Disaster Lending: "Fair" Prices, but "Unfair" Access*

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Abstract

We find that under risk-insensitive loan pricing – a feature present in many government programs – marginal credit quality borrowers are less likely to receive credit. By restricting price flexibility, marginal applicants that would likely receive a loan at a higher interest rate are instead denied credit altogether. Our particular setting is the Small Business Administration's disaster-relief home loan program, where risk-based pricing is absent, but screening on credit quality remains. We find that this program denies more loans in areas with larger shares of minorities, subprime borrowers, and higher income inequality, even relative to private market denial rates. Thus, despite ensuring "fair" prices, risk-insensitive pricing may lead to "unfair" access to credit. As a consequence, the government's own lending program ends up denying credit to minority and poor borrowers at a higher rate than private markets.

Keywords: credit access, discrimination, income inequality, government lending, unintended consequences

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1 Introduction

Prices play a central role in the efficient allocation of resources in market-based economies. Credit markets are no different. Nearly all theoretical and empirical work in banking is grounded on the basic idea that lending rates should reflect the credit risk of borrowers, with riskier borrowers paying higher interest rates on their loans. However, a number of lending programs conducted by government agencies and development banks around the world violate this principle and charge rates that do not vary according to credit risk. That is, these lending programs typically offer borrowers a subsidized interest rate without (or with limited) risk-based pricing. In the many cases where the price is fixed, all borrowers who receive credit do so at the same interest rate. Policymakers often debate the costs and benefits of these design choices including the ongoing debate on the need for interest rate caps in some lending markets. While such risk-insensitive lending programs seem "fair" in the sense that they treat all borrowers equally in terms of pricing, they may end up being "unfair" to lower-quality borrowers who would only be deemed creditworthy under a risk-sensitive pricing mechanism. In this paper, we study the consequences of these fixed-price government lending programs on the allocation of credit using an important U.S. government lending program: disaster-relief home loans administered through the Small Business Administration (SBA).[1]

The typical goal of many government lending programs, including the disaster lending program that we study, is to alleviate frictions in access to credit for marginal or "underserved" borrowers. Given this focus, it is reasonable to expect that marginal borrowers would have better access to credit through government lending programs compared to private markets. To

[1] We focus on the disaster-relief loan program because of data availability. The application of our work is much broader. For example, the World Bank's International Bank for Reconstruction and Development lent more than 500 billion dollars between 1946 and 2017, interest rates on some of these loans do not vary across countries within the same year. Also, the U.S. government alone currently has over 50 loan programs covering a wide range of borrowers: farmers, veterans, students, small business owners and homeowners and there are vast numbers of programs with similar features around the world. See https://www.govloans.gov/loans/browse-by-category for further details.

that end, the programs often include subsidized, risk-insensitive lending rates. However, there is typically an opposing force limiting the government's ability to provide credit: governments face pressure to minimize taxpayer losses. The combination of tax-dollar stewardship with a risk-insensitive lending rate creates a difficult tension. The program's inability to charge higher, risk-appropriate interest rates to lower credit quality applicants makes the potential cost of lending to them too high. Thus, borrowers who are only creditworthy at a higher interest rate may be denied credit altogether. This suggests that marginal borrowers may face greater loan denial rates relative to a risk-sensitive pricing mechanism that can provide them access to credit at higher interest rates.[2] We study which of these two forces – broad access to credit or tax-dollar stewardship – dominates and if marginal borrowers have better or worse credit access in these programs compared to risk-sensitive lending programs. Our main results show that the fixed-price lending program performs poorly in providing credit to marginal and underserved populations. Further, they perform worse than both private-market and government-insured risk-sensitive pricing schemes.

The objective of the SBA Disaster loan program is to provide access to credit for households and businesses that are victims of natural disasters such as hurricanes, fires, and earthquakes. The loans are given at a highly-subsidized fixed-rate to all borrowers who qualify. We study the home loan program, i.e., loans provided to households, where the screening process is similar to a typical mortgage application. SBA loan officers screen loan applicants for creditworthiness using standard credit indicators such as credit score, income, employment, and assets. The SBA is vigilant to avoid fraud and to generally be good stewards of taxpayer dollars. Higher-risk borrowers are simply denied credit rather than being charged a higher interest rate to compensate for their risk. Such rationing is likely to be particularly painful in settings like the aftermath of natural disasters when access to credit to rebuild is critical,

[2] Just as in a market setting with a price ceiling, it naturally follows that there is likely to be excess, unmet demand. At a broad level, our work relates to one of the oldest debates in economics about the trade-offs involved in a fixed price system versus a market price system. In labor economics, for example, dating back at least to Stigler (1946), there have been numerous studies evaluating the costs and benefits of minimum wage legislation. A related issue arises in health insurance policy (e.g., Bundorf, Levin, and Mahoney, 2012).

and the applicants' willingness to pay higher interest rates is high.

We obtained data on the credit allocation decisions for the SBA disaster-relief home loan program for victims of natural disasters using a Freedom of Information Act request. The data cover over a million loan applications across the United States between 1991 and 2015 and allow us to conduct our empirical analysis at a granular level. In contrast to most publicly available databases of government lending programs, our data contain both approved and denied applications for these government loans.

We test for the effect of risk-insensitive loan pricing by comparing the loan denial rates of applicants from areas with a higher need for price discrimination (NPD) to loan denial rates of applicants from areas with lower NPD. We define high-NPD areas as those with a greater mass in the "marginal" portion of the credit quality distribution. These areas are characterized by a higher need for risk-based pricing to receive credit. We use three proxies for NPD in our tests: areas with a larger share of minority population, areas with a larger share of subprime borrowers based on FICO scores, and areas with higher income inequality. We hypothesize that the combination of borrower screening for credit quality and the inflexibility in setting prices leads to higher denial rates for applicants from these marginal areas. Alternatively, government programs – which often have explicit goals to reach and support such higher-risk and underserved areas – may be better equipped to provide credit in these areas, which would lead to a relatively lower denial rate in these areas.

Differences in denial rates across high- and low-NPD areas are likely even in private markets with risk-sensitive pricing because of baseline differences in credit risk or rationing due to asymmetric information.[3] Therefore, to tease out the effect of risk-insensitive pricing, we employ an empirical strategy that compares denial rates of the government-run, fixed-price (SBA) scheme to denial rates in that same area of risk-sensitive pricing schemes including private-market and government-insured mortgage lending. The risk-sensitive

[3]The core idea behind this channel is that raising the interest rate beyond a point can result in adverse selection in the borrower pool: as interest rates reach high levels, the quality of the willing borrowers at that rate deteriorates (Stiglitz and Weiss, 1981).

pricing benchmarks incorporate baseline credit rationing and any potential biases that persist in those markets. Thus, they capture variation in access to credit that is unrelated to risk-insensitive lending.[4] Our tests therefore examine whether there is *excess* credit rationing of the high-NPD groups in the SBA's risk-insensitive pricing program compared to lending with risk-based loan pricing.

We use home refinancing loan applications from the Home Mortgage Disclosure Act (HMDA) dataset[5] as our risk-sensitive benchmark because this is the private-market lending category that is closest to SBA home loans: both these loans are geared toward borrowers who are already home owners. We also use Federal Housing Administration (FHA) loans as another counterfactual. FHA loans are issued by private banks but are insured by the government. Despite government insurance, FHA loans do not follow a fixed-price, risk-insensitive pricing scheme. Because FHA and SBA exhibit similarities with respect to incentives, constraints, and target borrower population, comparing the denial rates across these two programs allows us to tease out the difference in credit access that arises due to lack of risk-based pricing.

We primarily focus on the minority share of the applicant's county as our key NPD measure. Minority share captures both hard and soft information about the borrower pool in ways beyond what is captured by subprime share and income inequality. Bayer, Ferreira, and Ross (2016) show that minority borrowers default at a higher rate even conditional on observables like credit score. This can be potentially due to unobserved credit risk factors such as lower levels of wealth, higher employment and income volatility, or weaker access to informal financing networks like friends and family, among other things (e.g.,see Smith, 1995; Charles and Hurst, 2002; Ziliak, Hardy, and Bollinger, 2011). Additionally, the Federal Housing Finance Agency includes minority population as a key criterion in designating an area

[4]For example, Munnell, Tootell, Browne, and McEneaney (1996) and Dougal, Gao, Mayew, and Parsons (2018) show that minorities have lower access to credit in private markets. Dobbie, Liberman, Paravisini, and Pathania (2018) find bias in UK consumer lending against immigrants and older applicants as a result of misalignment of incentives between loan officers and their employer

[5]The HMDA dataset contains the vast majority of home loan applications in the US. Important for our tests, it includes property locations and application approval/denial decisions.

as "underserved."[6] The use of minority share also allows us to document the disparate impact (i.e., heterogeneity in consequences) of the risk-insensitive interest rates across demographic groups. Fair access to credit for minority borrowers has been one of the central themes of U.S. banking regulation over the past fifty years with regulations such as the Fair Housing Act (1968), the Equal Credit Opportunity Act (1974), and the Community Reinvestment Act (1977). These regulations are intended to ensure private lenders provide fair access to credit across borrowers of different race, religion, gender, etc. In contrast to steering private market behavior to serve government objectives, we are able to examine how the government's own direct lending to its citizens fares on this dimension.

Using loan-level data, we find that the SBA program denies loan applications at a significantly higher rate in counties with a greater need for price discrimination, and this differential exists even after controlling for the local HMDA private-market denial rate. The result holds for each of the three proxies of NPD we use – subprime share, minority share, and income inequality of the county – but the relationship between denial and minority population share is the strongest. The result is not explained by income or the extent of losses incurred in the disaster. A one-standard-deviation increase in minority population is associated with a 3.3 percentage points higher denial rate. With the average denial rate in our sample at 46%, these results are economically significant. In sum, these results provide evidence that the loans in this scheme are not reaching borrowers in high-minority areas at the same rate as low-minority areas even after accounting for baseline differences in denial rates using the HMDA data.

We next collapse our SBA loan-level data to county-year denial rates. Using these data and the HMDA denial rates for the same county (in the most recent non-disaster year), we estimate the difference in denial rates across the different schemes (SBA vs. risk-sensitive

[6]The FHFA considers census tracts to be underserved if they fall below income thresholds and/or above minority population thresholds. The FDIC also finds that underserved (unbanked and underbanked) areas are characterized by low income and high minority populations (Burhouse, Chu, Goodstein, Northwood, Osaki, and Sharma, 2014).

pricing programs) for counties with different NPD. We find that a one-s.d. increase in minority share corresponds to a 2.7 pps higher denial rate under the SBA program relative to the risk-sensitive HMDA loans. Similar results hold when we compare denial rates in the SBA program to FHA loans, which are government insured but retain flexible pricing. Interestingly, in these tests, we find no evidence that the FHA loan applicants are denied at a higher rate in areas with a greater need for price discrimination. In other words, in a government-insured lending program with risk-sensitive loan pricing, we find no difference in denial rates across NPD. Examining across quartiles of minority share, we find applicants from counties in the top quartile of minority share experience a denial rate that is 8pps higher than the denial rate in the low-minority-share counties after controlling for the corresponding FHA loan denial rate.

These results paint a clear picture. Despite some concerns and issues surrounding the behavior of private markets in providing "fair" access to credit, risk-sensitive loan programs – both private market and government insured – grant loans to a significantly larger fraction of borrowers in high-minority areas as compared with the SBA's risk-insensitive lending program. To the extent a key goal of the government is to provide equal access to credit for all demographic groups and particularly to underserved areas, the SBA's risk-insensitive pricing program fares worse in achieving this goal compared to its flexible-pricing counterparts.

Finally, we consider some alternative explanations for the results. First, we examine whether the results are driven by taste-based discrimination (i.e., prejudice against high-NPD areas) by the SBA program. If this were true, we would expect to see relatively better default performance in high-NPD areas since the bar for approval would be higher. We find no such results. Second, we consider whether high-NPD areas' credit quality is relatively more sensitive to natural disasters. If this were true, we could attribute the differential denial rate to relatively larger drops in credit quality for high-NPD areas. We test for whether the average drop in credit quality from before to after the disaster is relatively larger for high-NPD areas, and we find no difference across the groups. Finally, we perform a battery of robustness tests showing the results are not driven by a particular time period, disaster type, or by the size of the disaster.

We provide some context on the economic importance of our results by estimating the additional loans that would have been approved under a risk-sensitive pricing scheme. Our estimates suggest that about 45,000 additional homeowners (about 4% of the size of the program) would have received loans, which adds up to a grand total of about $1.5 billion. The economic importance of this number is amplified by the setting since the marginal value of credit is especially high in the aftermath of a natural disaster.

2 Related Literature

Our paper is related to several strands of literature. The first is government intervention in setting prices in a number of contexts such as labor, health insurance, or rental markets to name a few (e.g., see Stigler, 1946; Bundorf et al., 2012). Rose (2014) provides a recent synthesis of the literature on the consequences of price and entry controls on a broad spectrum of industries. Closer to our paper is recent work on the mortgage market. Government-sponsored enterprises (GSEs) can affect borrower access to credit through their role in the secondary market for residential mortgages. Specifically, GSEs can effectively dampen regional dispersion in pricing. Hurst, Keys, Seru, and Vavra (2016) show that the GSEs charge similar prices (after conditioning on observables) across different areas even though there is significant variation in predictable default risk across geographic regions. Kulkarni (2016) also find a lack of geographical variation in GSE mortgage rates after controlling for borrower characteristics, and further that this can lead to rationing in regions with borrower-friendly laws. Adelino, Schoar, and Severino (2016) argue that the credit expansion before the 2008 crisis was driven by inflated optimism about home prices, making lenders insensitive to borrower and loan characteristics. Our paper is also related to the effects of regulation in private credit markets such as the effect of 19th century usury laws on access to credit by Benmelech and Moskowitz

(2010) and the effect of an interest rate ceiling on access to credit in Chile by Cuesta and Sepulveda (2018). While these papers also find an adverse impact of credit market regulations on the quantity of credit, our paper is the first one to study the implications of risk-insensitive pricing on minorities and other marginal borrowers, a finding that has important implications for regulations on fair access to credit across different demographics of society. Further, our study is the first one to analyze the effectiveness of government lending programs in reaching minority and poor borrowers as compared to private market outcomes.

Second, our paper is related to work that studies some costs of price discrimination and how it contributes to unfair prices. In the foreign exchange derivatives market, for example, Hau, Hoffmann, Langfield, and Timmer (2018) show that unsophisticated borrowers face discriminatory, higher prices. In mortgage markets, Bartlett, Morse, Stanton, and Wallace (2017) analyze loan rejection rates and document that unsophisticated and impatient borrowers face worse borrowing conditions, and show that fintech lenders are less likely to discriminate than traditional lenders. In contrast to these studies, our paper shows important costs when price discrimination is not allowed. Specifically, while risk-insensitive pricing may mitigate some potential downsides of price discrimination, we show that this benefit comes at the cost of a higher denial rate for marginal borrowers.

Finally, our paper is also related to the literature on government intervention in credit markets. Much prior work notes that certain credit subsidies may increase aggregate welfare in the presence of information frictions (Stiglitz and Weiss, 1981; Smith, 1983; Mankiw, 1986; Gale, 1990, 1991). Recent papers, such as Bachas and Yannelis (2018), show that the volume of small business lending is highly responsive to federal loan guarantees. Similarly, Brown and Earle (2017) study the SBA program and find that access to credit has large effects on employment. Howell (2017) shows that federal grants affect both innovation as well as future fundraising for small firms. We contribute to this debate by studying a government program that affects millions of people when, perhaps, they need government intervention the most. In this regard, our paper is also related to the empirical literature investigating private lending activity following a natural disaster. Morse (2011), for example, uses natural disasters to investigate whether payday lenders ease credit constraints of poor residents. Collier, Haughwout, Kunreuther, Michel-Kerjan, and Stewart (2016) study how firms use credit and insurance protection in their effort to recover after natural disasters. Berg and Schrader (2012) analyze whether bank relationships improve credit access following aggregate shocks using a volcanic eruption in Ecuador to identify an exogenous increase in loan demand. Cortés (2014), Chavaz (2016) and Cortés and Strahan (2017) study whether response to credit demands by borrowers hit by natural disasters vary by lender size, scope, and local competition structure. In particular, Cortés and Strahan (2017) show that it is the smaller banks that help smooth the credit demand shocks.

3 SBA Disaster Loan Program

The Small Business Administration (SBA) Disaster Loan Program provides loans to individuals and businesses who are victims of disasters declared by the President or the SBA. Since program inception, over 1.9 million loans totaling over $47 billion have been approved by the SBA (Lindsay, 2010). Our study focuses on loans made to individuals (not businesses). Borrowers use these loans to repair or replace real estate and personal property beyond what is covered by home insurance.

In the wake of a disaster, the SBA must process loan applications, perform inspections, make lending decisions, contract with borrowers, and disburse funds. Loan officers from the SBA assess applicants' creditworthiness when determining whether or not to approve the loan. The lending decision is based on a number of factors that largely mirror the typical mortgage application process: an acceptable credit history, an ability to repay loans, and collateral (if available). Documentation includes items such as prior tax filings and documentation of employment. The application approval decision cannot be explicitly driven by an applicant's race, color, national origin, or gender. During the loan review process, an appraiser will verify the applicant's loss, and the size of the loan will be capped by the amount of approved loss.

Although projecting loan performance is a driving influence in the screening process, the SBA does not price loans differentially according to applicant risk. The loan interest rate is determined by a statutory formula based on the government's cost of borrowing. For individuals seeking home loans, there are only two possible interest rates: a lower rate for borrowers who do not have "credit available elsewhere" (a classification determined by the SBA) and a higher rate for borrowers who do have credit available elsewhere. The interest rates are calculated for each disaster given the government's current cost of borrowing. For individuals determined to have credit available elsewhere, the statutory rate is the government's cost of borrowing on similar-maturity debt obligations plus an additional charge not to exceed one percent, with an overall maximum interest rate of 8%. For individuals without credit available elsewhere, the statutory rate is one-half the government's cost of borrowing plus an additional charge not to exceed one percent, with a maximum rate of 4%.[7] For both types of borrowers, the rate is typically lower than the current interest rate on a 30-year mortgage. Thus it is in the interest of every potential borrower to apply for these loans, minimizing any selection bias concerns in the pool of applicants. The determination of credit available elsewhere is made by the SBA based on the applicant's credit score, cash flow, and assets (SBA Standard Operating Procedure (2015)). The vast majority of borrowers in our sample receive the lower rate. Importantly, there is no variation in the interest rate across borrowers based on credit risk (conditional on the credit-available-elsewhere designation). For illustrative purposes, we provide the interest rate menu for Texas counties affected by Hurricane Harvey (Disaster TX-00487) in Figure A.1. Table A.1 provides details on the interest rate caps, repayment terms, and eligible borrowers for each type of loan.

The SBA is not a profit-maximizing institution, as evidenced by the subsidized interest rates on the disaster loans. The SBA does, however, balance the objective of lending to borrowers in need (and any accompanying externalities) against the budgetary costs incurred

[7] The formula for statutory rates is provided in Section 7 of the Small Business Act.

by increasing capital availability at subsidized rates. Said differently, there is a strong emphasis on being a good steward of taxpayer dollars as shown by the fact that the SBA explicitly screens applicants based on their creditworthiness. Anecdotal evidence indicates there is significant scrutiny of the SBA disaster loan program's performance in both its efficiency in allocating capital and overall budgetary costs. For example, a 1997 congressional budget office report raised concerns about the SBA disaster loan program's budgetary costs and suggested increasing the interest rate on loans to reduce these costs (Congressional Budget Office (1997)). This focus on screening combined with the inflexibility in interest rates may lead to greater denials of borrowers of marginal creditworthiness than if the SBA were allowed to adjust interest rates based on borrower credit quality. We discuss this idea further in the next section.

4 Research Design

When lenders have flexibility in pricing loans, they can charge interest rates based on the risk profile of the borrowers (i.e., price discriminate). On the other hand, fixed-price lending programs coupled with screening ration some borrowers from the market. Once the expected loss rate on the loan exceeds the rate the lender can charge, the borrower is simply denied credit rather than charged a higher rate commensurate with their risk.[8] The importance of risk-sensitive pricing in allocating credit to high-risk borrowers motivates our key hypothesis: areas with a higher fraction of applicants with marginal credit quality have higher denial rates due to risk-insensitive pricing.

Figure 1 summarizes our core idea. The graph plots the market-determined interest rate as a function of borrower credit risk. All borrowers below the credit threshold denoted by *Market Threshold* are denied credit even with a risk-sensitive pricing mechanism. This happens because lenders, even those in the private market, are unable to observe the true

[8] In our setting the relevant threshold is the fixed rate the SBA charges plus the subsidy of the program.

credit quality of borrowers, and hence deny credit to borrowers with sufficiently high observed credit risk. We also plot the SBA's interest rate as a function of credit risk. The SBA function is a flat line below the market interest rate. The line is flat since the interest rate does not vary with credit risk. The line is below the market interest rate since the SBA prices its loans at a subsidized rate that is below the market rate for all borrowers.[9] The SBA makes all loans to individuals above the threshold denoted by *SBA Threshold*. This threshold is determined by the maximum subsidy SBA is willing to pass on to borrowers. For borrowers that fall below this threshold, SBA simply refuses credit instead of adjusting its price. Thus, there are excess denials in SBA lending compared with the private-market benchmark. Our empirical tests are aimed at teasing out this excess denial by exploiting variation across areas that differ in terms of the fraction of the population that falls between the private-market and SBA thresholds (i.e., variation in the share of applicants with marginal credit quality). We examine if applicants from areas with a greater need for price discrimination (NPD) experience higher excess denial rates.

As can be seen in Figure 1, a positive correlation between areas with higher *NPD* and SBA loan denial rate is not fully conclusive about the effect of risk-insensintive pricing on denial rates. Such correlation alone could simply be capturing baseline heterogeneity in factors such as overall average credit quality or the information environment (leading to higher rationing) that would lead to the same outcome in private markets where pricing is flexible. We need to account for this effect. Our setting is attractive because we are able to observe the credit allocation decision in the private lending market for the same areas. Specifically, we observe the approval/denial decision of applications for home mortgage loans made by nearly all private lenders in the U.S. For every county, we are able to obtain data on denial rates for all borrowers in the HMDA data set for non-disaster years. Our primary analysis controls for the denial rate in the HMDA database for all refinancing loans made in that county in the most recent non-disaster year.

[9]Our main idea remains the same if the SBA rate is above the market determined rate for the best risk borrowers. However, this is not the case in the data.

The idea behind our main empirical specification is simple: if the HMDA denial rate is a sufficient statistic of private market rationing, then we should be able to isolate the effect of the *NPD* variable using the following regression model estimated with all SBA loans:

$$deny_{i,c,d,t} = \alpha + \psi NPD_{c,t} + \rho(HMDA\ Denial)_{c,t} + \Gamma X_{i,c,t} + \delta_{d,t} + \zeta_s + \epsilon_{i,c,t}. \tag{1}$$

$deny_{i,c,d,t}$ is an indicator variable equal to one if loan application i, originated from county c following a disaster-type d in year t, was denied. $NPD_{c,t}$ is the need for price discrimination in county c at time t. We use three proxies for need for price discrimination: the minority share, the subprime share, and the income inequality (Gini coefficient) of the application county. These three proxies should capture the relative mass of applicants in the county credit quality distribution between the private-market risk-sensitive threshold and the SBA risk-insensitive threshold. For most of our analysis, we focus on minority share. The use of this variable as our main proxy for NPD is motivated by a large literature on racial differences in lending markets, which has shown evidence of observable and unobservable differences in credit quality across groups. In particular, the minority share of the population is strongly correlated with credit scores and has also been shown to be strongly related to other important drivers of mortgage credit quality including wealth and volatility of income and employment. $HMDA\ Denial_{c,t}$ is the private-market denial rate for county c in the most recent non-disaster year for a disaster in year t. This variable captures the baseline credit rationing in the home mortgage market. $X_{i,c,t}$ includes county- and loan-level control variables, which we discuss in greater detail in Section 5.

We include state fixed effects (ζ_s) to separate out the effect of any state-by-state differences in the implementation of SBA disaster loans. As noted earlier, these loans come under the federal program, and therefore they have the same terms for all borrowers irrespective of where the disaster strikes. However, there may be a concern about differences in the implementation at the state level. We also include a fixed effect that is *disaster-type* $\times$ *year* specific (denoted

$\delta_{d,t}$). This fixed effect, by construction, soaks away variations that are specific to a certain type of disaster in a given year (e.g., hurricanes in 2005, which have a separate dummy from hurricanes in 2006). Inclusion of disaster-type fixed effects in the model allows us to control for differences in lending policies or borrower needs or characteristics across different types of disasters. By interacting the disaster type with year of the disaster, we are able to remove the effect of macroeconomic trends, including issues such as budgetary constraints of the government or variation in national policies concerning these programs. In the end, this specification allows us to exploit the cross-sectional variation in the need for price discrimination across different counties, holding fixed statewide differences and time-varying disaster-type differences in SBA's lending policies.

Our next specification exploits within county-year variation in loan denial rate across the SBA disaster loan program and private markets. For this test, we construct a data set at the level of county×disaster-year and compute the respective SBA denial rate. In other words, we collapse the loan-level data to county level for each disaster-year. For each observation, we then create a corresponding observation where we replace the SBA denial rate with the county's HMDA denial rate, as described above. Thus, for each county×disaster-year we have an observation for each of the two loan programs: one with the SBA denial rate and one with the HMDA denial rate as the dependent variable. We then estimate the following regression specification with observations for county c, loan program p, year t:

$$denial\ rate_{p,c,t} = \alpha + \delta\mathbb{1}[SBA_{p,c,t}] + \theta(\mathbb{1}[SBA_{p,c,t}] \times NPD_{c,t}) + \zeta_{c,t} + \epsilon_{p,c,t} \tag{2}$$

$\zeta_{c,t}$ indicates county-year fixed effects. Thus our specification is able to exploit within-county variation in denial rate across the SBA and HMDA programs. By including this level of granular fixed effects, we alleviate concerns that unobserved county-year heterogeneity is driving our key findings. In this specification, $\hat{\delta}$ represents the average difference in risk-insensitive SBA and risk-sensitive HMDA denial rates. The estimate of interest is $\hat{\theta}$, which indicates the differential sensitivity in denial rates to NPD between the SBA and HMDA lenders. $\hat{\theta} > 0$ indicates that the relationship between NPD and denial rates is even stronger in the government-directed SBA program as compared with the private-market HMDA counterpart.

In additional tests, we use the denial rate of Federal Housing Administration (FHA) program loans as our counterfactual measure of loan denial instead of the broader HMDA denial rate. The FHA denial rate is a good counterfactual for our study for a number of reasons. First, FHA loans are also insured by the government, so the FHA program shares some similar incentives and constraints as the SBA. Second, FHA loans are priced by the private-market lenders that issue them, so we are comparing a risk-insensitive loan program (SBA) to a risk-sensitive loan program (FHA). Third, the borrower pool in the FHA loan program is typically composed of more marginal-quality borrowers, which may be more representative of the borrowers in the SBA pool.

5 Data and Sample

We obtained the data on SBA Disaster individual loans through a Freedom of Information Act request. A key feature that distinguishes our data from the publicly available disaster data is that we have loans that were denied in addition to those that were approved. Our final data set includes around 1.2 million loan applications from 1991 to 2015. These data include the state and county of the applicant, the applicant's verified loss as a result of the disaster (e.g., property damage), the disaster description (e.g., Hurricane Andrew), the loan approval or denial decision (*SBA Denial*), and default (i.e., chargeoff) data on approved loans.

Table 1, Panel A, presents the number of applications and denial rates across different types of disasters. Nearly half of the applications in our sample are from hurricanes. The broad category of "severe weather" has nearly one-third of our applications. These loan applications are in response to disasters including tornadoes, severe thunderstorms, hail, and flooding. There are also a substantial number of applications following earthquakes, with the majority of those coming in response to the 1994 Northridge earthquake in Los Angeles, California. As we can see from the table, there is variation in the denial rate across different types of disasters, but it is broadly in the range of 40-50%.

In Panel B of Table 1, we list the top ten disasters in terms of number of loan applications in our sample. Hurricane Katrina, is the largest disaster, with over 200,000 applications. While some of the largest disasters cluster around 2004-2005, there is clearly variation in the timing of disasters over time. This variation allows us to separate the effect of macroeconomic trends from the main effect we are interested in.

Figure 2 shows the geographical variation in the number of applications during our sample period, with the largest number of applications coming from the Gulf Coast and California. Figure 3 presents the time series of applications and denial rates during the sample. The denial rate varies in the range of 30-60% over the sample period.

We obtain data on private-market lending from the Home Mortgage Disclosure Act (HMDA) data for the years 1991-2015. These data include the vast majority of home purchase and refinancing loan applications and lending decisions in the U.S. for that time period. To most closely mirror the SBA applicants (most of whom already own their home), we focus on the HMDA refinancing applications. From these applications, we compute the county-level denial rate for refinancing loans during the most recent year in which the county did not experience a disaster and match this to the relevant SBA loan applications in that county. The HMDA denial rate at the county level (*HMDA denial*) serves as our control for the baseline variation in denial rates in private markets.[10] We also use the denial rate for the subsample of HMDA loan applications that are made through the FHA program.

[10]The results are similar using contemporaneous year or averages of two or three prior years.

We use three key explanatory variables in our tests. We refer to them broadly as the *Need for Price Discrimination* or *NPD* measure. Our first measure is the fraction of the minority population in the county from the Census. The motivation for this proxy is discussed in Section 4. The second *NPD* measure is the percentage of individuals with Equifax subprime credit scores (<660) in a county, which is only available from 1999 onwards. This data is from the St. Louis Federal Reserve (FRED) database. The third *NPD* measure is the level of income inequality in the area. Such areas have borrowers on both extremes of the income distribution, and thus the underlying credit dispersion is likely to be higher. We use the county-level Gini index from the U.S. Census and American Community Survey data to measure income inequality. We obtain this measure for 1990, 2000, and 2010. We assign the 1990 Gini measure for disasters during 1991-1999, the 2000 Gini measure for disasters during 2000-2009, and the 2010 Gini measure for disasters during 2010-2015.

The U.S. Census data also provides county population, and the St. Louis Federal Reserve (FRED) database provides the county-level per capita income data. In addition, we obtain data on verified losses incurred by the borrower as assessed by SBA appraisers from the SBA database.

Table 2 presents summary statistics for the variables used in our regression analysis. All dollar amounts are adjusted to year-2000 dollars. There is substantial variation in the subprime share, minority share, Gini, income, and population of the counties in the sample. The SBA denial rate of 46% is considerably higher than the average HMDA denial rate of 21% and FHA denial rate of 12%.

6 Results

6.1 SBA Denial Rate Across Areas

We begin our analysis by documenting the relationship between the approval/denial decision by the SBA and the need for price discrimination (NPD) in the disaster-struck county. Our initial tests examine two measures of NPD: the subprime share of the county and the minority share of the county. We estimate regression equation (1). We standardize all continuous independent variables to have mean zero and unit standard deviation, and we cluster the standard errors at the county level.

Table 3 presents the results. Columns (1)-(3) present the results using subprime share as the NPD proxy, and columns (4)-(6) present the results using minority share.[11] In columns (1) and (4), we present results for the base specification controlling only for state and disaster-year fixed effects. We find that a one-standard-deviation higher subprime share is associated with an increase of 3.8 percentage points (p-value<0.01) in the loan denial rate. Similarly, a one-standard-deviation higher minority share is associated with a denial rate that is 4.6 percentage points higher. These results suggest that areas with greater NPD experience significantly higher loan denial rates.

We next include controls for per capita income, population, verified loss, and the HMDA denial rate. The HMDA denial rate is the denial rate in the most recent year without a disaster as described in Section 5.[12] The underlying identifying assumption is that conditional on the HMDA denial rate, there is no remaining unobserved credit rationing that would occur with risk-sensitive pricing that correlates with subprime (or minority) share and the denial rate in disaster loans. The comprehensive nature of the HMDA data set and the comparability

[11]The number of observations is smaller when subprime share is included because we only have subprime share data from 1999 onwards.

[12]In unreported tests, we also use the HMDA denial rate for the year following the disaster and find similar results. This mitigates potential concerns about disasters having a disproportionate impact on credit quality in high-NPD areas. We provide an additional test for differential sensitivity in Section 6.4.

of lending products in the HMDA loan market and SBA disaster loans provide support for this assumption. In columns (2) and (5), we report the results for the main regression specification that includes other county- and loan-level control variables. As expected, areas with higher private market denial rate experience higher denial rates in the SBA program, but the inclusion of the HMDA denial rate and other control variables does not explain away the relationship between NPD and loan denial. The point estimates on the NPD proxy slightly decrease to 2.3 and 3.3 percentage points (p-value<0.01) for subprime and minority share, respectively. These estimated coefficients are highly significant and economically important.

In columns (3) and (6), we examine the effect across NPD quartiles. The effect increases monotonically as one moves from the lowest to the highest quartile of NPD. We find counties in the highest subprime share quartile have a denial rate that is 4.3 percentage points (p-value=0.02) higher than the lowest subprime share quartile. We find larger effects when using minority share as the measure of NPD: top-quartile minority counties have a denial rate that is 8.3 percentage points (p-value<0.01) higher than the bottom-quartile minority share counties. Compared with the sample average denial rate of around 46%, applicants from counties with the highest minority share have close to an 18% higher chance of being denied.

We include both the subprime share of the county and the minority share of the county in the regression presented in column (7). We find that the minority share of the county remains economically and statistically highly significant, while subprime share is insignificant. This suggests that the minority share of population may capture both the measured credit quality of the area as well as other unmeasured credit quality factors (with respect to credit score) such as lower wealth, lower income, and more volatile employment that are known to characterize higher-minority areas. Minority share may, therefore, better capture the size of the mass of borrowers in an area that has marginal credit quality. For this reason, we use minority share as our main proxy of NPD throughout the remainder of the paper. Our results remain qualitatively similar for subprime share as the proxy for NPD.

6.2 Difference-in-Differences: SBA versus HMDA

In our next test, we present a difference-in-differences estimation for SBA versus HMDA lending across areas with different racial composition. We estimate equation (2) using county-year denial rate as the unit of observation, and with county-year fixed effects. The estimates, therefore, give us within-county-year differences in denial rates for SBA versus private lending across different levels of minority population.

Columns (1)-(3) of Table 4 present the results. The results in column (1) indicate the SBA program has about 21 percentage points higher denial rate compared to the HMDA loans. This is consistent with the descriptive statistics presented earlier where we find an average denial rate of 46 percentage points for SBA and 21 percentage points for the HMDA loans. Column (2) presents the results for the specification that includes the interaction between the SBA dummy variable and minority share of the county. Our estimates show that the denial rate under the SBA program is 2.7 percentage points higher for counties with one standard deviation higher minority population as compared to the corresponding denial rate under the HMDA loans. Column (3) of the Table shows that the excess denial rate for minority population increases monotonically as we move from the lowest to the highest quartile of minority population in a county. These estimates are statistically significant and economically large: in the largest quartile of minority population areas the SBA denies loans at a rate that is 6.4 percentage points higher than in the lowest quartile areas (relative to the HMDA denial rates).

6.2.1 Federal Housing Administration Program

We next compare the denial rates in the SBA disaster loan program to the denial rates in the Federal Housing Administration (FHA) loan program to further tease out the risk-insensitive loan channel. By comparing SBA loans to FHA loans, we minimize any concerns about potential differences between the SBA and private market lenders and potential concerns about differences in the borrower pool between the SBA and HMDA. The U.S. government's FHA loan program provides insurance against default risk for private lenders that make loans that fit the FHA guidelines. This program has similar objectives and constraints as the SBA. The pool of FHA borrowers is likely riskier than the general population and may better represent the pool of SBA applicants. The important difference between the two programs is that the FHA loans are not restricted to a particular, risk-insensitive lending rate like the SBA loans. We run the same difference-in-differences analysis but with the FHA denial rate instead of the HMDA denial rate.

Columns (4)-(6) of Table 4 presents the results. A similar pattern emerges as in the previous tests, except the difference between the SBA and the risk-sensitive pricing benchmark are even more striking. Examining the results in column (5), we see the coefficient estimate on the interaction of the SBA indicator variable and *zMinority* is 3.4 percentage points. Column (6) shows that the relationship is particularly strong in the highest quartile of minority-share counties. SBA applications from high-minority-share counties are 7.8 percentage points more likely to be denied a loan than applications from low-minority-share counties relative to the corresponding denial rates in the FHA program.

In unreported tests, we estimate the regression with state-year effects instead of county-year fixed effects, which allows us to identify the sensitivity of FHA denial rates to minority share. Unlike in the SBA program, we find that the minority share of the population is unrelated to FHA denial rates. Despite the FHA also being a government subsidized lending program, these results suggest their ability to adjust prices may be a critical feature to ensure "fair" access to credit.

The difference in denial rates between the SBA and FHA are unlikely to be explained by differences in incentives across lenders or differences in applicant type. By comparing two government programs with relatively similar borrower pools, these tests provide further evidence on the disparity in denial rates across the high and low need for price discrimination areas that is due to the SBA's risk-insensitive pricing mechanism.

6.3 Income Inequality: An Alternative Measure of NPD

The previous results show that the differential denial rate between high- and low-minority share areas in the risk-insensitive SBA loan program is not explained by the denial rates in the private market. To provide further evidence on the risk-insensitive pricing channel, we examine the relationship between the county's Gini index (i.e., income inequality) and SBA denial rates by performing similar difference-in difference tests (regression equation 2) to the minority regressions except with Gini as the NPD cross-sectional variable of interest. By construction, higher Gini areas have a greater dispersion in credit quality and, consequently, a greater need for price discrimination in lending markets. Thus a positive relationship between Gini and SBA denial rates would further support the risk-insensitive channel of loan denial. These tests also reduce concerns that the minority population is not measuring NPD but rather is related to some other unobserved factor that correlates with the denial decision.

Table 5 presents the results, where we use the FHA denial rate as our comparison group. We find that the need for price discrimination, here measured by Gini, is strongly related to SBA denial rates. A one-standard-deviation increase in income inequality is associated with a denial rate that is 2.4 percentage points higher for SBA loans relative to FHA loans (column 2). Column (3) indicates that Gini and minority share have independent explanatory power for SBA denial rates, with the effect of minority share being about three times as large. In columns (4-5), we present estimates using the county quartile indicators of Gini and minority share of population which again show the independent explanatory power of both NPD variables. Taken together with our main results, these tests provide strong support that borrowers from areas with a greater need for price discrimination experience much higher denial rates in the SBA loan program, and this is not being driven by some unique unobserved characteristics related to minority share and denial rates.

6.4 Discrimination and Other Potential Alternative Explanations

In this section, we first examine whether the results may be driven by taste-based discrimination. We then discuss potential concerns about violations of a key assumption in our tests: that differences between the pool of SBA applicants and the pool of private-market applicants do not vary systematically according to NPD (after controlling for other important covariates). In this vein, we discuss the possibility of differential sensitivities to disasters, differential access to alternative funding sources, and differences in ability to provide the necessary documentation. None of these alternatives are likely to explain our results. Finally, we test whether our results are driven by a particular time period, disaster type, or by the size of the disaster.

Taste-Based Discrimination:

We now consider the alternative explanation that taste-based discrimination (i.e., prejudice) against minority borrowers is driving the results. While it is hard to empirically assess this important question with observational data, there are predictions that arise from taste-based discrimination that can be tested with the ex-post default performance of these loans. If minority borrowers are denied credit purely because of prejudice, then conditional on getting a loan, the average minority borrower is likely to be of better credit quality. Said differently, borrowers in higher minority share areas need to cross a higher hurdle to obtain credit. Given this higher hurdle, approved loans in these areas should have a lower default rate under this hypothesis. We estimate an OLS default model with minority and income inequality as the explanatory variables, and Table 6 presents the results. We do not find any evidence that high-minority-share or high-income-inequality areas default at lower rates. Thus, these results do not provide support for taste-based discrimination in SBA lending.

Differential Sensitivity:

One potential channel through which the pool of SBA applicants and the pool of private-market applicants may be systematically different across areas with high versus low NPD is if high-NPD areas are more sensitive to natural disasters relative to low-NPD areas. That is, even for observably identical areas, is the underlying credit quality of high NPD areas disproportionately damaged by natural disasters? If the credit quality distribution shifts more for high-NPD areas, then our pre-disaster HMDA and FHA controls may not pick up this relative change in credit quality.

To address this potential concern, we examine changes in the credit quality distribution from pre- to post-disaster across high- and low-minority counties. Specifically, we test whether the change in subprime share (measured in percentage points) from one year before a disaster to one year after a disaster is related to the share of minorities with the following regression.

$$Subprime_{t+1} - Subprime_{t-1} = \zeta Minority_{c,t} + \delta_{d,y} + \Sigma_{state} + \Gamma X_{i,c,t} + \epsilon_{i,c,d,t} \tag{3}$$

If the credit quality of high-minority areas is more-negatively impacted, we should see a positive and significant coefficient on minority share ($\hat{\zeta} > 0$). Table 7 presents the results. We actually find *negative* point estimates on minority share, and they are economically and statistically insignificant. This test does not support the hypothesis that the credit quality of high-minority areas has differential sensitivity to natural disasters relative to low-minority areas.

Alternative sources of funding:

Another concern may be the that individuals in low-NPD areas may have greater access to alternative funding sources besides the SBA (e.g., private market credit access, self-financing, financing through informal networks, or supplemental insurance proceeds). Additionally, there may be variation in the level of collateral across low- and high-NPD areas. There are a few reasons why any differences on these dimensions are unlikely to be driving our results. First, we control for the private market and FHA denial rates, which should capture most sources of variation in alternative sources of capital.

Second, if low-NPD areas have greater access to alternative sources of funding, then this should bias our tests against finding a result. For example, suppose that in the low-NPD areas, a large percentage of the potential SBA applicant pool has greater access to alternative funding while zero potential applicants in high-NPD areas have alternative sources. For high-NPD areas, all potential borrowers apply for an SBA loan, so there is no distortion in the applicant pool, and thus the pool should be fairly comparable to the private market applicant pool. For low-NPD areas, the highest quality borrowers may select out of the SBA pool, leaving, on average, a worse pool of SBA borrowers.[13] Together, this will lead to a relative *decrease* in the average applicant credit quality in the *low*-NPD areas compared to the counterfactual private market applicant pool. As a result, the relative denials (SBA compared with the private market) should be *higher* in the low-NPD areas if this is the case, which works in the opposite direction of our findings.

Lack of paperwork or banking history:

A related concern may be that applicants from high-minority areas are unable to produce the necessary paperwork to receive a loan or do not have a banking history. This is also unlikely. The vast majority of SBA applicants are homeowners, which means they have likely obtained a mortgage in the past and produced such paperwork. This rules out a number of these alternatives since having a bank account, producing the necessary employment documentation, etc. and other SBA requirements are also needed to apply for most mortgages.

[13] Additionally, it is unlikely that those in need of funding will opt for a private-market option since the SBA loan financing terms will almost always dominate. The SBA statutory rate for borrowers with "Credit Available Elsewhere" (the highest rate) is at most one percentage point above the government's cost of borrowing for similar maturities.

Time Periods, Disaster Size, and Disaster Types:

In Appendix Table A.2, we run our baseline regressions on sub-periods of our sample (roughly equally divided by observations). We find that our results are present in all subsamples except 1990-1994 (which was dominated by the Northridge Earthquake that was largely in a single county), with the largest effect during the early- to mid-2000s. In columns (6) and (7), we show that the effect is not concentrated only in large (one of the top ten) or small disasters, as these two subsamples have similar estimates.

The earlier tests control for disaster-type×year fixed effects which capture the average denial rate within a disaster-type in a given year. These controls alleviate concerns that a certain type of disaster leads to both intrinsically higher denial rates and is more likely to strike high-NPD areas. We next test whether a single type of disaster is driving our main results. To do this, we re-estimate our baseline regression, excluding each of the five types of disasters one at a time. Appendix Table A.3 shows that no single disaster type is driving our results.

6.5 Economic Significance

To further illustrate the economic importance of the results, we provide an estimate of the credit that would have been extended if all counties were in the lowest minority-share quartile. To do this, we multiply the number of loan applications in the 2nd, 3rd, and 4th quartiles of minority share by the difference in approval rates between these counties and the lowest quartile counties. We use the estimates in column (6) of Table 3 as the estimated differences in approval rate. This calculation provides an estimate of the additional loans that would have been available to borrowers in higher minority counties had they experienced the same denial rate as the low minority counties. We then multiply these numbers by the average loan amount for approved loans to get a rough idea of the dollar amount (year-2000 dollars) of “missing” loans. Table 8 shows the computation.

The calculation suggests that about \$1.58 billion of additional loans would have been granted under conditions where the price is flexible and based on the riskiness of the borrower. In terms of the number of loans, our estimates show that about 45,000 more homeowners would have had access to credit during these critical post-disaster time periods.

7 Discussion & Conclusions

We document a substantially higher denial rate of applications for SBA disaster loans in counties with a greater need for price discrimination. Applicants in high-minority-share areas, areas with higher subprime populations, and more income inequality are denied access to government-provided credit at a disproportionately higher rate relative to the private lending market, despite these applicants often being the intended recipient of government assistance programs (and also a focus of government regulation in private-market lending). This relationship persists after accounting for a benchmark private-market denial rate constructed from HMDA loans, which takes into account both raw credit quality and equilibrium credit rationing.

We argue that the lack of risk-sensitive pricing is a key factor behind this finding. The setup of the SBA disaster loan program does not allow for borrowers to be charged an interest rate based on their credit risk, which is a stark departure from the risk-sensitive pricing seen in private lending markets. As a result, some creditworthy borrowers who are sufficiently good credit risks at a higher interest rate are instead denied credit altogether under this program. We provide further evidence of this channel by comparing SBA denial rates with the denial rates in a government-insured private lending market: home loans subsidized by the Federal Housing Administration (FHA), which allows for flexible loan pricing. We find no relationship between the need for price discrimination and loan denial rates in the FHA program. Further, the FHA denial rates cannot explain the differential in SBA denial rates across high and low NPD areas.

Risk-insensitive pricing is a pervasive feature of government lending programs around the world, and it is often motivated by fairness and equality in access to credit. However, our results document some important adverse consequences of loan programs with this feature. By failing to use a more-flexible, risk-sensitive pricing mechanism to help allocate credit, government lending programs may be unintentionally neglecting many of the marginal, yet still creditworthy, borrowers that they are setting out to help.

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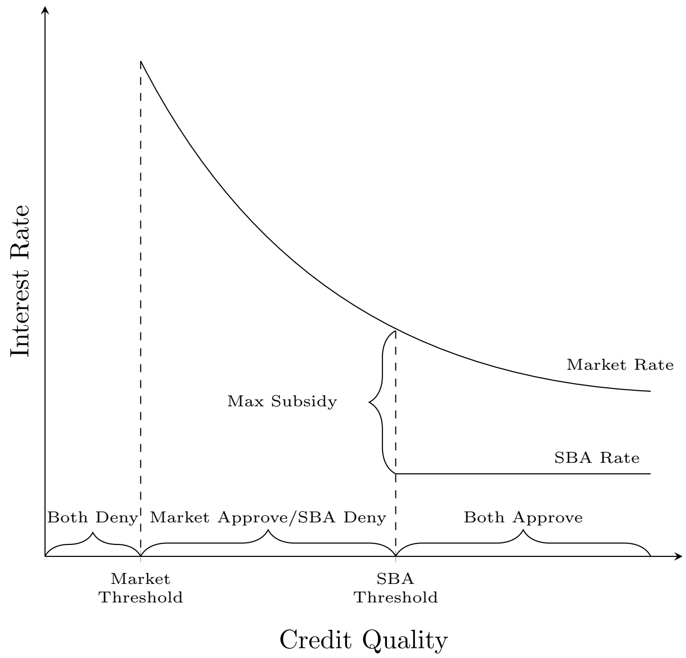

Figure 1: Credit Rationing
This figure illustrates the credit allocation decision with risk-insensitive and subsidized loan pricing (SBA) compared to the credit allocation with risk-sensitive (market) pricing.

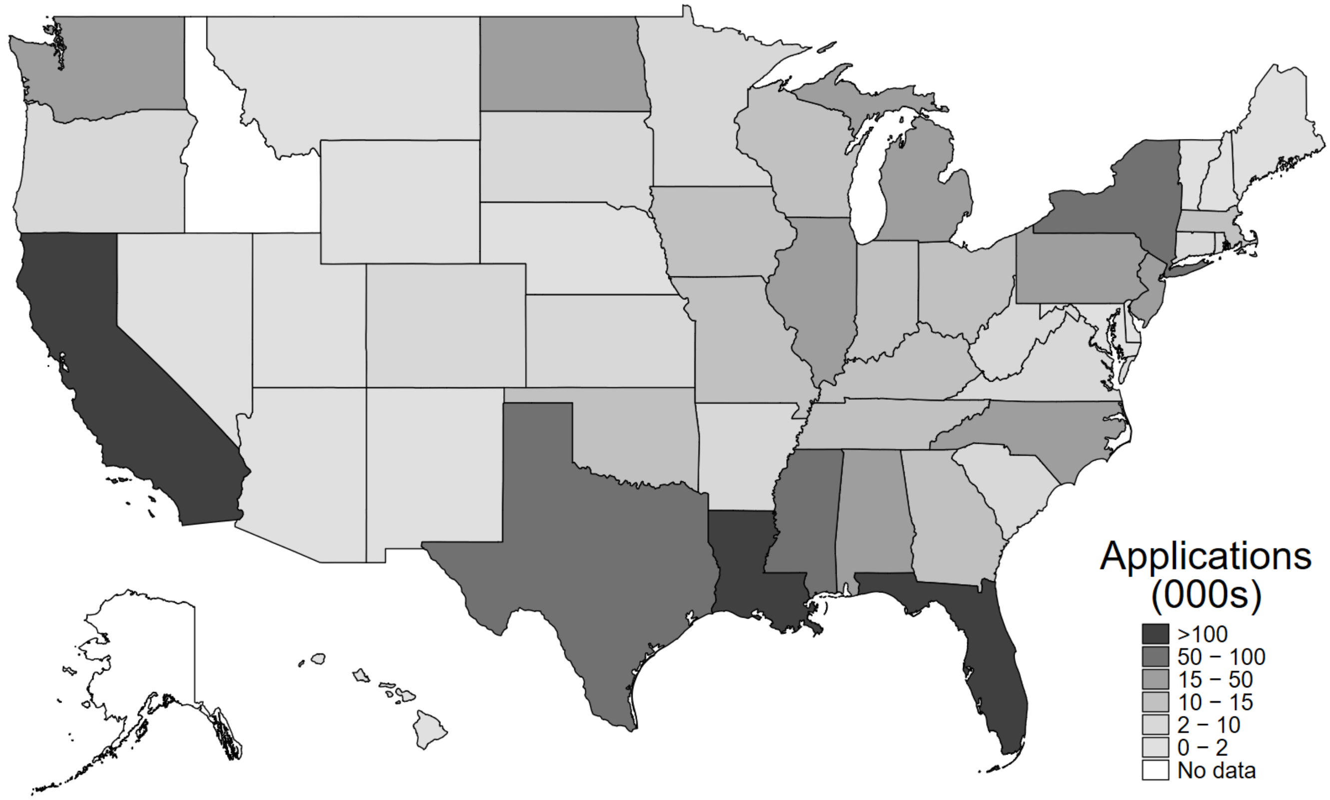

Figure 2: Geographical Distribution of Total Applications
This figure presents the number of disaster loan applications during the sample period of 1991-2015 for each state.

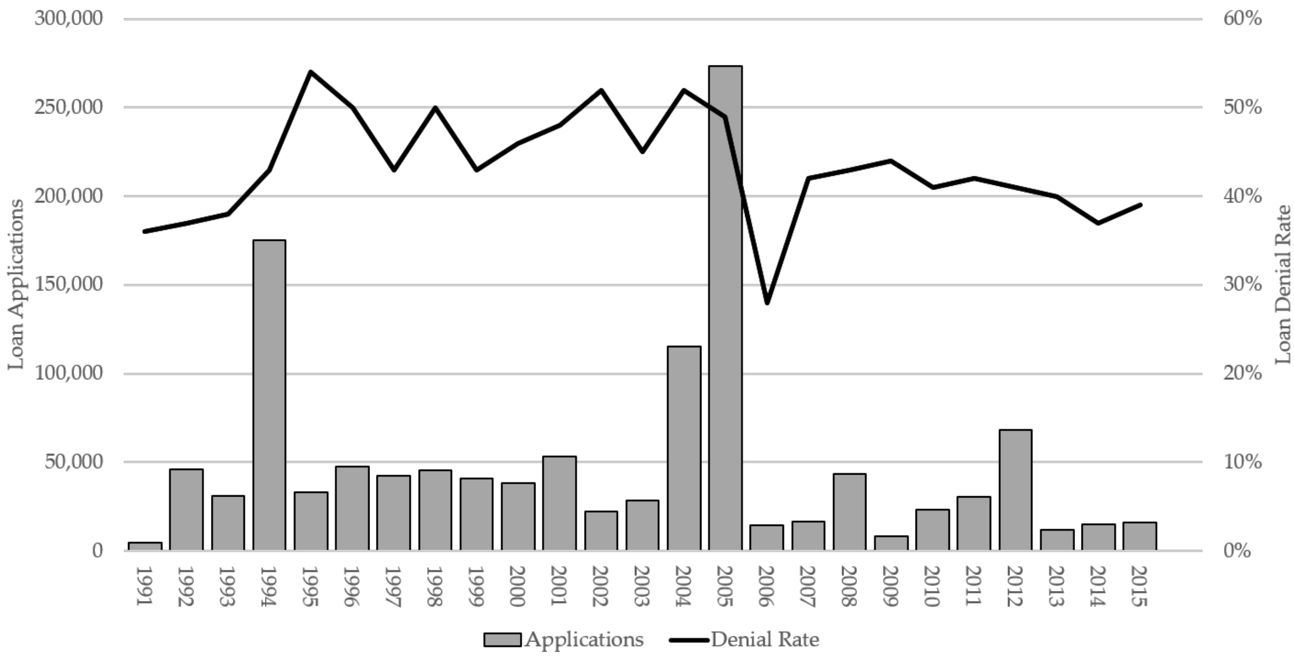

Figure 3: Applications and Denials Over Time
This figure presents the annual number of SBA disaster-relief home loan applications (left axis) and loan denial rates (right axis) for each year in the sample.

Table 1: Disaster Summary Statistics

This table presents loan application summary statistics by disaster and disaster type. Panel A presents the volume of applications and denial rates for the different types of disasters in the sample. Panel B presents statistics from the ten largest disasters (by loan application count) in the sample.

Panel A: Disaster Types

	applications	denial rate
Hurricane	571,357	48%
Severe Weather	432,938	44%
Earthquake	175,986	43%
Tropical Storm	55,784	49%
Fire	12,603	45%

Panel B: Ten Largest Disasters

Disaster	Year	applications	denial rate
Hurricane Katrina	2005	206,201	48%
Northridge Earthquake	1994	159,603	43%
Hurricane Sandy	2012	55,267	41%
Hurricane Andrew	1992	31,792	38%
Hurricane Ivan	2004	30,364	50%
Hurricane Rita	2005	33,107	56%
Tropical Storm Allison	2001	31,740	51%
Hurricane Floyd	1999	24,635	41%
Hurricane Wilma	2005	26,864	48%
Hurricane Frances	2004	23,645	56%

Table 2: Sample Summary Statistics

This table presents the sample summary statistics. *Subprime* is the share of the county population that is subprime (data starting from 1999), *Minority* is the share of the county population that is not white, *Gini* is the Gini index of the county as described in Section 5, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *HMDA Denial* is the county-level denial rate for applications for home refinancing loans from the Home Mortgage Disclosure Act in the most recent non-disaster year, and *FHA Denial* is the county-level denial rate for applications for home refinancing loans insured by the Federal Housing Administration in the most recent non-disaster year. For the sample of loan applications (application sample), *SBA Denial* for a given home or business disaster loan application is an indicator equal to one if the loan application was denied, *VerifiedLoss* is the loss of the applicant as a result of the disaster as verified by SBA officials. For approved loans (Default Sample), we report statistics on the loan *amount*, the *maturity* in months and whether or not the loan was charged-off (*Default*).

variable	mean	sd	min	p25	p50	p75	max	N
County Statistics:								
Subprime	0.35	0.07	0.08	0.30	0.37	0.41	0.62	811,133
Minority	0.39	0.22	0.00	0.19	0.37	0.63	0.98	1,207,081
Gini	0.45	0.04	0.32	0.43	0.46	0.47	0.60	1,207,081
Per capita income (000)	34.08	16.85	6.59	20.66	31.24	38.89	217.44	1,207,081
ln(Population)	13.01	1.83	9.12	11.78	13.03	14.50	16.01	1,207,081
HMDA denial	0.21	0.06	0.00	0.17	0.21	0.25	1.00	1,207,081
FHA Denial	0.12	0.09	0.00	0.71	0.11	0.14	1.00	1,196,000
SBA Loans (Application Sample):								
SBA denial	0.46	0.50	0.00	0.00	0.00	1.00	1.00	1,207,081
Verified Loss (000)	50.77	72.52	0.70	9.35	22.44	54.82	384.33	1,207,081
Amount (000)	38.35	50.61	0.08	8.64	18.84	45.27	756.20	655,605
SBA Loans (Default Sample):								
Amount (000)	32.74	41.79	0.01	8.40	17.10	40.00	561.90	727,993
Maturity	214.84	128.55	1.00	96.00	192.00	360.00	963.00	727,993
Default	0.08	0.27	0.00	0.00	0.00	0.00	1.00	727,993

Table 3: SBA Loan Denial and Need for Price Discrimination: Subprime and Minority Share

This table presents OLS estimates from the regression of SBA home loan denial (*SBA Denial*) for a given home disaster loan application on measures of need for price discrimination (*NPD*) and various controls and fixed effects. *NPD* is measured by the *Subprime* (FICO <660) share of the county population (columns 1-3) and *Minority* race share of the county population (columns 4-6). Both measures are included in column 7. *Subprime Xq* (*Minority Xq*) is the Xth quartile of *Subprime* (*Minority*) with the first quartile (e.g., lowest subprime share) as the omitted category, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *VerifiedLoss* is the loss of the applicant as a result of the disaster as verified by SBA officials. *HMDA-RecentND* is the denial rate for applications of home loan refinancing in the county in the most recent year in which there was no disaster. *Subprime* data are only available from 1999 onwards (thus smaller sample sizes in the regressions). *Disaster-Year FE* are fixed effects for each disaster type and year combination (e.g., hurricanes in 2004), and each regression includes state fixed effects. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by county.

	Subprime			Minority			Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
zSubprime	0.038***	0.023***					0.006
	(<0.01)	(<0.01)					(0.37)
Subprime 2q			0.002				
			(0.81)				
Subprime 3q			0.013				
			(0.48)				
Subprime 4q			0.043**				
			(0.02)				
zMinority				0.046***	0.033***		0.029***
				(<0.01)	(<0.01)		(<0.01)
Minority 2q						0.021***	
						(0.01)	
Minority 3q						0.044***	
						(<0.01)	
Minority 4q						0.083***	
						(<0.01)	
zSubprime×zMinority							0.007*
							(0.09)
zPerCapitaIncome		0.015**	0.006		0.003	0.003	0.010
		(0.05)	(0.34)		(0.64)	(0.66)	(0.14)
zln(Population)		0.016***	0.020***		0.001	0.004	-0.006
		(<0.01)	(<0.01)		(0.86)	(0.38)	(0.32)
zVerifiedLoss		-0.067***	-0.067***		-0.074***	-0.074***	-0.067***
		(<0.01)	(<0.01)		(<0.01)	(<0.01)	(<0.01)
zHMDA-RecentND		0.410***	0.363***		0.264***	0.272***	0.273***
		(<0.01)	(<0.01)		(<0.01)	(<0.01)	(<0.01)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	811133	811133	811133	1207081	1207081	1207081	811133
R^2	0.019	0.039	0.039	0.021	0.039	0.038	0.040

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: County-Level Differences in Denial By Minority Share

For each county-year in the SBA dataset, we compute the home loan denial rate and append an additional observation to the dataset with the respective HMDA denial rate (columns 1-3) or FHA denial rate (columns 4-6). This table presents OLS estimates from the regression of county-level loan denial rates (SBA or HMDA/FHA) for disaster-affected counties on the minority share of population in the county, whether the observation represents the SBA denial rate, and their interaction.

$$\textit{denial rate} = \alpha + \delta\mathbb{1}[SBA] + \theta(\mathbb{1}[SBA] \times \textit{Minority}) + \epsilon$$

denial rate is the county denial rate for either SBA home loans or the HMDA/FHA denial rate, which is the denial rate for applications of HMDA/FHA loans in the county in the most recent year in which there was no disaster. $\mathbb{1}[SBA]$ is an indicator equal to one if the observation represents the SBA denial rate and zero if the observation represents the FHA denial rate. *Minority* represents the nonwhite share of the county population (its main effect is absorbed by the fixed effects), *Minority Xq* is the Xth quartile of the *Minority* with the first quartile (e.g., lowest minority share) as the omitted category (their main effects are absorbed by the fixed effects), *Disaster-Year FE* are fixed effects for each disaster type and year combination (e.g., hurricanes in 2004), and each regression includes county×year fixed effects (which absorb the main effects of Minority). All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by county.

	HMDA Benchmark			FHA Benchmark		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}[SBA]$	0.209***	0.209***	0.181***	0.276***	0.276***	0.243***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
$\mathbb{1}[SBA]$×zMinority		0.027***			0.034***	
		(<0.01)			(<0.01)	
$\mathbb{1}[SBA]$×Minority 2q			0.008			0.007
			(0.41)			(0.55)
$\mathbb{1}[SBA]$×Minority 3q			0.039***			0.047***
			(<0.01)			(<0.01)
$\mathbb{1}[SBA]$×Minority 4q			0.064***			0.078***
			(<0.01)			(<0.01)
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16882	16882	16882	16074	16074	16074
R^2	0.619	0.623	0.622	0.627	0.631	0.630

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: SBA Home Loan Denial and Income Inequality: County Diff-in-Diff

For each county-year in the SBA dataset, we compute the home loan denial rate and append an additional observation to the dataset with the respective FHA denial rate. This table presents OLS estimates from the regression of county-level loan denial rates (SBA or FHA) for disaster-affected counties on whether the observation represents the SBA denial rate, its interaction with the Gini index or minority share of population in the county, and county-year fixed effects (which absorb the main effects of Gini and Minority).

$$denial\ rate = \alpha + \delta \mathbb{1}[SBA] + \theta(\mathbb{1}[SBA] \times NPD) + \epsilon$$

denial rate is the county denial rate for either SBA home loans or the FHA denial rate, which is the denial rate for applications of FHA loans in the county in the most recent year in which there was no disaster. $\mathbb{1}[SBA]$ is an indicator equal to one if the observation represents the SBA denial rate and zero if the observation represents the FHA denial rate. *Gini* is an index that measures the income inequality in the county, *Gini Xq* is the Xth quartile of the *Gini* with the first quartile (e.g., lowest income inequality share) as the omitted category, *Minority* represents the nonwhite share of the county population, *Minority Xq* is the Xth quartile of the *Minority* with the first quartile (e.g., lowest minority share) as the omitted category, *Disaster-Year FE* are fixed effects for each disaster type and year combination (e.g., hurricanes in 2004), and each regression includes county×year fixed effects (which absorb the main effects of Minority and Gini). All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by county.

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}[SBA]$	0.276***	0.277***	0.276***	0.233***	0.223***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
$\mathbb{1}[SBA]$×zGini		0.024***	0.010**		
		(<0.01)	(0.04)		
$\mathbb{1}[SBA]$×zMinority			0.029***		
			(<0.01)		
$\mathbb{1}[SBA]$×Gini 2q				0.035***	0.028**
				(<0.01)	(0.01)
$\mathbb{1}[SBA]$×Gini 3q				0.060***	0.044***
				(<0.01)	(<0.01)
$\mathbb{1}[SBA]$×Gini 4q				0.080***	0.053***
				(<0.01)	(<0.01)
$\mathbb{1}[SBA]$×Minority 2q					0.003
					(0.83)
$\mathbb{1}[SBA]$×Minority 3q					0.034***
					(0.01)
$\mathbb{1}[SBA]$×Minority 4q					0.055***
					(<0.01)
County-Year FE	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16074	16074	16074	16074	16074
R^2	0.627	0.629	0.631	0.630	0.631

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Taste-Based Discrimination: Ex-Post Loan Performance

This table presents OLS estimates from the regression of an indicator equal to one if the loan defaults (i.e., charged off) on measures of the need for price discrimination (NPD) and various controls and fixed effects. *NPD* is measured by *Minority* race share of the county population (columns 1 and 2), and county income inequality as measured by the *Gini* index (columns 3 and 4). *ln(Amount)* is the log of the loan amount, *ln(Maturity)* is the log of the loan maturity in months, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *Disaster-Year FE* are fixed effects for each disaster type and year combination (e.g., hurricanes in 2004), and each regression includes state fixed effects. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by county.

	(1)	(2)	(3)	(4)
zMinority	0.013***	0.008***		
	(<0.01)	(<0.01)		
zGini			0.006***	0.002*
			(<0.01)	(0.09)
zln(Amount)		-0.036***		-0.037***
		(<0.01)		(<0.01)
zln(Maturity)		0.033***		0.033***
		(<0.01)		(<0.01)
zPerCapitaIncome		-0.004***		-0.007***
		(<0.01)		(<0.01)
zln(Population)		0.007***		0.012***
		(<0.01)		(<0.01)
State FE	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes
Observations	727993	727993	727993	727993
R^2	0.032	0.047	0.031	0.046

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Differential Sensitivity: Relative Changes in Subprime Share

This table presents OLS estimates from the regression of change in subprime share of the county population for each loan application from the year before the disaster until the year after the disaster ($Subprime_{t+1} - Subprime_{t-1}$), measured in percentage points, on the minority share of population in the county and various controls and fixed effects. *Minority* represents the nonwhite share of the county population, *Minority Xq* is the Xth quartile of the *Minority* with the first quartile (e.g., lowest minority share) as the omitted category, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *VerifiedLoss* is the loss of the applicant as a result of the disaster as verified by SBA officials. *Subprime* is the share of the population with FICO <660, and these data are only available from 1999 onwards (thus smaller sample sizes in the regressions). *Disaster-Year FE* are fixed effects for each disaster type and year combination (e.g., hurricanes in 2004), and each regression includes state fixed effects. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by county.

	(1)	(2)
zMinority	-0.033	
	(0.93)	
Minority 2q		-0.556
		(0.31)
Minority 3q		-1.027
		(0.22)
Minority 4q		-0.488
		(0.68)
zPerCapitaIncome	-0.214	-0.202
	(0.56)	(0.58)
zln(Population)	-0.426	-0.238
	(0.10)	(0.31)
zVerifiedLoss	0.195*	0.155
	(0.10)	(0.11)
State FE	Yes	Yes
Disaster-Year FE	Yes	Yes
Observations	781319	781319
R^2	0.519	0.538

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Economic Significance

This table presents a back of the envelope calculation of the additional number of loans and dollar amount of loans that would have been approved if all counties were low minority share counties given the SBA's current pricing scheme.

	Minority 1q	Minority 2q	Minority 3q	Minority 4q	Total
Actual Loans:					
Loan Application	301,411	302,150	301,138	302,382	1,207,081
Average Loan Amount ($)	$43,276.99	$41,840.68	$30,860.16	$36,258.10	
Point Estimates	-	2.1%	4.4%	8.3%	
Counterfactual loans:					
Additional Approved	-	6,345	13,250	25,098	44,693
Additional Amount ($Mn)	-	$265.49	$408.90	$910.00	$1,584.38

Date: 11/07/2017

U.S. Small Business Administration

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

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

occurring: *August 23 through September 15, 2017*

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

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

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

What Types of Disaster Loans are Available?

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

What are the Credit Requirements?

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

What are the Interest Rates?

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

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

Amendment #8

Figure A.1: Hurricane Harvey Fact Sheet

Table A.1: Loan Details

This table presents the types of loans and limits for each kind of loan in the SBA disaster lending program. Our paper studies loans to homeowners.

Loan Name	Eligible Borrowers	Borrowing Limit	Interest Rate Cap	Term Cap
Personal Property	Homeowners Renters	\$40,000	4 or 8%*	30 years
Real Estate	Homeowners	\$200,000	4 or 8%*	30 years
Business physical disaster loans	Businesses (any size) and Most private nonprofit organizations	\$2M+	4 or 8%*	30 years or 7* years
Economic injury disaster loans	Small business Small agricultural cooperative Most private nonprofit organizations	\$2M+	4%	-

* 8% and 7 years if credit available elsewhere, + limit can be waived by SBA if the business is a major source of employment.

Table A.2: Results Over Time and By Disaster Size

This table presents OLS estimates from the regression of SBA home loan denial (*SBA Denial*) for a given home disaster loan application on a measure of need for price discrimination (*NPD*) and various controls and fixed effects. *NPD* is measured by the *Minority* race share of the county population. Columns (1)-(5) represent the baseline estimate including only disasters occurring during the time noted in the column heading. We divide the sample to make roughly similar sample sizes. Columns (6) and (7) present estimates using applications related to the ten largest disasters and then all the rest, respectively. *Minority* represents the nonwhite share of the county population, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *VerifiedLoss* is the loss of the applicant as a result of the disaster as verified by SBA officials. *HMDA-RecentND* is the denial rate for applications of home loan refinancing in the county in the most recent year in which there was no disaster. *Disaster-Year FE* are fixed effects for each disaster type and year combination (e.g., hurricanes in 2004), and each regression includes state fixed effects. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by county.

	Time Period					Top Ten Disaster	
	1990-94	1995-99	2000-04	2005	2006-15	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
zMinority	-0.001	0.038***	0.049***	0.051***	0.024***	0.034***	0.034***
	(0.95)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zPerCapitaIncome	0.008	-0.017	0.039***	0.037***	-0.008	0.022***	-0.009
	(0.76)	(0.19)	(<0.01)	(0.01)	(0.11)	(0.01)	(0.13)
zln(Population)	0.027***	0.015**	0.002	-0.043***	-0.006	-0.012	0.011**
	(<0.01)	(0.01)	(0.74)	(<0.01)	(0.30)	(0.22)	(0.01)
zVerifiedLoss	-0.138***	-0.174***	-0.060***	-0.087***	-0.033***	-0.085***	-0.052***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zHMDA-RecentND	0.009**	0.022***	0.024***	0.010	-0.000	0.026***	0.018***
	(0.01)	(<0.01)	(<0.01)	(0.23)	(0.95)	(<0.01)	(<0.01)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	227686	207095	252562	271299	248439	593765	613316
R^2	0.032	0.053	0.038	0.062	0.021	0.044	0.036

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Results Excluding Each Type of Disaster

This table presents OLS estimates from the regression of SBA home loan denial (*SBA Denial*) for a given home disaster loan application on a measure of need for price discrimination (*NPD*) and various controls and fixed effects. *NPD* is measured by the *Minority* race share of the county population. Each column presents estimates from the baseline specification excluding the type of disaster noted in the column heading. *Minority* represents the nonwhite share of the county population, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *VerifiedLoss* is the loss of the applicant as a result of the disaster as verified by SBA officials. *HMDA-RecentND* is the denial rate for applications of home loan refinancing in the county in the most recent year in which there was no disaster. *Disaster-Year FE* are fixed effects for each disaster type and year combination (e.g., hurricanes in 2004), and each regression includes state fixed effects. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by county.

	Excluding Disaster Type				
	Earthquake (1)	Fire (2)	Hurricane (3)	Severe Weather (4)	Tropical Storm (5)
zMinority	0.031***	0.030***	0.039***	0.031***	0.031***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zPerCapitaIncome	0.006	0.006	-0.022***	0.018**	0.005
	(0.34)	(0.37)	(<0.01)	(0.02)	(0.45)
zln(Population)	0.002	0.002	0.012***	-0.014**	0.003
	(0.66)	(0.64)	(0.01)	(0.04)	(0.53)
zVerifiedLoss	-0.070***	-0.076***	-0.075***	-0.077***	-0.073***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zHMDA-RecentND	0.023***	0.022***	0.022***	0.020***	0.019***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
State FE	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1031095	1194494	667650	783746	1151339
R^2	0.041	0.039	0.036	0.038	0.039

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$