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. This program screens applicants on credit quality, but cannot price loans according to credit risk. 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.

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

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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 the banking literature is grounded in the idea that capital is more efficiently allocated when lending rates 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. These lending programs typically offer borrowers a subsidized interest rate without (or with limited) risk-based pricing. With a fixed price (i.e., lending rate), all borrowers who receive credit do so at the same interest rate. Policymakers often debate the costs and benefits of risk-insensitive pricing policies both in government-run programs and private markets including the ongoing debate on the need for interest rate caps in some lending markets.[1] 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 effect of risk-insensitive pricing in 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).[2]

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

[1] See, for example, the ruling and debate around CFPB (2017) regarding high-cost loans.

[2] 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.

better access to credit through government lending programs compared to private markets. To 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 responsible tax-dollar stewardship with a risk-insensitive lending rate creates a difficult tension. The 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.[3] We study which of these two forces – the objective to provide broad access to credit or tax-dollar stewardship – dominates by examining 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, the fixed-price program performs 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 where the screening process for the applying households 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 be good stewards of taxpayer dollars. The implication of a fixed lending rate combined with loan screening is that higher-risk borrowers may simply

[3]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).

be denied credit altogether. Such rationing is likely to be particularly painful in settings like the aftermath of natural disasters when access to credit to rebuild is critical, and the applicants' willingness to pay higher interest rates to access credit is particularly 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 following natural disasters across the United States between 1991 and 2015. 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 on credit allocation decisions 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. Motivated by prior work in the literature on mortgage lending, we use two main proxies for NPD in our tests: areas with a larger share of minority population and areas with a larger share of subprime borrowers based on FICO scores.[4] 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 high-NPD 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. In that case, we would expect a relatively lower denial rate in the high-NPD areas.

We primarily focus on the minority share of the applicant's county as our key NPD measure. Minority share has been shown to capture both hard and soft information about the borrower pool in ways beyond what is captured by subprime sharey. Bayer, Ferreira, and Ross (2016) show that minority borrowers default at a higher rate even conditional on observables like credit score. This can potentially be due to unobserved credit risk factors

[4]In robustness tests, we report results with a third NPD measure – level of income inequality.

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 as "underserved."[5] 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. A number of papers have examined the effectiveness of the government's interventions on credit access for minorities. We are the first paper to examine how the government's *own* direct lending to its citizens fares on this dimension.

We begin our analysis by documenting a positive correlation between NPD and SBA loan denial rates using application-level data. We find borrowers in areas with higher minority share and areas with higher fraction of subprime borrowers have significantly higher denial rates in the SBA disaster lending program. Of the two proxies for NPD, the effect for minority population is stronger. A one-standard-deviation increase in minority-share of the population is associated with a 3.2 percentage points higher denial rate, even after controlling for income or the extent of losses incurred in the disaster. With the average denial rate in our sample at 46%, these results are economically significant. We break all counties into quartiles based on the share of minority population and find a monotonic, positive relationship between minority share and denial rate. We find a similar relationship if we aggregate the data

[5] 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).

and examine patterns at the county-year-disaster-level rather than the application-level. Though applicants in these areas may be the target of government lending programs, these results provide evidence that the government's own lending program does not reach marginal borrowers at the same rate as other groups during a time of crisis.

What is the economic reason for the relative lack of credit access for applicants' in high minority areas? We argue that it is the lack of risk-sensitive pricing that is responsible for the disparate outcomes for borrowers across these areas. However, we face an empirical challenge in isolating the effect of risk-insensitive pricing: we must separate out differences in denial rates due to risk-insensitive pricing from differences that would occur even under a risk-based pricing scheme. There is likely a difference in denial rates across high- and low-NPD areas even in private markets with risk-sensitive pricing because of baseline differences in credit risk or levels of credit rationing due to asymmetric information.[6] Therefore, to tease out the effect of risk-insensitive pricing, we need a reasonable benchmark for the baseline risk-sensitive denial rate. Our empirical setting is attractive in this respect because we can observe virtually all home loan application decisions in the private (risk-sensitive) mortgage market during the sample period using the Home Mortgage Disclosure Act (HMDA) dataset. Important for our tests, HMDA includes property locations and application approval/denial decisions. This allows us to exploit *within-area variation* in denial rates across risk-insensitive and risk-sensitive lending programs (a) for the same area and (b) around the same time. The risk-sensitive pricing benchmark incorporates baseline credit quality, credit rationing, and any potential biases that persist in those markets.[7] Thus, they capture variation in access to credit that is unrelated to risk-insensitive lending. Comparing the SBA denial rate to a baseline private-market denial rate for the same county allows us to soak away all county-specific

[6] 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).

[7] 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.

unobserved heterogeneity that may be correlated with the decision to reject credit to a given borrower.

We use home refinancing loan applications from the HMDA dataset as our risk-sensitive benchmark because this is the private-market lending category that is closest to SBA home loans: both sets of loans are geared toward borrowers who are already home owners. In some specifications, we further refine the set of risk-sensitive benchmark loans to Federal Housing Administration (FHA) loans. The purpose of the FHA is to help provide credit to marginal borrowers. FHA loans are issued by private banks but are insured by the government. Unlike SBA home loans, however, FHA loans do not follow a fixed-price, risk-insensitive pricing scheme. Given the similarities between the FHA and SBA, 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 estimate within-county-year variation in loan denial rates across risk-insensitive and risk-sensitive lending programs by collapsing our SBA loan-level data to county-year-disaster type averages. Using these data and the HMDA denial rates for the same county-year unit, we estimate the difference in denial rates across the different schemes (SBA vs. risk-sensitive pricing programs) for counties with different NPD.[8] We find that a one-standard-deviation increase in minority share corresponds to a 2.7 percentage points 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 the government-insured but risk-sensitive loan pricing FHA program we find no difference in denial rates across NPD. Examining across quartiles of minority share,

[8]For the loans from HMDA, we use denial rates from the most recent non-disaster year to ensure that our results are not driven by any interaction effect between private markets and the SBA program. Our results do not change if we use HMDA denial rates from the same year as the disaster or averages of the two or three prior years.

we find applicants from counties in the top quartile of minority share experience an SBA denial rate that is approximately 8 percentage points higher than the SBA denial rate in the low-minority-share counties after differencing out the corresponding county-level baseline 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.

Since our estimates are based on within-county-year differences, our results cannot be explained by differences in unobserved characteristics of high- and low-NPD areas at the time of the disaster. However, there are two potential threats to our identification strategy. The first one relates to the role of taste-based discrimination against minority borrowers. The second concern is related to the comparability of borrowers in the disaster lending market with HMDA or FHA borrowers that we use as the benchmark for risk-sensitive denial rates.

We first consider the alternative that our 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. Using detailed data on the default behavior of all approved borrowers in our sample, we find no support for taste-based discrimination.

On the second concern, for our identification strategy to fail it must be the case that the difference in the average quality of borrowers in the SBA pool and HMDA/FHA pool becomes disproportionately worse for high-minority areas precisely during disasters as compared to the corresponding difference for other areas. Thus, the real concern is whether high-minority areas' credit quality is relatively more sensitive to natural disasters as compared to other areas. If this were true, we could attribute the differential denial rate to relatively larger drops in credit quality for high-minority areas, and not to the lack of risk-sensitive pricing. We test for whether the average drop in credit quality, as measured by FICO scores, from before to after the disaster is relatively larger for minority areas, and we find no difference across high- and low-minority areas. Further, risk-sensitive (HMDA and FHA) lenders are likely to incorporate the effect of differences in sensitivity to these disasters on a borrower's payment likelihood even for a non-disaster loan. For example, a lender is likely to anticipate the effect of a hurricane or storm in a coastal area on a borrowers' credit outcome even during regular lending decisions. Hence, using the private market denial rate as the benchmark already accounts for all such anticipated unobserved differences that may not be captured in the FICO scores.

Finally, we provide a number of robustness tests for our results. We find similar results using income inequality as an alternative measure of NPD and when examining business loans instead of home loans. We find similar results across sub-periods of our sample, across large and small disasters, and are not driven by any particular disaster or disaster type. These results rule out additional alternative explanations for our results.

To provide some context on the economic importance of our results, we use our main estimates to conduct a back-of-the-envelope calculation of the additional credit that would have been extended if the SBA program allowed for risk-sensitive pricing. Our calculation suggests that about 69,000 additional homeowners would have received loans (a 10% increase in loan approvals), which adds up to a grand total of about $2.2 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 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 processes loan applications, performs inspections, makes lending decisions, contracts with borrowers, and then disburses funds. SBA loan officers assess an applicant's creditworthiness when determining whether or not to approve a 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). Requested documentation includes items such as prior tax filings and employment records. 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 loss. As is also the case for the private market, the application approval decision cannot be explicitly driven by an applicant's race, color, national origin, or gender.

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" – based on the applicant's credit score, cash flow, and assets (SBA Standard Operating Procedure (2015)) – 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.[9] For both types of borrowers, the

[9]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

rate is typically lower than the prevailing private-market interest rate on a 30-year fixed-rate mortgage. For Hurricane Harvey in 2017, the respective SBA rates (1.75% and 3.5%) were both below the Freddie Mac average rate of around 3.9%. See Figure A.1 for the fact sheet for Hurricane Harvey (Disaster TX-00487), which includes these details. Thus, it is in the interest of every potential borrower to apply for these loans, and this minimizes selection bias concerns in the pool of applicants. Importantly, the SBA loan rate cannot be adjusted based on an applicant's credit risk. For applicant's of marginal creditworthiness, the interest rate cannot be increased to a point in which the risk-return tradeoff is sufficient for approval. Rather than charging a higher rate commensurate with higher risk, the loans are simply denied.

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 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 denial rates for 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.

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

3 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, if lenders are unable to adjust the rate of the loan to match the borrower's creditworthiness, there may be excess credit rationing. 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 to compensate for the applicant's higher risk.[10] This idea motivates our key hypothesis: as a result of risk-insensitive pricing in the SBA program, loan applications from areas with a greater share of marginal-credit-quality individuals will have higher denial rates.

Figure 1 summarizes our core idea. The graph plots the private 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 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.[11] 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 the SBA lending program 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

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

[11] 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.

falls between the private-market and SBA thresholds (i.e., variation in the share of applicants with marginal credit quality). Specifically, we examine if applicants from areas which have a greater need for price discrimination (NPD) to receive credit experience higher excess denial rates.

We use two main proxies for the need for price discrimination: the minority share and the subprime share of the county population. We use a third proxy, the county income inequality (Gini coefficient), as an addition measure for robustness. These three proxies aim to capture the relative mass of applicants in the credit quality distribution for a county between the private-market risk-sensitive threshold and the SBA risk-insensitive threshold. Subprime share captures the percentage of the population with a credit score below 660. Areas with greater income inequality – a direct measure of income dispersion – should generally have a relatively higher proportion of borrowers who could benefit from price discrimination holding fixed the average level of income. 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. Moreover, high-minority areas have historically been a priority for legislation such as the Fair Housing Act, so examining how the government's own SBA lending program fares against a private-market benchmark is of additional interest.

Our first set of tests regress loan-level denial on NPD and other controls including state and disaster-type×year fixed effects. However, a positive correlation between an area's *NPD* and SBA loan denial rate is not fully conclusive about the effect of risk-insensitive pricing on denial rates. This correlation could also 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 separate out these effects. Thus an ideal research design would be to compare the denial rate for borrowers in the disaster lending program to the denial rate for identical borrowers under risk-sensitive loan pricing. While such a counterfactual is unobservable, we are able to observe a close substitute: the credit allocation decision in the private lending market (i.e., the regular mortgage market) for the same areas. We only use refinancing loan applications from the HMDA dataset because, like the SBA loan applications, these applications are from existing home owners. For every county, we obtain data on denial rates for all borrowers in the HMDA data set for the most recent non-disaster year and use this as a baseline denial rate. We then compare the within-county×year difference in denial rate for SBA vs. HMDA loans across areas with varying degree of *NPD*.

Specifically, we construct a data set at the level of county×year and compute the respective SBA denial rate. In other words, we collapse the loan-level SBA data to county level for each year (e.g., Dane County, Wisconsin, 2004). For each observation, we then create a corresponding observation where we replace the SBA denial rate with the county's private-market denial rate in the most recent non-disaster year. Thus, for each county×year in the SBA loan dataset, we have an observation for each of the two loan programs: one with the SBA denial rate and one with the private-market (risk-sensitive) denial rate as the dependent variable. We then estimate the following regression specification with observations for county c, loan program p, year t:

$$\textit{denial rate}_{p,c,t} = \alpha + \delta \mathbb{1}[SBA_{p,c,t}] + \theta(\mathbb{1}[SBA_{p,c,t}] \times NPD_{c,t}) + \zeta_{c,t} + \epsilon_{p,c,t} \quad (1)$$

$NPD_{c,t}$ is the proxy for need for price discrimination in county c at time t, which we standardize to have zero mean and unit standard deviation. $\mathbb{1}[SBA_{p,c,t}]$ is an indicator equal to one if the denial rate is for the SBA program. $\zeta_{c,t}$ 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. The county×year fixed effects also absorb any variation across counties in disaster type (we directly investigate heterogeneity in disaster types later). In this specification, $\hat{\delta}$ represents the average difference in risk-insensitive SBA and risk-sensitive private-market denial rates. The estimate of interest is $\hat{\theta}$, which indicates the differential sensitivity in denial rates to NPD between the risk-insensitive SBA program and the risk-sensitive private-market lenders. $\hat{\theta} > 0$ indicates that the relationship between NPD and denial rates is stronger in the government-directed SBA program as compared with the private-market counterpart.

We also use the denial rate of the Federal Housing Administration (FHA) loan program as a 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 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.

Our research design ensures that our results cannot be explained away by any time-invariant unobserved differences across counties or differences in denial rates across the SBA and risk-sensitive program. Thus, the remaining threat to our identification has to come from unobserved variation between the two programs across counties with varying levels of *NPD*. Two broad categories of potential sources of such variation are (i) differences in the SBA loan officers and private market loan officers attitude towards minority borrowers for reasons unrelated to risk-sensitive pricing, and (ii) disproportionate worsening of the borrower pool in the disaster lending program for high-*NPD* areas. We discuss these concerns and our empirical strategy to address them below.

The first concern is there may be taste-based discrimination (Becker, 1957) by the SBA officers. If these officers deny credit to minorities based on prejudice, then this behavior can explain our results. In the case of taste-based discrimination, applicants from high-minority areas who receive credit under the disaster loan program must be of better credit quality than applicants from low-minority areas since high-minority area borrowers have to cross a higher hurdle to get the loan. We directly test this idea with a test that compares the ex-post default rates of approved loans across high- and low-minority areas. We discuss the details of this test later in the paper as we present the analysis.

The second concern related to our identification strategy is if borrowers experience a decline in their creditworthiness during the disaster period, then the private-market benchmark may end up underestimating their counterfactual denial rate for the disaster lending market. To the extent that loan officers in private markets anticipate the possible decline in credit quality due to a natural disaster, the effect of such a decline on our estimation strategy should be minimal. For example, private lenders are likely to incorporate such effects on credit quality in hurricane-prone areas even for non-disaster home loans since their estimate of creditworthiness for these borrowers is their creditworthiness over a long period of time. This would support the private-market denial rate from the risk-sensitive loan programs as a reasonable benchmark. Further, if such a deterioration is constant across areas with varying levels of *NPD* then our empirical strategy is unaffected because we are estimating the incremental denial rate for high-*NPD* areas as compared to relatively low-*NPD* areas. Our real concern is the following: the pool of disaster loan applicants in high-*NPD* areas is disproportionately worse than the risk-sensitive HMDA/FHA pool as compared to the corresponding difference for the low-*NPD* areas. We address this issue directly by examining changes in creditworthiness in counties before and after the disaster across different levels of *NPD*.

4 Data and Sample

We obtained the data on SBA Disaster home 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%. Panel B lists 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.

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.

We obtain data on private-market mortgage lending from the Home Mortgage Disclosure Act (HMDA) data for the years 1990-2015. 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. We match this rate to the relevant SBA loan applications by county and year. The HMDA denial rate at the county level (*HMDA denial*) serves as our control for the baseline variation in denial rates in private markets.[12] We alternatively use the denial rate for the subsample of HMDA loan applications that are made through the FHA program for some of our tests.

We use three key explanatory variables in our tests. We refer to them broadly as the *Need for Price Discrimination* or *NPD* measure. The motivation for these proxies are discussed in Section 3. Our first measure is the fraction of the minority population in the county from the Census. 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. For robustness, we use the level of income inequality in the area as a third *NPD* measure. 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

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

21% and FHA denial rate of 12%.

5 Results

5.1 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 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 of loan level regressions of whether an application was denied on *NPD* and control variables including state and disaster-type×year fixed effects. Columns (1)-(3) present the results using subprime share as the NPD proxy, and columns (4)-(6) present the results using minority share.[13] In columns (1) and (4), we present results for the base specification controlling only for state and disaster-type×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 4.5 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, and verified loss. Per capita income and population are county level variables. Verified loss is the amount of loss as determined by an SBA appraiser. This provides a good control for the need for borrowing at

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

the application level. As shown in Columns (2) and (5), including these controls does not change our main result. 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 6.4 percentage points (p-value<0.01) 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 10.4 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 a 23% higher likelihood 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 highly economically and statistically significant, while subprime share is insignificant. This suggests that the minority share of the population captures both the measured credit quality of the area as well as other unmeasured credit quality factors (with respect to credit score). The unmeasured factors may include 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 are qualitatively similar for subprime share as the proxy for *NPD*.

Since our key explanatory variables (*NPD*) are county specific, in our next specification we collapse all individual loan-level data to a county-level measure of denial rate. In this specification, we relate average county level loan denial rate to county level NPD characteristics. Table 4 presents the results. We find similar results at the county-level as the application-level, although the coefficients are typically smaller in magnitude.

Overall, our results so far establish an important correlation: the government's own lending program does not reach marginal borrowers – who are often the intended recipients of government programs – at the same rate as other groups. What could be the possible mechanism behind this result? In our next set of tests, we establish a link between lack of price discrimination in these programs and higher denial rate for marginal borrowers.

5.2 Within-County Variation: SBA versus HMDA

In this section, we analyze the within-county differences in denial rates between SBA and private market lending programs across areas with different racial composition. To do so, we estimate equation (1) by regressing county×year denial rates (SBA or private market) on the minority-share of the population, an indicator for the loan program, and their interaction. We also include county×year fixed effects, which will absorb the main effect of the minority share of the population (which does not vary within county×year). The estimates, therefore, examine whether the within-county×year difference in denial rates across SBA and private-market lending is greater for high-minority areas. As discussed earlier, such a research design ensures that our results are not driven by time-invariant county characteristics or the average differences in lending decisions across SBA and the risk-sensitive private market loans (HMDA).

Columns (1)-(3) of Table 5 present the results. The results in column (1) indicate the SBA program has about 21 percentage points higher denial rate compared to the private market 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 a one-standard-deviation higher minority share of the population as compared to the corresponding denial rate in the private market. Column (3) shows that the excess denial rate 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 private market denial rates). In sum, in the risk-insensitive SBA lending program, applicants from high minority areas are denied credit at a much higher rate relative to the private market.

5.2.1 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 applications to FHA applications, we minimize 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 perform the same tests as above, but with the FHA denial rate instead of the HMDA denial rate.

Columns (4)-(6) of Table 5 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 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 the FHA's 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.

5.3 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 tests (regression equation 1) 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 pricing channel. 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 6 presents the results. In these tests 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 Which Alternative Explanations Can We Rule Out?

Our identification strategy relies on the idea that within the same county×year, outcomes in the HMDA and FHA provide a good risk-sensitive lending counterfactual denial rate. As discussed earlier, our identification strategy takes care of unobserved heterogeneity across the lending programs (HMDA/FHA versus SBA) as well as across different counties. However, there are two key threats to our identification strategy. First, if SBA loan officers are more likely to engage in taste-based discrimination against minority borrowers compared to private lenders, then our results could simply be explained by such biases. Second, if the borrower pool in high-minority areas becomes especially worse in terms of creditworthiness at the time of disaster compared to the corresponding change for low-minority areas, then our results can be explained away by the change in borrower pool, and not by the lack of risk-sensitive pricing. We address these and other potential concerns below.

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 7 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 to Disaster:

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.

$$Subprime_{t+1} - Subprime_{t-1} = \zeta Minority_{c,t} + \delta_{d,y} + \Sigma_{state} + \Gamma X_{i,c,t} + \epsilon_{i,c,d,t} \tag{2}$$

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 8 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.

FEMA Assistance:

FEMA provides disaster assistance as grants to individuals. As a requirement to receive this grant, the borrowers must show that they have applied to SBA's disaster lending program and have been denied credit. If minority borrowers strategically apply (relative to other borrowers) for SBA loans with an intention to get denied so that they are eventually able to get the grant from FEMA, then our results could be driven by such "fake" applicants in the disaster loan pool. To address this concern, we turn to the applications for the SBA's *business* disaster loans. FEMA assistance is not available for business loans. Hence business loans provide an attractive setting where the effect of such "fake" applicants is not present. We estimate our base model using the SBA business loan denial rate and present the results in the Appendix Table A.2. We find similar results for businesses as home loans. We find businesses in high minority areas are denied credit at a significantly higher rate, making it unlikely that our main results are driven by fake applicants distorting the application pool.

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.[14] 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.

[14] 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.

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, and other SBA requirements are also needed to apply for most mortgages.

Time Periods, Disaster Size, and Disaster Types:

In Table 9, 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 25) or small disasters, as both subsamples exhibit a significant relationship between minority share and relative denial rates in the SBA program. In our final test, we look at 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. Table 10 shows that no single disaster type is driving our results.

7 Discussion and Conclusion

7.1 Economic Significance

In this section, we provide some context on the economic importance of our results by providing 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 5 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.

The calculation suggests that about $2.19 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 68,605 more homeowners would have had access to credit during these critical post-disaster time periods.

7.2 Related Literature

Our paper is connected to several strands of literature. It is most directly related to the literature on 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 finds 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 literature which studies the effects of regulation in private credit markets such as the effect of 19th century usury laws on access to credit (Benmelech and Moskowitz, 2010) and the effect of an interest rate ceiling on access to credit in Chile (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 borrowers and, more generally, marginal borrowers as compared to the private market.

Our paper is also related to the literature on 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) and Mullins and Toro (2017), show that 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.

7.3 Conclusions

We document a substantially higher denial rate for SBA disaster loan applications 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. This disparity occurs 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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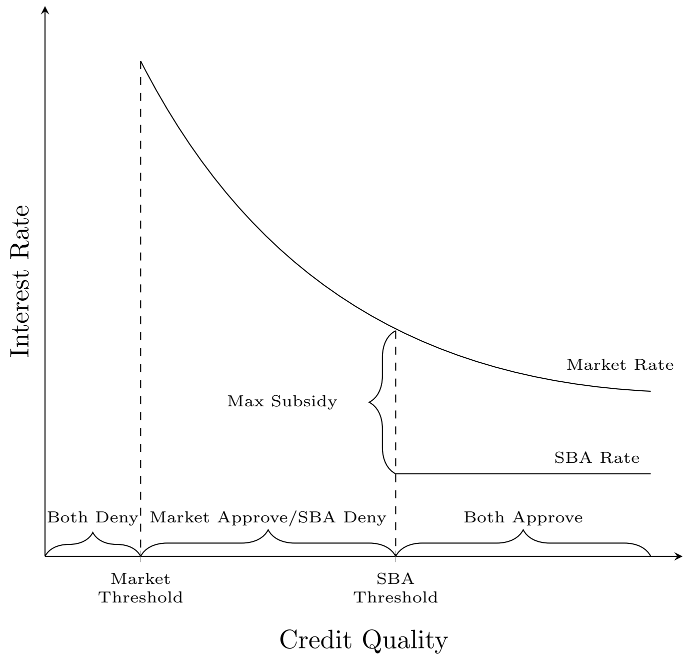

Figure 1: Credit Rationing
This figure illustrates the credit allocation decision with risk-insensitive and subsidized loan pricing (SBA) compared to the credit allocation with risk-sensitive (market) pricing.

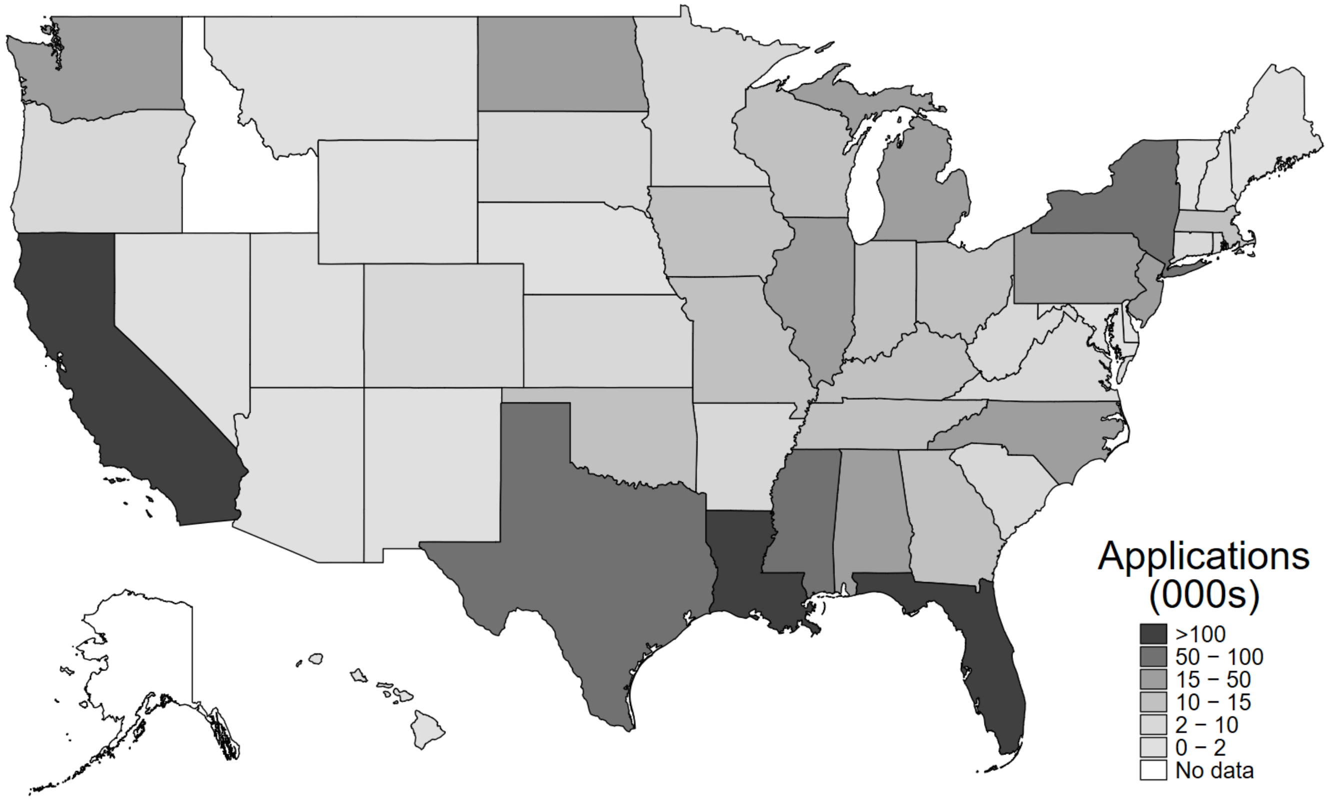

Figure 2: Geographical Distribution of Total Applications
This figure presents the number of disaster loan applications during the sample period of 1991-2015 for each state.

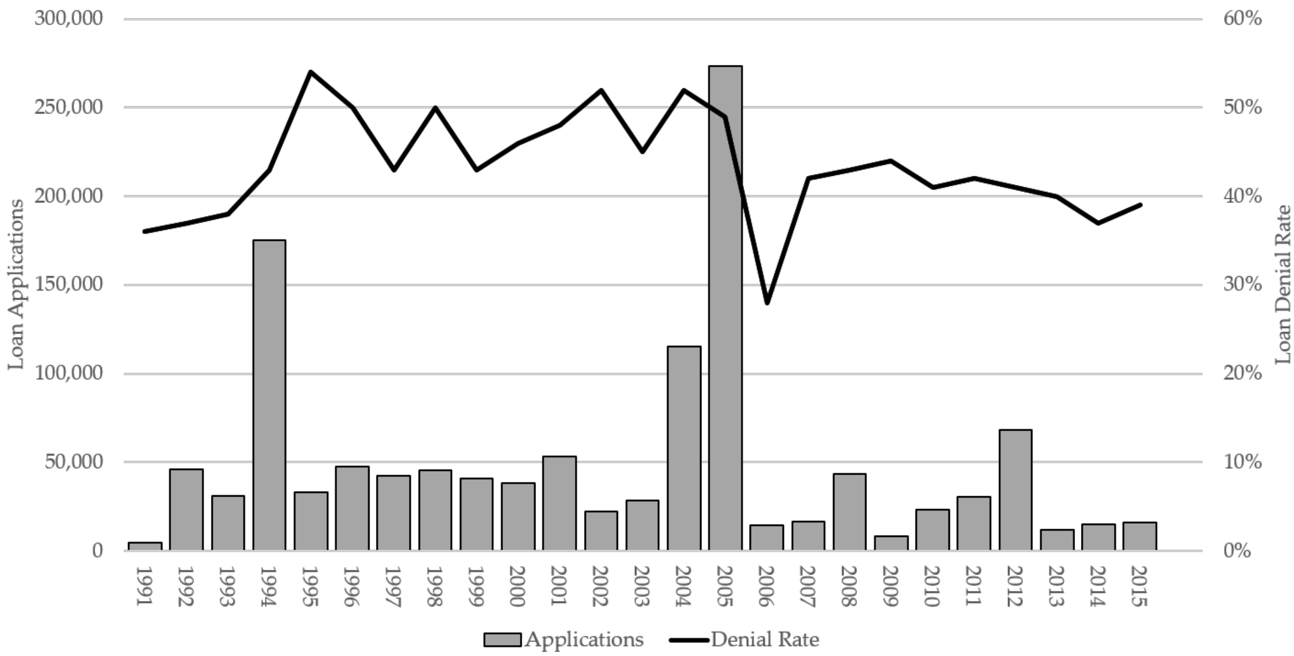

Figure 3: Applications and Denials Over Time
This figure presents the annual number of SBA disaster-relief home loan applications (left axis) and loan denial rates (right axis) for each year in the sample.

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 4, *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: Application-Level 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 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. *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***	0.032***					0.007
	(<0.01)	(<0.01)					(0.34)
Subprime 2q			0.005				
			(0.65)				
Subprime 3q			0.018				
			(0.33)				
Subprime 4q			0.064***				
			(<0.01)				
zMinority				0.045***	0.039***		0.038***
				(<0.01)	(<0.01)		(<0.01)
Minority 2q						0.028***	
						(<0.01)	
Minority 3q						0.056***	
						(<0.01)	
Minority 4q						0.104***	
						(<0.01)	
zSubprime × zMinority							0.006
							(0.12)
zPerCapitaIncome		0.006	-0.005		-0.005	-0.006	0.003
		(0.42)	(0.39)		(0.40)	(0.38)	(0.69)
zln(Population)		0.011**	0.018***		-0.006	-0.003	-0.013**
		(0.02)	(<0.01)		(0.20)	(0.55)	(0.01)
zVerifiedLoss		-0.068***	-0.068***		-0.075***	-0.074***	-0.067***
		(<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	822497
R^2	0.019	0.038	0.038	0.021	0.038	0.038	0.040

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

Table 4: County-Level SBA Loan Denial and Need for Price Discrimination: Subprime and Minority Share

This table presents OLS estimates from the regression of the county-level average SBA home loan denial (*SBA Denial*) for a given county-year 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 county-level average loss of the applicants as a result of the disaster as verified by SBA officials. *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	0.023***	0.017***					0.001
	(<0.01)	(0.01)					(0.94)
Subprime 2q			0.019*				
			(0.09)				
Subprime 3q			0.025*				
			(0.09)				
Subprime 4q			0.035**				
			(0.04)				
zMinority				0.028***	0.028***		0.028***
				(<0.01)	(<0.01)		(<0.01)
Minority 2q						-0.012	
						(0.16)	
Minority 3q						0.000	
						(0.97)	
Minority 4q						0.038***	
						(<0.01)	
zSubprime × zMinority							-0.002
							(0.62)
zPerCapitaIncome		-0.007	-0.011		-0.021***	-0.024***	-0.012
		(0.38)	(0.19)		(<0.01)	(<0.01)	(0.13)
zln(Population)		-0.003	-0.003		-0.007	-0.001	-0.011**
		(0.51)	(0.56)		(0.13)	(0.82)	(0.05)
zVerifiedLoss		-0.025***	-0.025***		-0.029***	-0.030***	-0.024***
		(<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	6019	6019	6019	8497	8497	8497	6019
R^2	0.112	0.119	0.119	0.105	0.115	0.113	0.123

p-values in parentheses

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

Table 5: 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.

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

denial rate is the county-year denial rate for either SBA home loans or the HMDA/FHA denial rate. For HMDA/FHA loans, the denial rate is for applications 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 *Minority* with the first quartile (e.g., lowest minority share) as the omitted category (their main effects are absorbed by the fixed effects). Each regression includes county×year fixed effects (which absorb the main effects of Minority and *Disaster-Year FE*). 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
Observations	16882	16882	16882	16074	16074	16074
R^2	0.617	0.621	0.621	0.625	0.629	0.629

p-values in parentheses

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

Table 6: County-Level Differences in Denial By Income Inequality

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).

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

denial rate is the county-year denial rate for either SBA home loans or FHA loans. For FHA loans, the denial rate is for applications 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 *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 *Minority* with the first quartile (e.g., lowest minority share) as the omitted category. Each regression includes county×year fixed effects (which absorb the main effects of *Minority*, *Gini*, and *Disaster-Year FE*). 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
Observations	16074	16074	16074	16074	16074
R^2	0.625	0.627	0.630	0.628	0.630

p-values in parentheses

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

Table 7: 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 8: 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 9: Results Over Time and By Disaster Size

This table presents results for our main regression specification across sub-periods and across disasters of different size. 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. We present OLS estimates from the regression of county-level loan denial rates (SBA or 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.

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

denial rate is the county-year denial rate for either SBA home loans or FHA loans. For FHA loans, the denial rate is for applications in the county in the most recent year in which there was no disaster. *Minority* represents the nonwhite share of the county population. Each regression includes county×year fixed effects (which absorb the main effects of Minority and *Disaster-Year FE*). All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. In columns (1)-(5), the regressions are run by time period with the header indicating the included years. In columns (6) and (7), the regressions are run separately for large and small disasters. The regression in column (6) includes only top 25 disasters by application count and the regression in column (7) only includes the non-top 25 disasters. Standard errors are clustered by county.

	Time Period					Top 25 Disaster	
	1990-96	1997-2000	2001-04	2005-09	2010-15	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}[SBA]$	0.339***	0.330***	0.325***	0.260***	0.162***	0.367***	0.262***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
$\mathbb{1}[SBA]\times$zMinority	0.046***	0.031***	0.073***	0.047***	0.020***	0.019**	0.026***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.04)	(<0.01)
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2560	2686	3592	3652	3584	2288	13774
R^2	0.677	0.663	0.661	0.628	0.578	0.747	0.618

p-values in parentheses

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

Table 10: Results Excluding Each Type of Disaster

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 the minority share of population in the county, whether the observation represents the SBA denial rate, and their interaction. In each regression, we exclude a type of disaster with the excluded disaster indicated at the head of the column.

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

denial rate is the county-year denial rate for either SBA home loans or FHA loans. For FHA loans, the denial rate is for applications 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). Each regression includes county×year fixed effects (which absorb the main effects of Minority and *Disaster-Year FE*). 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)
$\mathbb{1}[SBA]$	0.277***	0.276***	0.260***	0.349***	0.273***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
$\mathbb{1}[SBA]$×zMinority	0.035***	0.034***	0.027***	0.022***	0.032***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
County-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	15958	15590	13716	3808	15212
R^2	0.629	0.629	0.618	0.723	0.626

p-values in parentheses

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

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: Business Loans: County-Level Differences in Denial By Minority Share
For each county-year in the SBA dataset, we compute the business 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 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.

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

denial rate is the county-year denial rate for either SBA business loans or FHA loans. For FHA loans, the denial rate is for applications 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), Each regression includes county×year fixed effects (which absorb the main effects of Minority and *Disaster-Year FE*). 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)
$\mathbb{1}[SBA]$	0.260***	0.259***	0.214***	0.335***	0.333***	0.292***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
$\mathbb{1}[SBA]$×zMinority		0.031***			0.038***	
		(<0.01)			(<0.01)	
$\mathbb{1}[SBA]$×zMinority 2q			0.025*			0.011
			(0.06)			(0.49)
$\mathbb{1}[SBA]$×zMinority 3q			0.072***			0.066***
			(<0.01)			(<0.01)
$\mathbb{1}[SBA]$×zMinority 4q			0.083***			0.086***
			(<0.01)			(<0.01)
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12210	12210	12210	11630	11630	11630
R^2	0.638	0.641	0.642	0.668	0.672	0.672

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