Evidence from the danish mortgage market. American Economic Review. (forthcoming).

Bai, J. and S. Ng (2008). Forecasting economic time series using targeted predictors. Journal of Econometrics 146(2), 304–317.

Bakkensen, L. A. and L. Barrage (2022). Going underwater? flood risk belief heterogeneity and coastal home price dynamics. The Review of Financial Studies 35(8), 3666–3709.

Begley, T. A., U. Gurun, A. K. Purnanandam, and D. Weagley (2020). Disaster lending.

Behrer, A. P. and V. Bolotnyy (2023). Moving to adaptation?: Understanding the migratory response to hurricanes in the united states.

Belloni, A., D. Chen, V. Chernozhukov, and C. Hansen (2012). Sparse models and methods for optimal instruments with an application to eminent domain. Econometrica 80(6), 2369–2429.

Belloni, A., V. Chernozhukov, and C. Hansen (2014a). High-dimensional methods and inference on structural and treatment effects. The Journal of Economic Perspectives 28(2), 29–50.

Belloni, A., V. Chernozhukov, and C. Hansen (2014b). Inference on treatment effects after selection among high-dimensional controls. The Review of Economic Studies 81(2), 608–650.

Belloni, A., V. Chernozhukov, C. Hansen, and D. Kozbur (2016). Inference in high-dimensional panel models with an application to gun control. Journal of Business & Economic Statistics 34(4), 590–605.

Benmelech, E. and N. K. Bergman (2009). Collateral pricing. Journal of Financial Economics 91(3), 339–360.

Berger, A. N., W. S. Frame, and V. Ioannidou (2011). Tests of ex ante versus ex post theories of collateral using private and public information. Journal of Financial Economics 100(1), 85–97.

Berger, A. N. and G. F. Udell (1990). Collateral, loan quality and bank risk. Journal of Monetary Economics 25(1), 21–42.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. The Quarterly Journal of Economics 98(1), 85–106.

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

Bernstein, A., M. T. Gustafson, and R. Lewis (2019). Disaster on the horizon: The price effect of sea level rise. Journal of financial economics 134(2), 253–272.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. The American Economic Review 75(4), 850–855.

Bhutta, N., J. Dokko, and H. Shan (2017). Consumer ruthlessness and mortgage default during the 2007 to 2009 housing bust. The Journal of Finance 72(6), 2433–2466.

Billings, S. B., E. A. Gallagher, and L. Ricketts (2022). Let the rich be flooded: the distribution of financial aid and distress after hurricane harvey. Journal of Financial Economics 146(2), 797–819.

Blomquist, S., W. K. Newey, A. Kumar, and C.-Y. Liang (2021). On bunching and identification of the taxable income elasticity. Journal of Political Economy 129(8), 000–000.

Boot, A. W. and A. V. Thakor (1994). Moral hazard and secured lending in an infinitely repeated credit market game. International Economic Review, 899–920.

Cadena, B. C. and B. J. Keys (2013). Can self-control explain avoiding free money? evidence from interest-free student loans. Review of Economics and Statistics 95(4), 1117–1129.

Calomiris, C. W., M. Larrain, J. Liberti, and J. Sturgess (2017). How collateral laws shape lending and sectoral activity. Journal of Financial Economics 123(1), 163–188.

Caner, M. (2009). Lasso-type gmm estimator. Econometric Theory 25(1), 270–290.

Carson, J. M., C. M. Ellis, R. E. Hoyt, and K. Ostaszewski (2020). Sunk costs and screening: Two-part tariffs in life insurance. Journal of Risk and Insurance 87(3), 689–718.

Cerqueiro, G., S. Ongena, and K. Roszbach (2016). Collateralization, bank loan rates, and monitoring. The Journal of Finance 71(3), 1295–1322.

Chan, Y.-S. and A. V. Thakor (1987). Collateral and competitive equilibria with moral hazard and private information. The Journal of Finance 42(2), 345–363.

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

Chernozhukov, V., C. Hansen, and M. Spindler (2015). Post-selection and post-regularization inference in linear models with many controls and instruments. The American Economic Review 105(5), 486–490.

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

Coco, G. (2000). On the use of collateral. Journal of Economic Surveys 14(2), 191–214.

Cohen, A. and L. Einav (2007). Estimating risk preferences from deductible choice. American economic review 97(3), 745–788.

Collier, B. J. and C. M. Ellis (2022). A demand curve for disaster recovery loans. Working Paper, *https://dx.doi.org/10.2139/ssrn.3839044*.

Costello, A. M. (2019). The value of collateral in trade finance. Journal of Financial Economics 134(1), 70–90.

del Valle, A., T. C. Scharlemann, and S. H. Shore (2022). Household financial decision-making after natural disasters: Evidence from hurricane harvey.

Deryugina, T., L. Kawano, and S. Levitt (2018). The economic impact of hurricane katrina on its victims: Evidence from individual tax returns. American Economic Journal: Applied Economics 10(2), 202–33.

Ersahin, N., R. M. Irani, and K. Waldock (2019). Can strong creditors inhibit entrepreneurial activity? The Review of Financial Studies.

Experian (2020). 2019 consumer credit review. Prepared by Matt Tatham, *www.experian.com/blogs/ask-experian/consumer-credit-review/*.

Fannie Mae (2019). Single-family fixed rate mortgage dataset. https://loanperformancedata.fanniemae.com/lppub/index.html.

Federal Register (1997). How are loans administered and serviced? Code of Federal Regulations, Title 13, Section 123.16.

Federal Register (2014). What are SBA's policies concerning the liquidation of collateral and the sale of business loans and physical disaster assistance loans, physical disaster business loans and economic injury disaster loans? Code of Federal Regulations, Title 13, Section 120.545.

Federal Reserve Bank of New York (2021). Quarterly report on household debt and credit.

FEMA (2019). Individual disaster assistance. Federal Emergency Management Agency.

Field, E. (2009). Educational debt burden and career choice: Evidence from a financial aid experiment at nyu law school. American Economic Journal: Applied Economics 1(1), 1–21.

Foote, C. L. and P. S. Willen (2018). Mortgage-default research and the recent foreclosure crisis. Annual Review of Financial Economics 10, 59–100.

FRED (2020, Mar). 30-year fixed rate mortgage average in the united states. Federal Reserve Economic Database, Federal Reserve Bank of St. Louis.

FRED (2023a, April). Finance rate on personal loans at commercial banks, 24 month loan. Federal Reserve Economic Database, Federal Reserve Bank of St. Louis.

FRED (2023b, April). Market yield on u.s. treasury securities at 1-year constant maturity, quoted on an investment basis. Federal Reserve Economic Database, Federal Reserve Bank of St. Louis.

Freddie Mac (2019). Single family loan-level dataset. http://www.freddiemac.com/research/datasets/sf_loanlevel_dataset.page.

Gallagher, J. and D. Hartley (2017). Household finance after a natural disaster: The case of hurricane katrina. American Economic Journal: Economic Policy 9(3), 199–228.

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

Ganong, P. and P. Noel (2020). Liquidity versus wealth in household debt obligations: Evidence from housing policy in the great recession. American Economic Review 110(10), 3100–3138.

Ganong, P. and P. Noel (2023). Why do borrowers default on mortgages? The Quarterly Journal of Economics 138(2), 1001–1065.

Gertler, M. and B. Bernanke (1989). Agency costs, net worth and business fluctuations. In Business cycle theory. Edward Elgar Publishing Ltd.

Gertler, P., B. Green, and C. Wolfram (2021). Digital collateral. Technical report, National Bureau of Economic Research.

Ghent, A. C. and M. Kudlyak (2011). Recourse and residential mortgage default: evidence from us states. The Review of Financial Studies 24(9), 3139–3186.

Goodman, L. S. and J. Zhu (2015). Loss severity on residential mortgages: evidence from freddie mac's newest data. The Journal of Fixed Income 25(2), 48–57.

Gross, T., R. Kluender, F. Liu, M. J. Notowidigdo, and J. Wang (2021). The economic consequences of bankruptcy reform. American Economic Review 111(7), 2309–41.

Guiso, L., P. Sapienza, and L. Zingales (2013). The determinants of attitudes toward strategic default on mortgages. The Journal of Finance 68(4), 1473–1515.

Gupta, A. and C. Hansman (2022). Selection, leverage, and default in the mortgage market. The Review of Financial Studies 35(2), 720–770.

Handel, B. R. (2013). Adverse selection and inertia in health insurance markets: When nudging hurts. American Economic Review 103(7), 2643–82.

Ioannidou, V., N. Pavanini, and Y. Peng (2019). Collateral and asymmetric information in lending markets.

Jimenez, G., V. Salas, and J. Saurina (2006). Determinants of collateral. Journal of Financial Economics 81(2), 255–281.

Jiménez, G. and J. Saurina (2004). Collateral, type of lender and relationship banking as determinants of credit risk. Journal of Banking & Finance 28(9), 2191–2212.

Karlan, D. and J. Zinman (2019). Long-run price elasticities of demand for credit: evidence from a country-wide field experiment in mexico. The Review of Economic Studies 86(4), 1704–1746.

Keys, B. J. and P. Mulder (2020). Neglected no more: Housing markets, mortgage lending, and sea level rise. Technical report, National Bureau of Economic Research.

Keys, B. J., D. G. Pope, and J. C. Pope (2016). Failure to refinance. Journal of Financial Economics 122(3), 482–499.

Kiyotaki, N. and J. Moore (1997). Credit cycles. Journal of political economy 105(2), 211–248.

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

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

Larsen, T. (2017). Hurricane harvey: Identifying the insurance gap. CoreLogic, corelogic.com/intelligence/hurricane-harvey-identifying-the-insurance-gap.

Liberman, A. (2016). The value of a good credit reputation: Evidence from credit card renegotiations. Journal of Financial Economics 120(3), 644–660.

Loftsgordon, A. (2022). Foreclosure of SBA Disaster Loans. NOLO.com, https://www.nolo.com/legal-encyclopedia/foreclosure-of-sba-disaster-loans.html.

Luck, S. and J. A. Santos (2019). The valuation of collateral in bank lending. Available at SSRN 3467316.

Mian, A. and A. Sufi (2014). What explains the 2007–2009 drop in employment? Econometrica 82(6), 2197–2223.

Nakajima, M. and I. A. Telyukova (2017). Reverse mortgage loans: A quantitative analysis. The Journal of Finance 72(2), 911–950.

NOAA (2022). U.S. billion-dollar weather and climate disasters. U.S. National Oceanic and Atmospheric Administration, DOI: 10.25921/stkw-7w73.

Office of Disaster Assistance (2018). Standard operating procedure, Disaster Assistance Program. Small Business Administration, 31 May 2018.

O'Malley, T. (2020). The impact of repossession risk on mortgage default. The Journal of Finance.

Pan, G., Z. Pan, and K. Xiao (2023). The shadow cost of collateral. Available at SSRN 3984585.

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

SBA (2020). Sba disaster guide. Small Business Administration, sba.gov/sites/default/files/disaster_assistance_transcript_1.pdf, Accessed 6 May 2020.

Schultz, J. and J. R. Elliott (2013). Natural disasters and local demographic change in the united states. Population and Environment 34, 293–312.

Simonsohn, U., J. P. Simmons, and L. D. Nelson (2020). Specification curve analysis. Nature Human Behaviour 4(11), 1208–1214.

Sydnor, J. (2010). (Over) insuring modest risks. American Economic Journal: Applied Economics 2(4), 177–99.

Thoemmes, F. J. and E. S. Kim (2011). A systematic review of propensity score methods in the social sciences. Multivariate behavioral research 46(1), 90–118.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society. Series B (Methodological) 58(1), 267–288.

Treasury Offset Program (2021). How TOP works. https://fiscal.treasury.gov/top/how-top-works.html.

Tutz, G., M. Schmid, et al. (2016). Modeling discrete time-to-event data. Springer.

Walsh, M. W. (2017). Homeowners (and taxpayers) face billions in losses from Harvey flooding. New York Times, 28 August 2017, https://www.nytimes.com/2017/08/28/business/dealbook/flood-insurance-harvey.html.

Zevelev, A. A. (2020). Does collateral value affect asset prices? Evidence from a natural experiment in texas. The Review of Financial Studies. https://doi.org/10.1093/rfs/hhaa117.

Online Appendix A Example Forms

Hurricane Harvey Loan Fact Sheet

Date: 11/07/2017

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%

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?

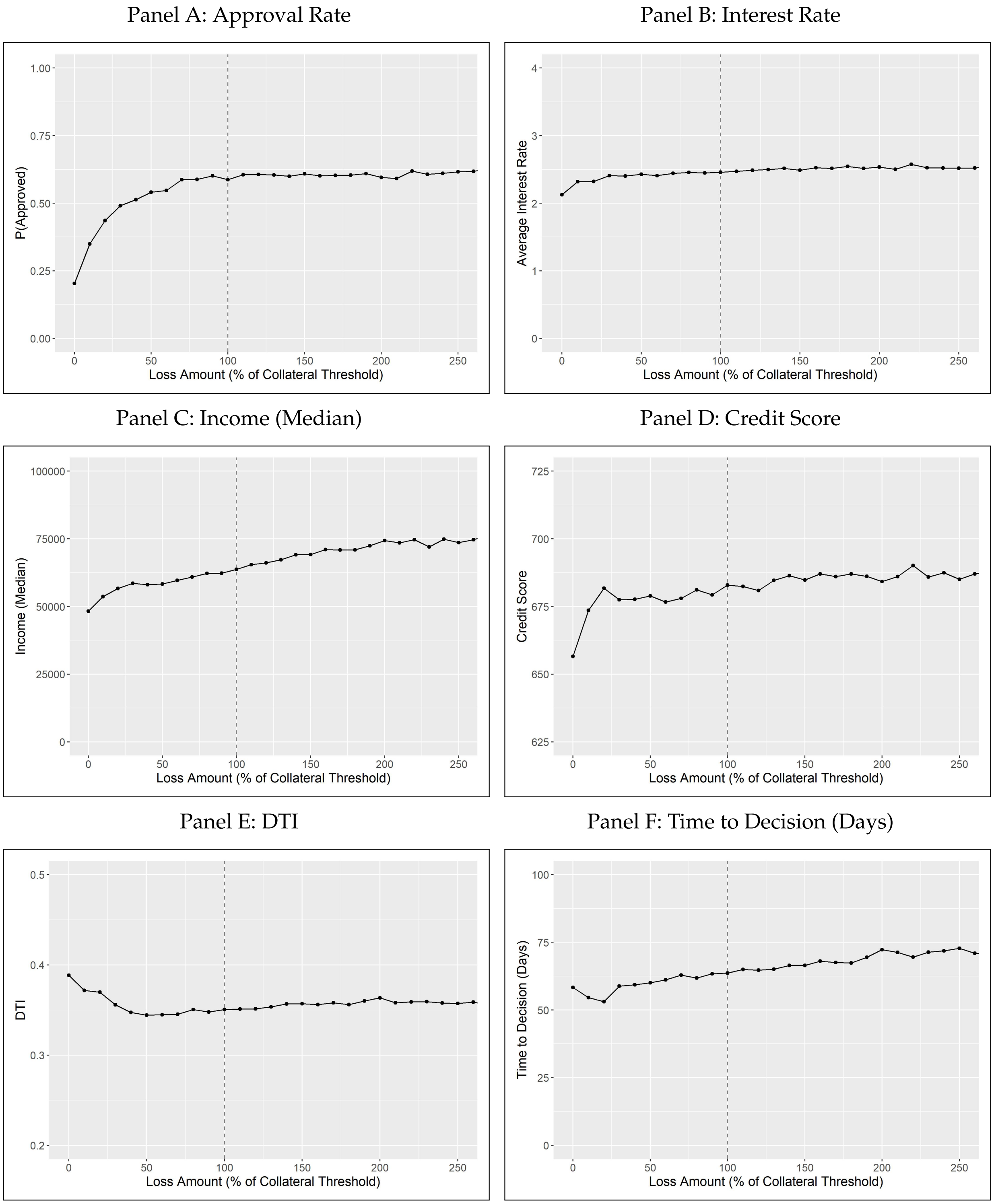
To protect each borrower and the Agency, SBA may require you to obtain and maintain appropriate insurance. By law, borrowers whose damaged or collateral property is located in a special flood hazard area must purchase and maintain flood insurance. SBA requires that flood insurance coverage be the lesser 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 11 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 11: 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 the program approves or declines the loan.

Online Appendix C Bunching Estimations, Supplementary Material

C.1 Distance to the Threshold and Household Characteristics

Table C1: Regression of the Distance to the Collateral Threshold on Household Characteristics

	Dependent variable:
	Loss Distance
Credit Score (00s)	-1.153
	(0.944)
ln(Monthly Income)	1.173
	(1.244)
Home Equity ($00,000s)	0.273
	(0.664)
Debt-to-Income Ratio	0.949
	(3.658)
Self Employed	-4.412
	(3.019)
Age	0.129
	(0.109)
LTV	-0.639
	(3.497)
Disaster FEs	Yes
Loss Size FEs	Yes
Data Level	Loan
Observations	83,256
Residual Std. Error	288.439

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents the results of regressing the distance from the household's loss amount to the collateral threshold on household characteristics. Standard errors, clustered at the disaster level, are in parenthesis.

C.2 Traditional Bunching Bunching Methods

C.2.1 Estimation

This method constructs a counterfactual based on the excess mass at the bunch point and the distribution of selected loan amounts $h(l^*)$. We estimate the distribution of households' ideal loan amounts $h(\hat{l})$ by first fitting an approximation on the portion of the density either not subject to collateral requirements (where $\hat{l}_i < c$) or sufficiently far above and then extrapolating the approximation over the portion of the density that is subject to the requirements.[31]

[31] 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).

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

$$\begin{aligned} n_j &\approx h(l_i; \beta_p, \gamma_m, \rho_r, \theta_k) \\ &= \sum_{p=0}^{P} \beta_p (\overline{l_j})^p + \sum_{m=c}^{\overline{l_M}} \gamma_i \mathbb{1}[\overline{l_j} = m] + \sum_{r \in R} \rho_r \mathbb{1}\left[\frac{\overline{l_j}}{r} \in \mathbb{N}\right] + \sum_{k \in K} \theta_k \mathbb{1}\left[\overline{l_j} \in K \wedge \overline{l_j} \notin [c, \overline{l_M}]\right] + \varepsilon_j \end{aligned} \quad \text{(A1)}$$

The first term is an order P polynomial approximation of the density in the absence of bunching due to collateral or round numbers.[32] The second term is the alteration of the density in the bunching region $[c, \overline{l_M}]$ induced by the collateral requirements. c is the collateral threshold and $\overline{l_M}$ is the maximum loan amount from which borrowers move to instead borrow at the bunch point. The third term controls for the tendency of borrowers to bunch at round numbers R (every \$5,000 and \$1,000), where we observe a partial set before the bunching region. The final term represents the set of numbers K (\$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. We denote the binned histogram approximation of the distribution of ideal loan amounts as $\hat{b}_j$.

To estimate Equation (A1), we first determine the upper end of the bunching region $\overline{l_M}$ (following Kleven and Waseem, 2013). We set $\overline{l_M}$ just above the bunch point, then iteratively increase it until the estimated excess mass of bunchers is equal to the missing mass between the observed and counterfactual distributions. Following the determination of $\overline{l_M}$, we estimate Equation (A1) via OLS and block bootstrap at the disaster level.[33]

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 A1) to project over a potentially large range of loan amounts. Misestimation 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 forgo 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 more meaningful when estimating the upper end of the bunching region $\overline{l_M}$.[34]

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

[33] Specifically, we randomly re-sample at the disaster level and then re-estimate our coefficients of interest.

[34] 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.

C.2.2 Results

Table C2 provides the results from this bunching estimation. The third column describes bunching when the threshold is set at \$25,000. For this threshold, the bunching region ranges from \$25,000 to \$50,000, and in this range, 76% of borrowers move to the bunch point. On average, borrowers in the bunching region are willing to give up 42% (\$18,300) 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.

We can translate the estimates from Table C2 into a back-of-the-envelope net present value using Equation (5). To do so, we assume that households are able to access unsecured credit at an interest rate of 4 pp above the concurrent 30-year mortgage rate, save at a risk-free interest rate of 1%, and default at the program's average default rate of 12%. We find that by bunching at the threshold, the median household forgoes a benefit of \$26,000 in net present value.

Table C2: 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	73.29	78.25	76.04

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.

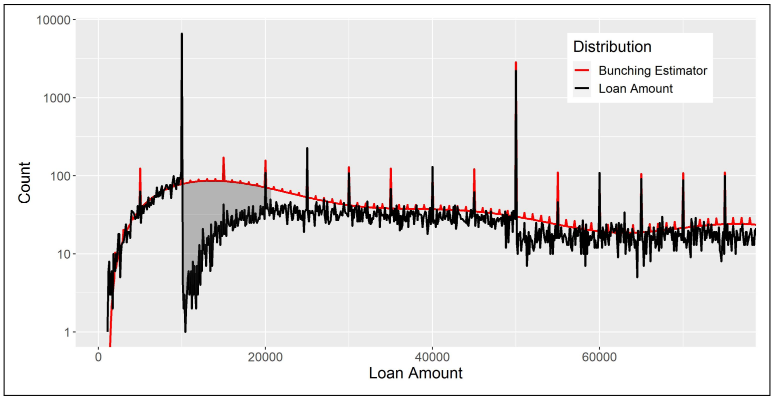
Graphical displays of our traditional bunching estimation are shown in Figure 12, with each sub-figure representing a different collateral threshold. The y-axis for all of the figures is in log scale. The black lines are the observed distribution (n_j). The red lines represent our estimated counterfactual distribution ($\hat{n_j}$). 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 at the collateral threshold (c)

and the shaded gray area represents the bunching region. The end point of the bunching region occurs where the sum of the "missing" borrowers ($\hat{n}_j$ - n_j) equals the excess mass at the threshold.

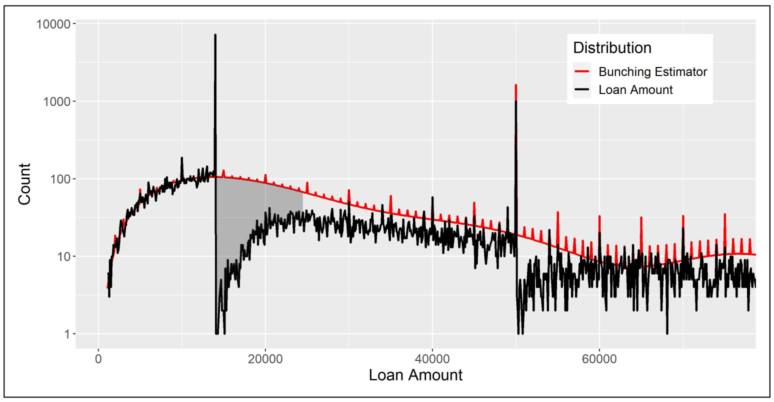
Figure 12 highlights two features of the estimation. First, in each panel, the counterfactual distribution closely fits consumers' selected loan amounts below the collateral threshold. Thus, the estimation successfully approximates consumers' selected loan amounts over a range of values where they are 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 (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.

Figure 12: Bunching Estimation, Traditional Method

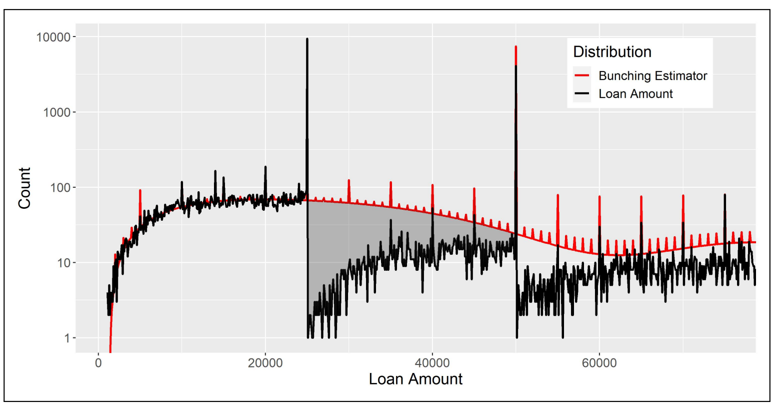
Panel A: $10,000 Threshold (2005-2007)



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 (n_j). The red lines represent our counterfactual distribution ($\hat{n_j}$). 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 ($\hat{n_j}$ - n_j) equals the excess mass at the bunch point.

C.3 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.[35] 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.[36] 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 C3 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

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

[36] 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.

The estimation using the original request 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 the collateral requirement never binds), the average initial request is nearly identical ($115 larger) to the average final loan amount.

Table C3: Matching and Observable Characteristics

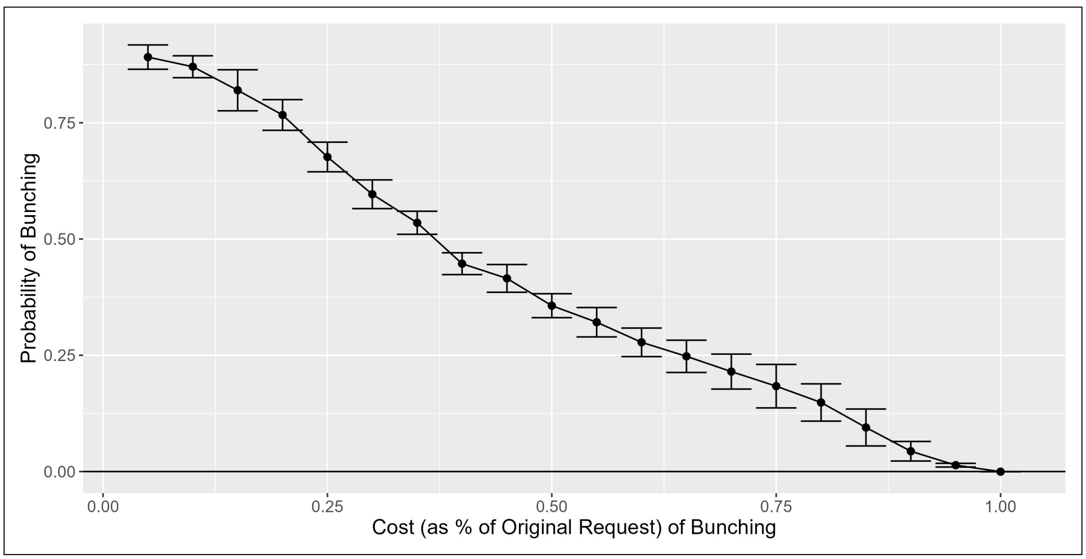
	Average Values			
	(1) Uninformative Bunchers	(2) Informative Bunchers Post-Match	(3) Informative Bunchers Pre-Match	(4) Informative Bunchers Leave-Out
Original Request Distance (%)	–	36.95	53.91	–
Total Loss	30,214	33,841	70,377	53,950
Home Value	184,797	186,212	225,383	193,431
LTV Ratio (%)	58.47	57.15	51.06	58.32
Interest Rate	2.63	2.62	2.37	2.57
Credit Score	687	689	696	688
ln(Monthly Income + 1)	8.47	8.48	8.54	8.48
Debt-to-Income Ratio (%)	35.25	34.86	35.21	34.29
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.

C.4 Results Using Applicants' Original Loan Requests as a Counterfactual

Figure 13 shows the results of our alternative bunching estimation (described in Equation 7) 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 forgo 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 $16,700 when the collateral threshold is $25,000). Around 15% will give up 75% of their ideal loan (i.e., give up $75,000 when the threshold is $25,000) to avoid posting collateral. Only 1% will give up more than 90% of their ideal loan.

Figure 13: 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.

C.5 Comparison of Bunching Estimation Results

Table C4 provides a summary of the methods and limitations of each of our three methods. Table 2 provides the estimated median collateral aversion for all three methods across the different thresholds.

Table C4: 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.

C.6 Bunching Estimation by Disaster Type

Table C5: Bunching Estimation: Subset Analysis

	(1)	(2)	(3)	(4)	(5)
	Small Disasters	Large Disasters	Hurricanes	Unnamed Storms and Flooding	Other Disasters
Median Collateral Aversion	0.32	0.38	0.36	0.38	0.40
	(0.016)	(0.009)	(0.013)	(0.014)	(0.013)
Share of Borrowers (%)	5.13	94.87	65.25	25.85	8.89

Note: This table presents the results of our original request bunching estimation using various subsets of the data. Column (1) only includes disasters with 100 or fewer borrowers. Column (2) only uses disasters with more than 100 borrowers. Column (3) only features hurricanes. Column (4) only features unnamed storms and general flooding. Column (5) features all other disasters and is predominantly composed of fires and earthquakes. Standard errors, in parentheses, are block bootstrapped at the disaster level.

Online Appendix D 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.[37] Figure 14, Panel A plots the two rates offered by the program over time against the rate for a 30-year fixed-rate mortgage (FRED, 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 14 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 14: 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.[38] 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

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

[37]This identification was developed by Collier and Ellis (2022) and much of this description is drawn from their paper.

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

Table D1: 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.

$$P(Bunch_{i,t}) = \beta_0 + \beta \widehat{Rate_{i,t}} + X_{i,t}\theta + \varepsilon_{i,t} \tag{A2}$$

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 (7); and β then gives the causal impact of interest rates on bunching behavior. Table D1 provides the results of the estimation.

Online Appendix E Mechanisms and Heterogeneity: Multivariate Regression

Table E1 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 E1: 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

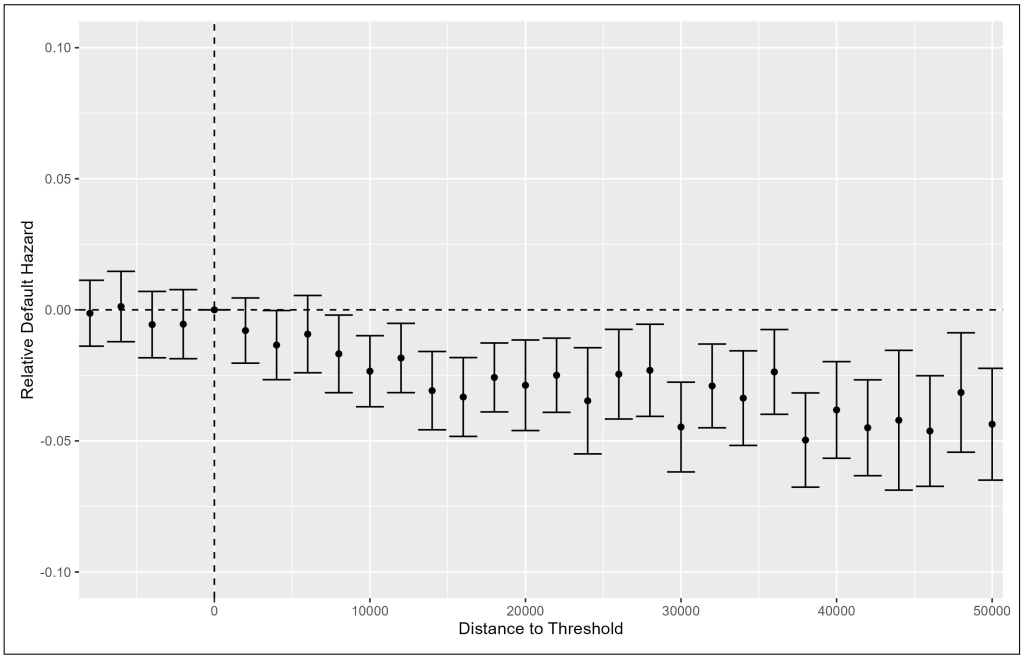
Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents the coefficients on covariates that may affect bunching decisions. The first column shows the estimation using all covariates and both disaster and original request bin fixed effects. The second and third column omit combinations of fixed effects. 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 F Moral Hazard Section, Supporting Material

F.1 Event Study

Figure 15 shows the impact of distance from the household's loss to the threshold on default hazard rates. Standard errors are clustered at the loss bin level as an "event study" style plot. We can test the exogeneity of our instrument through assessing the parallel trends prior to the bunching threshold. We find no visual evidence of non-parallel pretrends.

Figure 15: Event Study Figure for IV



Note: This figure shows the impact of distance from the household's loss to the threshold on default hazard rates. Standard errors are clustered at the disaster level.

F.2 Lasso Estimation

The interpretation of the coefficient on $\mathbf{Collateral_{i,t}}$ as "the effect" of collateral on default depends on the assumption that the direct effect of loan size on default (the second channel described above) 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.[39] 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

[39]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.

treatment variables allowing for instrumentation. Formally, our final model is

$$
\begin{aligned}
&\textbf{First Stage:} \\
P(Collateral_i) &= Z_{i,t}\gamma'_{Lasso} + v_{i,t} && \text{(A3)} \\
\text{where } \gamma'_{Lasso} &= \underset{\gamma}{\operatorname{argmin}} \left\{ \sum (P(Collateral_i) - \hat{Z}_{i,t}\gamma')^2 \right\} \text{ subject to } \|\gamma\|_1 \leq \lambda_1 \\
&\textbf{Second Stage:} \\
P(Defaulted_{i,t}) &= \hat{L}_{i,t}\beta'_{Lasso} + e_{i,t} && \text{(A4)} \\
\text{where } \beta'_{Lasso} &= \underset{\beta}{\operatorname{argmin}} \left\{ \sum (P(Defaulted_{i,t}) - \hat{L}_{i,t}\beta')^2 \right\} \text{ subject to } \|\beta\|_1 \leq \lambda_2 \\
&\textbf{Third Stage:} \\
P(Collateral_i) &= Z^P_{i,t}\gamma' + v_{i,t} && \text{(A5)} \\
Z^L_{i,t} &= (\overline{\mathbf{Distance_i}}; \hat{Z}_{i,t} \text{ such that } \gamma_{Lasso} \neq 0 \text{ or } \beta_{Lasso} \neq 0) \\
&\textbf{Fourth Stage:} \\
P(Defaulted_{i,t}) &= \hat{L}^p_{i,t}\beta' + e_i && \text{(A6)} \\
\hat{L}^p_{i,t} &= (\widehat{\mathbf{Collateral}}_\mathbf{i};\, ; \hat{L}_{i,t} \text{ such that } \gamma_{Lasso} \neq 0 \text{ or } \beta_{Lasso} \neq 0). \\
&\textbf{Controls:} \\
\hat{X}_i &= (log(LoanAmount_i), LoanAmount_i) \\
\hat{F}_{i,t} &= (\tau_t, LossBin_i, Disaster_i) \\
\hat{Z}_{i,t} &= (\overline{\mathbf{Distance_i}}; \hat{X}_i, \hat{F}_{i,t}, \hat{X}^2_i, \hat{X}^3_i, \hat{X}^4_i, \hat{X}^5_i) \\
\hat{L}_{i,t} &= (\mathbf{Collateral_i}; \hat{X}_i, \hat{F}_{i,t}, \hat{X}^2_i, \hat{X}^3_i, \hat{X}^4_i, \hat{X}^5_i)
\end{aligned}
$$

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 (A3) and (A4)) to make sure we incorporate the proper control variables for both models.[40] In Equations (A5) and (A6) 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 l_1) number of terms. This isolates the interpretation of $\widehat{\mathbf{Collateral}}_\mathbf{i}$ 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 F1. 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.

[40] In Equations (A3) and (A4), only the coefficients on loan amount variables are penalized. λ_1 and λ_2 are determined via 5-fold cross-validation separately for Equations (A3) and (A4).

Table F1: Moral Hazard Estimation

	Dependent variable:		
	Default Hazard		
	(1)	(2)	(3)
Collateral	-0.011^{*}		
	(0.006)		
Collateral (fit)		-0.029^{**}	-0.024^{**}
		(0.012)	(0.011)
ln(Loan Amount)	0.038^{***}	0.051^{***}	0.815^{***}
	(0.006)	(0.010)	(0.209)
ln(Loan Amount)^2			-0.039^{***}
			(0.010)
Loan Amount^2			0.006^{***}
			(0.002)
Loan Amount^4			-0.000^{***}
			(0.000)
Implied Percentage Change:	-0.13	-0.33	-0.27
Lasso Loan Size Controls	No	No	Yes
Disaster FEs	Yes	Yes	Yes
Time Since Origination FEs	Yes	Yes	Yes
Loss Size FEs	Yes	Yes	Yes
Data Level	Loan Year	Loan Year	Loan Year
Observations	864,057	864,057	864,057
Residual Std. Error	0.256	0.256	0.256

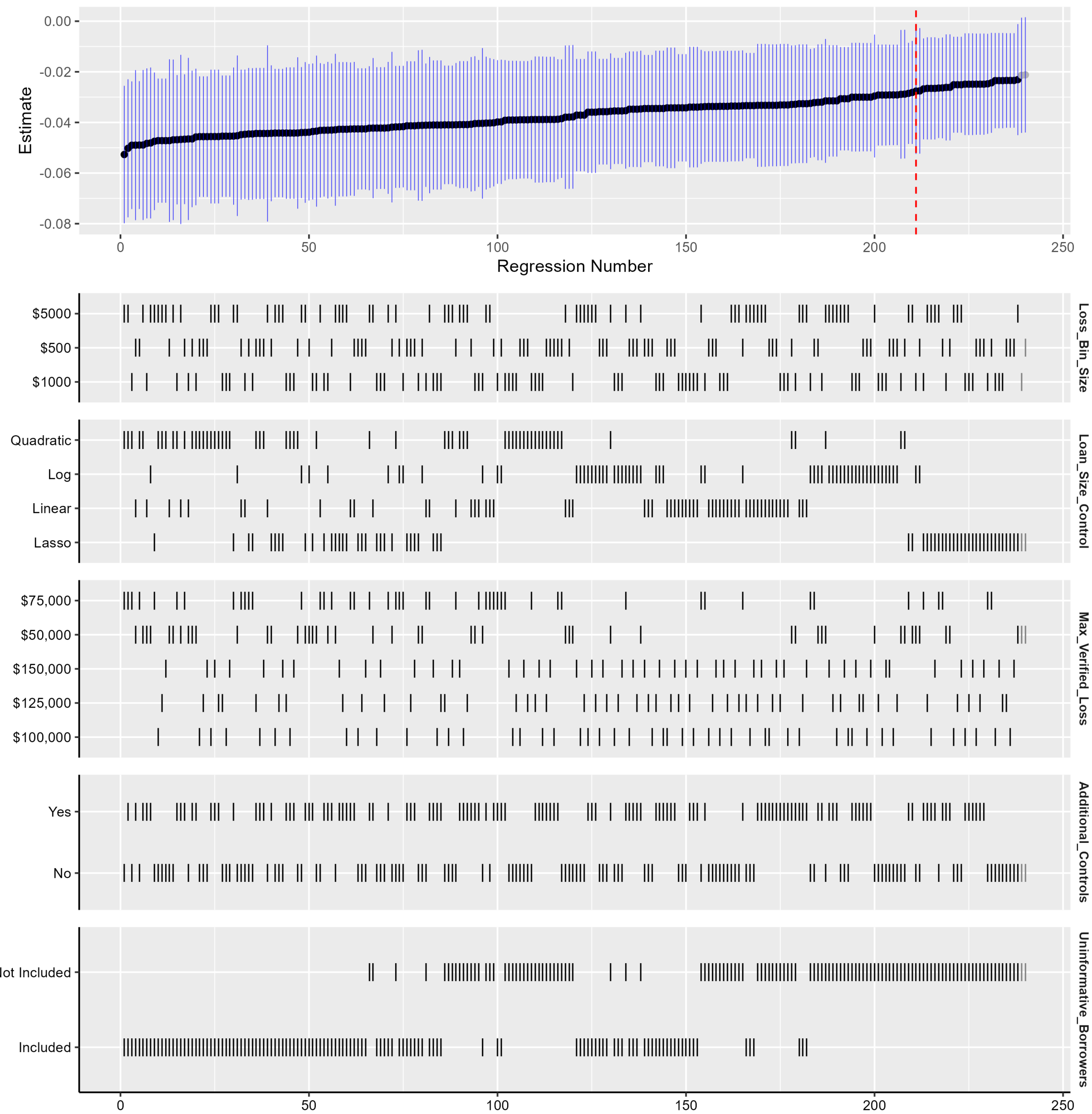
Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents the results of our two stage least squares moral hazard estimation (Equation 8). The final column includes our Lasso-selected controls for loan size. Standard errors, clustered at the disaster level, are in parenthesis.

F.3 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 16 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 16 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 16 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 16: 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 16 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.

Online Appendix G Structural Estimation Calculation Details

To solve for ϕ_i^*, we take a second-order Taylor approximation of each instance of $U()$, noting that $U(w_i + d) \approx U(w_i) + d * U'(w_i) + \frac{d^2}{2} * U''(w_i)$. The d_k terms represent the deviation from w_i in each instance. Specifically, d_1 and d_2 describe respectively repaying and defaulting on the collateralized loan and d_3 and d_4 describe respectively repaying and defaulting on the uncollateralized loan.

$$
\begin{aligned}
d_1 =& -\sum_{t=0}^{T_i-1} \left(\frac{1}{r_s}\right)^t p_i \\
d_2 =& -\psi - \phi_i^* \\
d_3 =& -\sum_{t=0}^{T_i-1} \left(\frac{1}{r_s}\right)^t p_{ui} \\
d_4 =& -\psi \\
V_i - V_{ui} =& \gamma_i \left(U(w_i) + d_1 * U'(w_i) + \frac{d_1^2}{2} U''(w_i)\right) \\
& + (1-\gamma_i) \left(U(w_i) + d_2 * U'(w_i) + \frac{d_2^2}{2} U''(w_i)\right) \\
& - \left((1-\gamma_{ui}) \left(U(w_i) + d_3 * U'(w_i) + \frac{d_3^2}{2} U''(w_i)\right)\right) \\
& - \left(\gamma_{ui} \left(U(w_i) + d_4 * U'(w_i) + \frac{d_4^2}{2} U''(w_i)\right)\right) \\
& = 0
\end{aligned}
$$

The $U(w_i)$ terms cancel out, giving:

$$
\begin{aligned}
V_i - V_{ui} =& \gamma_i \left(d_1 * U'(w_i) + \frac{d_1^2}{2} U''(w_i)\right) \\
& + (1-\gamma_i) \left(d_2 * U'(w_i) + \frac{d_2^2}{2} U''(w_i)\right) \\
& - \left((1-\gamma_{ui}) \left(d_3 * U'(w_i) + \frac{d_3^2}{2} U''(w_i)\right)\right) \\
& - \left((\gamma_{ui} \left(d_4 * U'(w_i) + \frac{d_4^2}{2} U''(w_i)\right)\right) \\
& = 0
\end{aligned}
$$

Next, we divide by $-U'(w_i)$ to turn the marginal utilities into constant absolute risk aversion parameter $\lambda = -\frac{U''(w_i)}{U'(w_i)}$. This gives:

$$
V_i - V_{ui} = \gamma_i \left(d_1 - \frac{d_1^2}{2} * \lambda\right)
$$

$$
\begin{aligned}
&+ (1-\gamma_i)\left(d_2 - \frac{d_2^2}{2} * \lambda\right) \\
&- \left((1-\gamma_{ui})\left(d_3 - \frac{d_3^2}{2} * \lambda\right)\right) \\
&- \left(\gamma_{ui}\left(d_4 - \frac{d_4^2}{2} * \lambda\right)\right) \\
&= 0
\end{aligned}
$$

The variable of interest ϕ_i^* only appears in d_2. Substituting for d_2 and rearranging terms yields:

$$
\begin{aligned}
0 =& \frac{-\gamma_i * \lambda}{2} \times (\phi_i^*)^2 \\
&- \gamma_i * (1 + \lambda * \psi) \times \phi_i^* \\
&- \gamma_i * \psi \left(1 + \psi^2 * \lambda\right) \\
&+ (1-\gamma_i)\left(d_1 - \frac{d_1^2}{2} * \lambda\right) \\
&- \left((1-\gamma_{ui})\left(d_3 - \frac{d_3^2}{2} * \lambda\right)\right) \\
&- \left(\gamma_{ui}\left(d_4 - \frac{d_4^2}{2} * \lambda\right)\right)
\end{aligned}
$$

We solve for the ϕ_i^*s with the quadratic formula and subtract equity to get ϕ_i^{A*}.[41]

We next use our estimate of ϕ_i^{A*} to estimate ϕ_i^A. Let ϕ_i^A be an unobserved latent variable, let X_i be a vector of controls (including disaster fixed effects), and let $\phi_i^A | X_i$ be distributed log-normal such that $\epsilon_i \sim N(0, \sigma)$.

$$
\begin{aligned}
log(\phi_i^A) &= \beta X_i + \epsilon_i \\
log(\phi_i^A) - log(\phi_i^{A*}) &= \beta X_i - log(\phi_i^{A*}) + \epsilon_i \\
\frac{log(\phi_i^A) - log(\phi_i^{A*})}{\sigma} &= \frac{\beta}{\sigma} X_i - \frac{1}{\sigma} * log(\phi_i^{A*}) + \frac{\epsilon_i}{\sigma} \\
\implies \frac{\epsilon_i}{\sigma} &\sim N(0,1) \\
P(Bunch_i) &= P\left(\frac{log(\phi_i^A) - log(\phi_i^{A*})}{\sigma} > 0\right) \\
&= P\left(\frac{\beta}{\sigma} X_i - \frac{1}{\sigma} * log(\phi_i^{A*}) + \frac{\epsilon_i}{\sigma} > 0\right) \\
&= P\left(\frac{\epsilon_i}{\sigma} > -(\frac{\beta}{\sigma} X_i - \frac{1}{\sigma} * log(\phi_i^{A*}))\right) \\
&= P\left(\frac{\epsilon_i}{\sigma} < (\frac{\beta}{\sigma} X_i - \frac{1}{\sigma} * log(\phi_i^{A*}))\right)
\end{aligned}
$$

[41] The quadratic equation allows for the unknown variable ϕ_i^* to be positive or negative. We assume that value is positive — that households dislike the penalties for defaulting on a collateralized, including losing home equity and being forced to relocate.

$$= \Phi\left(\frac{\beta}{\sigma}X_i - \frac{1}{\sigma} * log(\phi_i^{A*})\right)$$

Where in the last equation, Φ is the CDF of the standard normal distribution and thus is an estimable probit. Since we are directly estimating $-\frac{1}{\sigma}$ as the coefficient on $log(\phi_i^{A*})$, we can back out the raw values for all of the $\hat{\beta}$'s. We then use $\hat{\beta}X_i$ as our individual estimates of $\hat{\phi_i^A}$.