Disaster Lending: The Distributional Consequences of Government Lending Programs*

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Abstract

Residents of areas with a greater proportion of minorities are denied credit through the Small Business Administration's (SBA) disaster lending program at a significantly higher rate than areas with a lower proportion of minorities. This difference in denial rates is not explained by observable differences in credit risk and is larger than the corresponding difference in denial rates in private lending markets. We find no evidence that taste-based discrimination is driving this result. Rather, we find the difference in denial rates is likely driven by the SBA's use of risk-insensitive loan pricing, where the same interest rate is offered to all approved borrowers irrespective of their relative creditworthiness. This leads to outcomes where borrowers that would likely receive a loan at a higher interest rate are instead denied credit altogether. Overall, our findings highlight the importance of using market prices as a mechanism to allocate credit across borrowers. Programs that limit the use of this mechanism to ensure a "fair" price of credit across borrowers may have unintended "unfair" consequences on the quantity of credit.

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

JEL Classification: G21, G28, H81, H84

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1 Introduction

Fair access to credit for minority borrowers has been one of the central themes of U.S. banking regulation over the past fifty years. A number of government agencies enforce regulations like the Fair Housing Act (1968) and the Equal Credit Opportunity Act (1974) that are intended to ensure private lenders are providing fair access to credit across borrowers of different race, religion, gender, etc. But how does the government's own direct lending to its citizens fare on this dimension? Little is known about this vital question despite the fact that many government and supranational agencies around the world provide large volumes of loans in many different settings. Our paper is one of the first to address this question by analyzing the Small Business Administration's (SBA) disaster lending program which provides loans from the U.S. government to both households and businesses who are victims of natural disasters.

The SBA's disaster lending program provides an important setting to study the economics of government lending to minority borrowers in at least a couple of ways. First, these loans provide support to borrowers at a time of acute need for funds. Natural disasters such as hurricanes, fires, and earthquakes have devastating social and economic consequences. Affected populations face severe hardships ranging from loss of wealth and income to adverse health outcomes. Recovery from these crises becomes especially hard if there is limited private-market capital available to affected households and businesses. Thus, access to government-provided credit becomes especially important in this setting. Second, the SBA directly administers disaster loans. Compared to normal private-market lending where private lenders make decisions constrained by government regulations, this setting provides a clean study of direct government lending programs. This allows us to evaluate how the government lending program performs relative to the private market in terms of meeting the objective of equal access to credit.

Using a Freedom of Information Act request we obtained detailed information on the credit allocation decisions under this program for a large set of natural disasters. The data covers over 1.5 million loan applications across the U.S. between 1991-2015 and allows us to conduct our empirical analysis at a granular level. More importantly, while most publicly available databases of government lending programs only have information on loans that have been approved, our dataset allows us to analyze the approval/denial decision for these government loans.

The SBA provides disaster loans to both individuals (which we refer to as home loans) and businesses. We conduct our analyses separately for these two loan categories. We find the SBA denies loan applications at a significantly higher rate in counties with a larger minority population. The result is not explained away by the fraction of low FICO score borrowers in the county (subprime share), per capita income of borrowers, or the extent of losses incurred in the disaster. A one-standard-deviation increase in minority population is associated with a 4.2 percentage points higher denial rate in home loans; the corresponding effect is very similar at 4.3 percentage points for business loans. These effects are large: the average denial rate in our sample is 46% for home loans and 40% for business loans. Thus borrowers who reside in these areas are about 10% less likely to get a loan when disaster strikes as compared to borrowers who live in an area that has one standard deviation lower minority population. In sum, these results provide evidence that the disaster loans are not reaching borrowers in high-minority areas at the same rate as low-minority areas.

It is well known that even in private lending markets areas with higher credit risk are likely to have more credit rationing (Stiglitz and Weiss, 1981). The core idea behind this channel is that raising the interest rate beyond a point can result in adverse selection in the borrower pool: at very high interest rates only the inferior, credit-unworthy borrowers take loans. Hence, banks do not raise interest rates beyond a point and credit rationing arises even in market equilibrium under asymmetric information. It may be that residents of high-minority areas have higher credit risk that we do not fully account for in our initial tests. There is a large literature examining this issue in private markets which provides evidence of lower access to credit for minorities (see, e.g., Munnell, Tootell, Browne, and McEneaney, 1996). Are goverment-directed lending programs more effective than private markets in serving minority borrowers? We examine whether there is excess credit rationing of these groups by the government compared to the private market. Our empirical setting is attractive because we are able to observe the loan approval/denial outcome for comparable lending products in the private market for the same area. We use the denial rate in the home mortgage market, obtained from the Home Mortgage Disclosure Act (HMDA) database, as a base level of denial in the private market that occurs as a result of, among other things, informational frictions.[1] The HMDA denial rate should capture variation in denial rates due to both observable and unobservable differences in the credit quality distribution across counties. In these tests, we estimate the government lending program's denial rates across areas with varying levels of minority population *as compared* to corresponding differences in the denial rates in a comparable private lending market. Given the government's goal of alleviating frictions in access to credit for marginal borrowers, it may be argued that government lending programs should have relatively lower credit rationing for residents in minority areas as compared to the private market.

We show that the SBA loan denial rate remains significantly higher in counties that have a larger minority population even after controlling for the corresponding denial rate in private home mortgage markets. While it is indeed true that the SBA denial rate is higher in counties with a higher HMDA denial rate, this variable does not explain away the main result. Inclusion of the HMDA denial rate decreases the magnitude of the minority share coefficient by only about 10-20%. In an alternative specification, we use a difference-in-differences specification to examine whether there is a differential effect of minority status on denial rates across SBA verus HMDA lending. Indeed, we find that the relationship between the minority share of population and denial is about three times stronger in the government-directed SBA

[1]We focus particularly on HMDA refinancing loans because this is the private market lending category that is closest to SBA home loans: both these loans are geared towards borrowers who are already home owners.

program than the private market. These results paint a clear picture. Despite some concerns and issues surrounding the behavior of private markets in providing "fair" access to credit, private markets grant loans to a significantly larger fraction of borrowers in higher-minority areas as compared to the government lending program. To the extent a key goal of the government is equal access to credit for all demographic groups, the government fairs worse in achieving this goal than the private market lenders. What are the potential explanations for this result?

We argue that our results are due to a key feature of the design of the disaster lending program which is also a feature that is common across most government lending programs around the world – namely, the lack of risk-sensitive pricing (i.e., one price for all approved borrowers). In making the loan decision, the SBA engages in borrower screening by considering the borrower's credit history, repayment capacity, and collateral availability. By law, this information cannot be not used for loan pricing. Conditional on the approval of the loan, the SBA charges the same rate of interest to all borrowers of a given loan type (e.g., same rate for all home loans).[2] Thus, unlike private markets where both loan rate and quantity can be adjusted depending on borrower characteristics, under the SBA lending program it is only the quantity dimension that can be adjusted. Therefore, borrowers that may be creditworthy at a higher rate of interest if price discrimination were allowed are denied credit altogether under such a policy. If areas with higher share of minorities are likely to to have more borrowers that are creditworthy only at a higher interest rate than areas with lower minority share, then an unintended consequence of risk-insensitive pricing is simply a higher denial rate for such borrowers. Our results that document higher denial rates in high-minority counties is consistent with this channel.

We conduct an additional test to lend further support to the risk-insensitive pricing channel. In this test, we use an additional proxy for the need for price discrimination in

[2]The SBA charges a second rate, which is twice the baseline rate, to borrowers with clear access to another source of financing. The vast majority of borrowers receive the lower, baseline rate.

the lending market: the level of income inequality in the county. Holding fixed the average income of the county, counties with higher income inequality will have greater credit quality dispersion and, therefore, greater need for price discrimination. By construction, relatively more borrowers in high-income-inequality counties are likely to fall in the left tail of the credit distribution and, as a result, may not be creditworthy at a low interest rate. Like high-minority areas, these are areas which have a higher need for risk-sensitive pricing in order to gain access to credit. Indeed, we show that residents of high-income-inequality counties, as proxied by the Gini index, are denied credit at a much higher rate in the disaster lending program as compared to the private lending market.

An alternative explanation of our result is the possibility of taste-based discrimination. If the governments loan officer are prejudiced against minorities, we would expect higher denial rates in minority areas. In a seminal contribution, Becker (1957) argues that profit motivations can eliminate such discrimination in the market place. The lack of a profit motive for the SBA and its loan officers removes this market based discipline, and our next test examines whether such could be driving the results. We investigate this by examining the default performance of approved disaster loans. In the context of the labor market, Becker (1957) argues that if minorities are discriminated against due to employer taste (i.e., distaste for minorities), then, conditional on getting the job, minority performance should be relatively better. We apply the same idea to the lending market. If there exists taste-based discrimination in the SBA program against applicants from high-minority areas, then the marginal approved borrower in these areas should be of relatively higher quality. Hence, lower ex-post default rates for high-minority areas would support active taste-based discrimination. We do not find such evidence. We find that areas with a higher share of minority population and higher levels of income inequality have similar or slightly higher default rates, suggesting taste-based discrimination is not driving our results.

We provide some context on the economic importance of our results by estimating the additional loans that would have been approved in areas with a higher minority population had these areas experienced similar denial rates as lower minority population areas. If applicants, conditional on similar income, in all quartiles of minority population were to receive loans at the same approval rate as the first quartile (i.e., lowest minority population), our estimates show that about fifty-one thousand additional homeowners and eleven thousand additional businesses would have received loans, which adds up to a grand total of about $2.5 billion. This is economically large, especially because these loans are denied in the wake of a natural disaster when the marginal value of credit is especially high.

Overall, our paper documents important disparities in access to government-provided credit across areas with different racial composition and income inequality. Further, our results highlight important unintended consequences of the risk-insensitive pricing schemes that are typically employed by government lending programs. Clearly, there are some benefits of risk-insensitive pricing like the perception of fairness and perhaps allowing for faster processing of loans. Indeed the SBA's stated purpose is to provide "affordable, timely and accessible financial assistance." However, these benefits come at a significant cost in terms of a higher denial rate than would be observed under a risk-sensitive pricing scheme. The excess denial rates are especially severe for the populations that are often the intended target of government assistance: areas with higher minority populations and greater inequality.

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). Our study is also connected with the literature on the political economy of government economic interventions. This vast literature primarily focuses on the consequences of price and entry controls on a broad spectrum of industries (see Rose, 2014, for a recent synthesis of this literature).

Closer to our paper is recent work on the mortgage market, where risk-insensitive products are usually associated with the government-sponsored enterprises (GSE) the Federal National Mortgage Association and the Federal Home Loan Mortgage Corporation. These GSEs can affect borrower access to credit through their role in the secondary market for residential mortgages. Specifically, GSEs can discourage regional risk-sensitive pricing by only approving mortgage loans that they consider as GSE-conforming. Hurst, Keys, Seru, and Vavra (2016) show that the GSEs charge uniform prices across different areas even though there is significant variation in predictable default risk across regions. Kulkarni (2016) explores the interactions between GSE's uniform pricing policies and how it affects credit availability to borrowers 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 contributes to the underlying research theme of this literature.

2 SBA Disaster Loan Program

The Small Business Administration (SBA) Disaster Loan Program provides loans to businesses and individuals (homeowners and renters) that are victims of disasters declared by the President or SBA. Since program inception, over 1.9 million loans totaling over $47 billion have been approved by the SBA (Lindsay, 2010). For individuals, loans are available to repair or replace real estate and personal property. For businesses, there are two types of loans available: business physical disaster loans and economic injury disaster loans (EIDL). The business physical disaster loans can be used to repair or replace real property, machinery, equipment, fixtures, inventory, and leasehold improvements.[3] The economic injury disaster loans are made available if the business "is unable to meet its obligations and to pay its ordinary and necessary operating expenses."[4] The SBA's loans cover only the uninsured

[3] Additional funds are available to make improvements that will reduce the risk of future damage (up to 20% above real estate damage).

[4] https://disasterloan.sba.gov/ela/Information/EIDLLoans

portion of loss. There are statutory limits or caps on the loan amount, interest rate and repayment terms for SBA loans. Table A.1 provides details on these caps and eligible borrowers for each type of loan.

In the wake of a disaster, the SBA must process loan applications, perform inspections, make a lending decision, contract with the borrower, and disburse funds. The SBA assesses applicants' creditworthiness when determining whether or not to approve the loan. The lending decision is based on a number of factors: an acceptable credit history, an ability to repay loans, and collateral if collateral is available. The fact that the SBA screens applicants based on their creditworthiness indicates the SBA cares to some extent about the performance of their loan portfolio.

Although loan performance is considered in the screening process, the SBA does not differentially price loans according to applicant risk. The loan interest rate is determined by a statutory formula based on the government's cost of borrowing. Within a borrower type (individual, business or non-profit) there are only two possible interest rates that are charged; a lower rate for borrowers who do not have credit available elsewhere and a higher rate for borrowers who do have credit available elsewhere. The vast majority of borrowers receive the lower rate in our sample. Importantly, there is no variation in the interest rate across borrowers based on credit risk. For illustrative purposes, we provide the interest rate menu for Texas counties affected by Hurricane Harvey (Disaster TX-00487) in Figure A.1.

3 Research Design

Our initial analysis examines the relationship between the share of minorities in the applicant's county and the denial rate of SBA loans in that area. We regress the SBA denial rate on the minority share of the county while controlling for a host of variables potentially related to baseline loan denial rates. While simple, these first tests document an important relationship between the the racial composition of an area and access to government-directed credit.

We then examine some potential channels behind our initial results. In particular, we focus on the role of risk-insensitive pricing in the SBA lending scheme and the potential role of taste-based discrimination against minorities.

The role of price in allocating resources across different projects in an economy is a central concept in economic theory. Credit markets are no different. When lenders are able to charge interest rates based on the risk profile of the borrowers, more borrowers will have access to credit. Fixed-price lending programs, on the other hand, ration some borrowers from the market: once the expected loss rate on the loan exceeds the rate the lender can charge as compensation for the risk, the borrower is simply denied credit rather than charged a higher rate commensurate with their risk. The importance of risk-sensitive pricing in allocating credit to high risk borrowers motivates our key hypothesis: areas with higher fractions of borrowers with default risk above the SBA's default-risk cutoff point or borrowers that require a greater collection of soft information to determine credit quality have higher denial rates due to risk-insensitive pricing. To test this, we focus on the minority population of the county as a key measure for the need for price discrimination (NPD) in the following specification.

$$deny_{i,c,t} = \alpha + \psi NPD_{c,t} + \Gamma X_{i,c,t} + \epsilon_{i,c,t} \tag{1}$$

Our main proxy for NPD is the minority share of population in the county. This is motivated by the large literature showing that borrowers in minority areas borrow at a relatively higher interest rate from the private lending market. An additional proxy is county-level income inequality. Holding fixed the average level of credit risk, areas with higher dispersion in credit risk should have a relatively higher proportion of borrowers who could benefit from price discrimination.

We include state fixed effects to separate out the effect of any state-by-state differences in the implementation of SBA disaster loans. As noted earlier, these loans come under the federal program, and therefore they have the same terms for all borrowers irrespective of where the disaster strikes. However, there may be a concern about differences in the implementation at the state level, which we absorb with state fixed effects. We also include a fixed effect that is *disaster-type* $\times$ *year* specific. This fixed effect, by construction, soaks away variations that are specific to a certain type of disaster (say hurricanes) in a given year (say 2005). Inclusion of these fixed effects in the model allows us to control for differences in lending policies across different types of disasters, say earthquake relief from hurricane relief. At the same time, by interacting with year of disaster we are able to remove the effect of macroeconomic trends, including issues such as budgetary constraints of the government or variation in national policies concerning these programs. In the end, this specification allows us to exploit the cross-sectional variation in the need for price discrimination across different counties, holding fixed state wide differences and time-varying disaster-type differences in SBA's lending policies.

To better understand the source of the differential denial rates across areas, we compare the SBA denial rate to the private-market denial rate. We know that even in private lending markets, not all loan applicant receive credit. In markets with asymmetric information between lenders and borrowers, prices do not always clear the market for all borrowers. Specifically, some high-risk borrowers are rationed by banks that are able to engage in risk-sensitive pricing (Stiglitz and Weiss, 1981). Thus, the private-market level of denials is likely to be higher precisely in those markets with a relatively higher fraction of borrowers for which the information asymmetry is likely more severe. In comparing government SBA lending to private-market lending, a key challenge is to separate the effect of private-market equilibrium credit rationing from the denial rate we observe with SBA disaster loans.

Our core idea is summarized in Figure 1. The graph plots the market determined interest rate on the y-axis for borrowers with varying levels of observed credit risk on the x-axis. All borrowers below the credit threshold denoted by *Market Threshold* are denied credit even with a risk-sensitive pricing mechanism. This happens because the lender is unable to observe the true credit quality of borrowers and hence it denies credit to borrowers with very 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 since the SBA prices its loans at a subsidized rate that is below the market rate for all borrowers. 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. The SBA makes all loans that are 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 is excess denials in SBA lending, compared to the private market benchmark. Our next empirical tests are aimed at teasing out this excess denial by exploiting variation across areas that differ in terms of the fraction of the population that falls below this threshold.

This discussion also underscores the empirical difficulty in estimating the effect of risk-insensitive pricing on the SBA's credit allocation decision. The goal of an ideal research design is to estimate the proportion of borrowers that fall between the market threshold and the SBA threshold. We do not observe these thresholds. A positive correlation between areas with higher *NPD* and SBA loan denial rate could simply be capturing the fact that in such markets private lenders also ration credit at higher rates. We need to account for this effect. Our setting is attractive because we are able to observe the credit allocation decision in the private lending market for the same areas, namely the approval/denial decision in home mortgage loans made to practically all U.S. borrowers by all private lenders. For every county we are able to obtain data on denial rates for all borrowers in the HMDA dataset for non-disaster years. Our primary analysis controls for the denial rate in the HMDA database for all refinancing loans made in that county in the most recent non-disaster year. The idea behind this test is simple: if the HMDA denial rate is a sufficient statistic of private market rationing, then we should be able to detect the effect of the *NPD* variable using the following regression model estimated with all SBA loans:

$$deny_{i,c,t} = \alpha + \psi NPD_{c,t} + \rho(HMDA\ Denial)_{c,t} + \Gamma X_{i,c,t} + \epsilon_{i,c,t} \tag{2}$$

We also perform tests that examine differences in ex-post loan performance across groups. As we will describe more in the results section, taste-based discrimination has implications for the performance of loans that are actually granted to the groups that are discriminated against. Specifically, this theory would predict better default performance (i.e., lower default rates) for these areas.

4 Data and Sample

We obtained the data on SBA Disaster home and business 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 dataset includes around 1.5 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), and 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 for home loans and business loans separately. 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 loans applications are in response to disasters including tornadoes, severe thunderstorms, hail, and flooding. There is 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 some variation in the denial rate across different types of disasters, but it is broadly in the range of 40-50%: thus a number of loan applicants are denied credit in the disaster loan market.

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

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

We obtain data on private-market lending from the the Home Mortgage Disclosure Act (HMDA) data for the years 1991-2015. These data include the vast majority of home purchase and refinancing loan applications and lending decisions in the U.S. for that time period. To most closely mirror the SBA applicants (most of whom already own their home), we focus on the HMDA refinancing applications. From these applications, we compute the county-level denial rate for refinancing loans during the most recent year in which the county did not experience a disaster and match this to the relevant SBA loan applications in that county. The HMDA denial rate at the county level (*HMDA denial*) serves as our control for the baseline variation in denial rates in private markets.[5]

We use two key explanatory variables in our tests. We refer to them broadly as the *Need for Price Discrimination* or *NPD* measure. Our first measure is the fraction of the minority population in the county from the Census. The use of this variable as a proxy for NPD is motivated by a large literature on racial differences in lending markets. The second *NPD*

[5]The results are similar using contemporaneous year or averages of 2-3 prior years.

measure is the level of income inequality in the area. Such areas have borrowers on both extremes of the income distribution, and thus the underlying credit dispersion is likely to be higher. We use the county-level Gini index from the US 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 US Census data also provides county population and the St. Louis Federal Reserve (FRED) database provides the remaining county-level economic variables including per capita income and the percentage of individuals with Equifax subprime credit scores in a county, which is only available from 1999 onwards. In addition, we obtain data on verified losses incurred by the borrower due to the disaster according to 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 home and business denial rates of 46% and 40% is considerably higher than the average HMDA denial rate of 22%.

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 minority share of population in the disaster-struck county using the following baseline model:

$$deny_{i,c,t} = \alpha + \psi Minority_{c,t} + \Gamma X_{i,c,t} + \delta_{d,t} + \zeta_s + \epsilon_{i,c,t}, \quad (3)$$

where $deny_{i,c,t}$ is an indicator variable that equals one when the loan application i from county c at time t is denied. The key objective of this regression is to estimate ψ, which is the relationship between the minority share ($Minority_{c,t}$) and loan denial. $X_{i,c,t}$ is a vector of control variables that may also play a role in determining baseline variation in the denial decisions and includes per capita income, population, and the verified loss the applicant suffered which led to the loan application. Verified loss measures the extent of loss incurred by the applicant as a result of the natural disaster, and the loan grant decision and amount depends on this amount. $\delta_{d,t}$ is a vector of fixed effects for each disaster type and year combination (e.g., hurricane in 2004) and ζ_s is a vector of state fixed effects which control for any time-invariant fixed differences between states that may affect SBA loan denial rate. 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 for home loans. Columns (1)-(3) present results for the continuous, standardized measure of minority share. In column (1), we present results for the base specification before including controls. We find a one standard deviation higher minority share is associated with an increase of 4.7 percentage points (p-value<0.01) in the loan denial rate. In column (2), we show that including controls for per capita income, population and verified loss barely affects the point estimate on minority share which remains of similar magnitude at 4.2 percentage points (p-value<0.01). In column (3), we include the subprime share of the applicant's county as an additional control and the coefficient of interest is unchanged.[6] The inclusion of observable demographic variables does little to explain the disparity in denial rates across high and low minority share counties. In columns (4)-(6),

[6]The number of observations decreases because we only have subprime share data from 1999 onwards.

we examine the effect across quartiles of minority share. The effect increases monotonically as one moves from the lowest to highest quartile of minority share. We find counties in the highest quartile have 10.2 to 12.8 percentage points (p-value<0.01) higher denial rate than the lowest bracket depending on the specification. This effect is economically large. Compared to the sample average denial rate of around 46%, the counties with the highest minority population have close to a 25% higher chance of being denied.

We repeat these tests for business loans in Table 4 and find statistically and economically similar results to the home loan tests. Home loans are often tied to the collateral values, whereas business loans are often (though not exclusively) tied to future cash flows of the business. The consistency of our estimates across both these types of loans suggests that our results cannot be explained away by any difference in the type of loan demanded by minority borrowers. The results show that the SBA denies loan applications at a significantly higher rate for borrowers in counties with a greater minority share of the population. However, the results so far are silent about what the denial rate would have been if these borrowers were to approach private lending markets. Our next set of tests address this question through the use of HMDA data.[7]

5.2 Controlling for private-market credit rationing

Our goal for the next tests is to separate out the extent of credit rationing that occurs in the private market due to, among other things, informational frictions. We do so with a series of tests using outcomes in the private home mortgage market. In our first test, we include the HMDA home refinancing loan denial rate as a control variable. The HMDA denial rate is the denial rate in the most recent year without a disaster as described in Section 4 (*HMDA denial*). The underlying identifying assumption is that conditional on the HMDA denial rate, there is no remaining unobserved credit rationing that would occur with risk-sensitive

[7]For brevity, we only present the results for home loans in the remainder of the paper. In the Online Appendix, we present the additional estimates using business loans results and find similar results.

pricing that correlates both with minority share and the denial rate in disaster loans. The comprehensive nature of the HMDA dataset and the comparability of lending products in the HMDA loan market and SBA disaster loans provides support for this assumption.

Table 5 presents the results. Counties with higher denial rates in the private lending market are indeed denied at a higher rate in the government-directed lending market. A one-standard-deviation increase in the HMDA denial rate is associated with an increase of 1.8–2.3 percentage points (p-value<0.01) in the rate of denial in SBA home loans. However, the inclusion of this variable does not explain away the coefficient on minority share. Columns (1)-(3) present the results for the continuous minority share measure, and indicate that a one-standard-deviation increase in minority share is associated with a 3.1 – 4.0 percentage points (p-value<0.01) higher denial rate. Examining the regressions using the minority quartile indicator variables in columns (4)–(6), strong monotonicity in the effect and even convexity across minority quartiles remains. The highest-quartile minority share counties experience 7.8 – 10.5 percentage points higher denial than the lowest-quartile minority share counties. Across the specifications, about 25% of the effect of minority share on the SBA denial rate can be explained away by the private market denial rate. What remains, however, is an economically large disparity in credit access from the government-directed SBA lending program between high- and low- minority areas even after accounting for the private-market denial rate.

To further contrast the decision making between government and private lending programs, we present a simple difference-in-difference estimation for SBA versus HMDA lending across areas with different racial composition. We construct a dataset at the level of county-disaster-year and compute the SBA denial rate for the dependent variable. For each observation, we then create a corresponding observation where we replace the SBA denial rate with the county's HMDA denial rate as described earlier. Thus, for each county-disaster-year we have two observations: one with the SBA denial rate and one with the HMDA denial rate. We then estimate the following regression specification.

$$
\begin{aligned}
\textit{denial rate}_{i,p,c,t} = & \alpha + \delta \mathbb{1}[SBA]_{i,p,t} + \psi \textit{Minority}_{c,t} \\
& + \theta(\mathbb{1}[SBA_{i,p,t}] \times \textit{Minority}_{c,t}) + \Gamma X_{i,p,c,t} + \epsilon_{i,p,c,t}
\end{aligned} \tag{4}
$$

In this specification, $\hat{\delta}$ is the fixed difference in SBA and HMDA rates and the estimate of interest is $\hat{\theta}$, which indicates the differential sensitivity in denial rates to minority share between the SBA and HMDA lenders, where $\hat{\theta} > 0$ indicates that the positive relationship between racial composition and denial rates is even stronger in the government-directed SBA program as compared to the private-market HMDA counterpart.

Table 6 presents the results. The coefficient on the SBA dummy variable reflects the higher average denial rate of about 20 percentage points on SBA loans, and the coefficient on *Minority* reflects the relatively higher denial rates for high-minority areas in the private market. The key point estimate is the interaction between SBA status and minority which is 0.27 (p-value<0.01) in column (3) of the table. Thus, a one-standard-deviation increase in minority share increases the likelihood of denial by about three times as much for SBA loans as compared the private-market loans. We find similar results when examining the quartiles of minority share in columns (4)-(6). In sum, a higher minority share corresponds to higher denials in both government-directed and private markets, but the effect is much larger in government-directed lending.

5.3 Risk-Insensitive Pricing

The previous results show that the differential denial rate between high- and low-minority share areas is not explained by the denial rates in the private market. There are two potential explanations for the observed pattern: it is due to a particular design feature of the SBA loan program or due to taste-based discrimination. We examine each of these explanations in turn.

A key feature of the SBA disaster loan program is that the interest rate charged on loans does not vary according to borrower credit quality. The SBA does screen applicants on a number of dimensions, but, conditional on approval, all borrowers of a broad type (e.g., those with no credit available elsewhere) pay the same interest rate. This risk-insensitive loan pricing scheme can lead to the denial of applicants that would likely qualify for a loan at a higher interest rate. For these borrowers, price discrimination or, said differently, risk-sensitive pricing is necessary to obtain credit. Because the SBA cannot price discriminate, areas with greater need for price discrimination (NPD) experience greater rates of denial. Because high-minority share areas are likely areas with greater dispersion in true credit quality and, thus, have a greater need for price discrimination, applicants from these areas are denied at higher rates than in private markets with risk-sensitive pricing.

There may be concerns minority population is not measuring NPD, but rather is related to some other unobserved factor unrelated to NPD that correlates with the denial decision. 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 a similar test to the minority regressions except with Gini as the cross-sectional variable of interest. The motivation for using Gini is that higher Gini areas will, by construction, have a greater dispersion in credit quality and, therefore, greater need for price discrimination in lending markets. If higher-Gini areas experience greater denial rates even after controlling for the average per capita income, then this is consistent with risk-insensitive pricing leading to greater denial rates.

We present the results in Table 7. We find the need for price discrimination is strongly related to SBA denial rates even after controlling for a host of variables. A one-standard-deviation increase in income inequality is associated with 2.8 – 3.4 percentage points higher denial rate. In regressions using Gini quartile indicator variables, we find the denial rate increases monotonically with income inequality, and the relationship is convex. Counties with the greatest income inequality experience 6.6 – 9.1 percentage points higher denial rates than the most equal counties. Taken together with our main results, these test provide strong support that borrowers from areas with a greater need for price discrimination experience much higher denial rates.

Next, we examine the second potential channel: taste-based discrimination (i.e., prejudice) against minority borrowers. 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 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 those areas need to cross a higher hurdle to obtain credit. Given this higher hurdle, those approved in these areas would 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 8 presents the results. Across specifications and for both home and business loans, we do not find any evidence that high-minority or high-Gini areas default at a lower rate. These results suggest that taste-based discrimination in SBA lending is quite unlikely.

5.4 Differential Sensitivity

Are high-minority areas more sensitive to disasters than low-minority areas? That is, even for observably identical areas, is the underlying credit quality of high-minority areas disproportionately damaged by natural disasters? If the credit quality distribution shifts more for high-minority areas, then our pre-disaster HMDA control will 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 from one year before the disaster to one year after disaster is related to the share of minorities. If high minority counties are more negatively impacted, we should see a positive and significant coefficient regressing the change in subprime share on the minority share. Table 9 presents the results of this regression where the dependent variable is $(Subprime_{i,c,t+1} - Subprime_{i,c,t-1})$ and is measured in percentage points. We find negative point estimates on the minority share, and they are economically and statistically insignificant. Therefore, we find no evidence that a differential sensitivity of credit quality to natural disasters in high-minority areas is driving our results.

5.5 Economic Significance

To further illustrate the economic importance of the results, we provide an estimate of the credit that would have been extended if all counties were in the lower minority share quartile. To do this, we multiply the number of loan applications in the 2nd, 3rd, and 4th quartile 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 for home loans. The business loan differences in approval rate are from a similar specification for business loans (see the Online Appendix). This calculation provides an estimate of the additional loans that would have been available to borrowers in higher-minority counties had they experienced the same denial rate as the low-minority counties. We then multiply these numbers by the average loan amount for approved loans to get a rough idea of the dollar amount (year 2000 dollars) of "missing" loans. Table 10 shows the computation.

The calculation suggests that about $1.7 billion of additional home loans and $800 million of additional business loans would have been granted under typical, private market conditions where the price is flexible to move according to the riskiness of the borrower. In terms of number of loans, our estimates show that about fifty-one thousand more homeowners and eleven thousand more businesses would have had access to credit during the critical time periods immediately following a natural disaster.

6 Discussion & Conclusions

We document a significantly higher denial rate of applications for government assisted loans in counties with a higher share of minorities. These areas are expected to have a higher denial rate based on their distribution of credit quality as evidenced by higher denial rates in the private market. Our key finding is to document that these high-minority areas have higher denial rates even after accounting for a benchmark private-market denial rate, which takes into account both raw credit quality and equilibrium credit rationing. Thus, compared to private markets, this direct government lending program denies credit to these populations at a significantly higher rate. Despite these borrowers often being the intended recipient of government assistance programs (and also a focus of government regulation in private-market lending), our results show that loans do not reach these borrowers at the same rate as borrowers who live in counties with lower minority population.

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 documenting significantly higher denial rates in areas with greater income inequality, our proxy for the need for price discrimination. 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 important adverse consequences of loan programs with this feature. Thus, 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 creditworthy borrowers that they are setting out to help.

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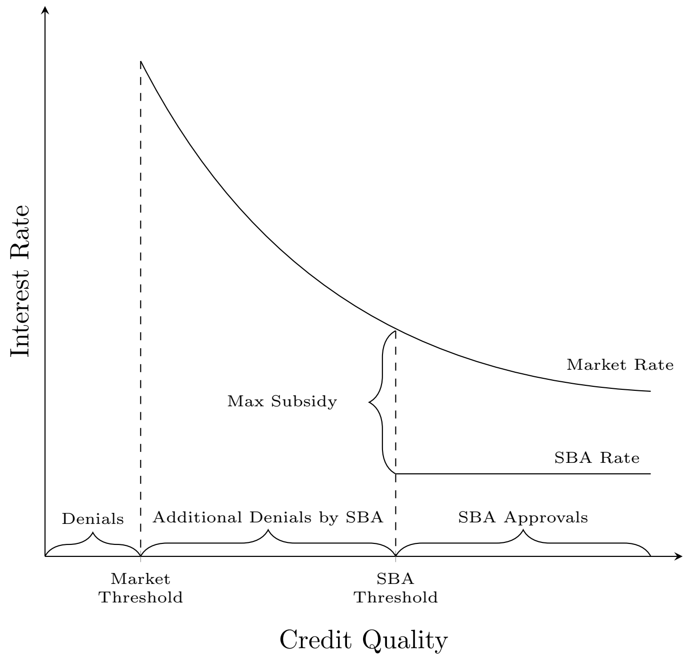

Figure 1: Credit Rationing
This figure illustrates the credit allocation decision with risk-insensitive and subsidized loan pricing compared to the credit allocation with risk-sensitive (market) pricing.

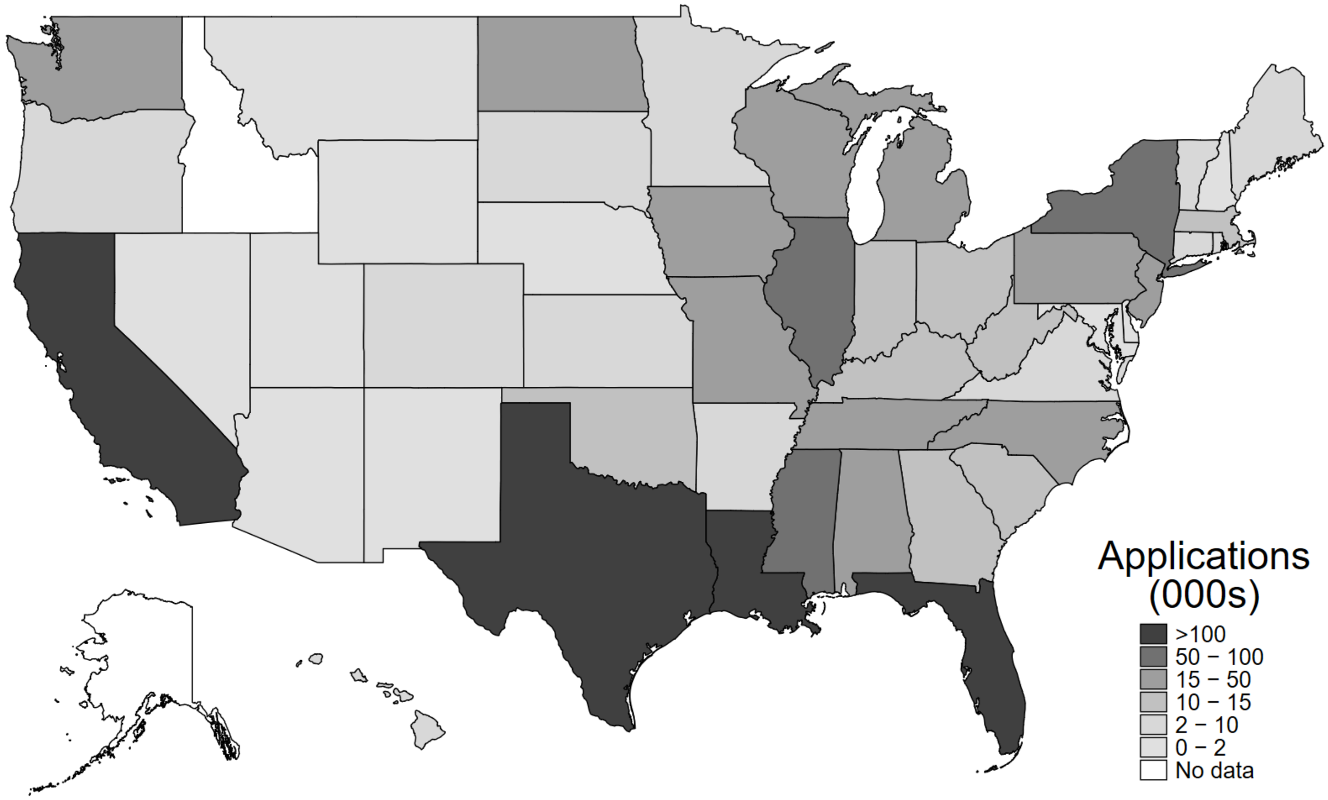

Figure 2: Geographical Distribution of Total Applications
This figure presents the number of disaster loan application during the sample period of 1991-2015 for each state.

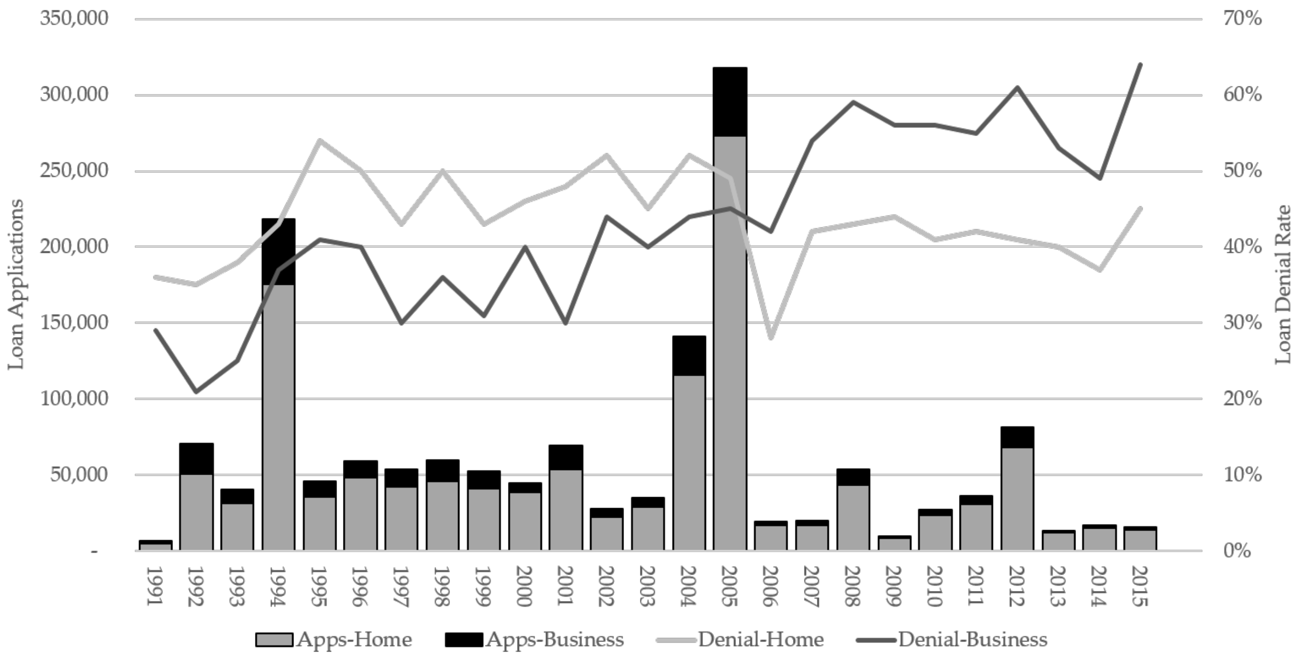

Figure 3: Applications and Denials Over Time
This figure presents the annual number of loan applications (left axis) and loan denial rates (right axis) for home and business loans for each year in the sample.

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

	Home		Business		
	applications	denial rate	applications	denial rate	Total
Hurricane	571,357	48%	120,464	44%	691,821
Severe Weather	432,938	44%	86,208	41%	519,146
Earthquake	175,986	43%	41,753	38%	217,739
Tropical Storm	55,784	49%	11,418	46%	67,202
Fire	12,603	45%	16,846	17%	29,449

Panel B: Ten Largest Disasters

		Home		Business		
Disaster	Year	applications	denial rate	applications	denial rate	Total
Hurricane Katrina	2005	206,201	48%	33,430	45%	239,631
Northridge Earthquake	1994	159,603	43%	38,835	37%	198,438
Hurricane Sandy	2012	55,267	41%	10,927	61%	66,194
Hurricane Andrew	1992	31,792	38%	8,121	24%	39,913
Hurricane Ivan	2004	30,364	50%	8,172	43%	38,536
Hurricane Rita	2005	33,107	56%	4,263	47%	37,370
Tropical Storm Allison	2001	31,740	51%	4,878	51%	36,618
Hurricane Floyd	1999	24,635	41%	8,047	29%	32,682
Hurricane Wilma	2005	26,864	48%	5,593	41%	32,457
Hurricane Frances	2004	23,645	56%	5,312	45%	28,957

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, and *HMDA-Denial* is the average county-level denial rate for applications for home refinancing loans from the Home Mortgage Disclosure Act 2007-2015 database, excluding years in which there was a disaster. *SBA Denial* for a given home or business disaster loan application is an indicator equal to one if the loan application was denied, and *VerifiedLoss* is the loss of the applicant as a result of the disaster as verified by SBA officials. For approved loans we report 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
Subprime	0.35	0.07	0.08	0.30	0.37	0.41	0.62	982,680
Minority	0.40	0.22	0.00	0.20	0.39	0.63	0.98	1,525,357
Gini	0.46	0.04	0.32	0.43	0.46	0.47	0.60	1,525,357
Per capita income (000)	33.45	17.24	6.04	19.98	30.58	38.16	217.44	1,525,357
ln(Population)	13.00	1.80	9.10	12.00	13.00	15.00	16.00	1,525,357
HMDA denial	0.22	0.04	0.07	0.19	0.22	0.24	0.42	1,525,357
Home Loans:								
SBA denial	0.46	0.50	0.00	0.00	0.00	1.00	1.00	1,248,668
Verified Loss (000)	49.90	71.77	0.70	9.07	21.93	53.84	384.33	1,248,668
Amount (000)	32.74	41.79	0.10	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	0.28	0.00	0.00	0.00	0.00	1.00	727,993
Business Loans:								
SBA denial	0.40	0.49	0.00	0.00	0.00	1.00	1.00	276,689
Verified Loss (000)	70.89	170.65	0.00	2.94	15.28	54.16	1195.98	276,689
Amount (000)	75.06	168.63	0.10	10.00	27.90	73.70	18013.10	168,431
Maturity	204.23	125.23	1.00	84.00	180.00	360.00	749.00	168,431
Default	0.09	0.28	0.00	0.00	0.00	0.00	1.00	168,431

Table 3: Home Loans: SBA Denial and Minority Share

This table presents OLS estimates from the regression of SBA home loan denial (*SBA Denial*) for a given home disaster loan application on 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)	(3)	(4)	(5)	(6)
zMinority	0.047***	0.042***	0.042***			
	(<0.01)	(<0.01)	(<0.01)			
Minority 2q				0.046***	0.028***	0.023***
				(<0.01)	(<0.01)	(0.01)
Minority 3q				0.084***	0.054***	0.044***
				(<0.01)	(<0.01)	(<0.01)
Minority 4q				0.128***	0.107***	0.102***
				(<0.01)	(<0.01)	(<0.01)
zPerCapitaIncome		-0.006	0.003		-0.007	0.006
		(0.28)	(0.64)		(0.30)	(0.32)
zln(Population)		-0.005	-0.016***		-0.001	-0.011**
		(0.27)	(<0.01)		(0.84)	(0.02)
zVerifiedLoss		-0.075***	-0.067***		-0.075***	-0.067***
		(<0.01)	(<0.01)		(<0.01)	(<0.01)
zSubprime			0.003			0.010
			(0.65)			(0.10)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1248668	1248668	822497	1248668	1248668	822497
R^2	0.021	0.038	0.040	0.021	0.038	0.040

p-values in parentheses

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

Table 4: Business Loans: SBA Denial and Minority Share

This table presents OLS estimates from the regression of SBA home loan denial (*SBA Denial*) for a given business disaster loan application 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)	(3)	(4)	(5)	(6)
zMinority	0.038***	0.043***	0.044***			
	(<0.01)	(<0.01)	(<0.01)			
Minority 2q				0.025***	0.028***	0.025***
				(<0.01)	(<0.01)	(<0.01)
Minority 3q				0.055***	0.060***	0.054***
				(<0.01)	(<0.01)	(<0.01)
Minority 4q				0.100***	0.106***	0.103***
				(<0.01)	(<0.01)	(<0.01)
zPerCapitaIncome		-0.002	0.006		-0.001	0.012*
		(0.65)	(0.22)		(0.83)	(0.05)
zln(Population)		-0.010*	-0.029***		-0.006	-0.025***
		(0.08)	(<0.01)		(0.29)	(<0.01)
zVerifiedLoss		0.001	0.006**		0.001	0.006**
		(0.75)	(0.02)		(0.76)	(0.02)
zSubprime			0.002			0.011*
			(0.70)			(0.08)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276689	276689	160183	276689	276689	160183
R^2	0.065	0.065	0.059	0.064	0.065	0.059

p-values in parentheses

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

Table 5: SBA Home Loan Denial and Minority Share: Controlling for Private-Market Denial Rate

This table presents OLS estimates from the regression of SBA home loan denial (*SBA Denial*) for a given home disaster loan application 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. *HMDA-RecentND* is the denial rate for applications of home loan refinancing in the county in the most recent year in which there was no disaster. *Subprime* 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)	(3)	(4)	(5)	(6)
zMinority	0.040***	0.031***	0.033***			
	(<0.01)	(<0.01)	(<0.01)			
Minority 2q				0.044***	0.019**	0.016*
				(<0.01)	(0.02)	(0.06)
Minority 3q				0.078***	0.040***	0.035***
				(<0.01)	(<0.01)	(<0.01)
Minority 4q				0.105***	0.076***	0.078***
				(<0.01)	(<0.01)	(<0.01)
zPerCapitaIncome		0.005	0.011		0.006	0.014**
		(0.37)	(0.13)		(0.36)	(0.03)
zln(Population)		0.002	-0.009*		0.006	-0.005
		(0.67)	(0.09)		(0.21)	(0.39)
zVerifiedLoss		-0.074***	-0.066***		-0.074***	-0.067***
		(<0.01)	(<0.01)		(<0.01)	(<0.01)
zHMDA-RecentND	0.023***	0.022***	0.018***	0.023***	0.023***	0.019***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zSubprime			0.002			0.008
			(0.74)			(0.19)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1207081	1207081	811133	1207081	1207081	811133
R^2	0.022	0.039	0.040	0.022	0.039	0.040

p-values in parentheses

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

Table 6: SBA versus HMDA: County-level Difference in Differences
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. This table presents OLS estimates from the regression of county-level loan denial rates (SBA or HMDA) for disaster-affected counties on the minority share of population in the county, whether the observation represent the SBA denial rate, and their interaction.

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

denial rate is the county denial rate for either SBA home loans or *HMDA-RecentND*, which is the denial rate for applications of home loan refinancing 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 HMDA denial rate. *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. *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)	(5)	(6)
zPerCapitaIncome	-0.028***	-0.028***	-0.028***	-0.031***	-0.031***	-0.031***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zln(Population)	-0.013***	-0.013***	-0.013***	-0.009***	-0.009***	-0.009***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zMinority	0.027***	0.027***	0.013***			
	(<0.01)	(<0.01)	(<0.01)			
$\mathbb{1}[SBA]$		0.209***	0.209***		0.209***	0.181***
		(<0.01)	(<0.01)		(<0.01)	(<0.01)
$\mathbb{1}[SBA]\times$zMinority			0.027***			
			(<0.01)			
Minority 2q				-0.007	-0.007	-0.011**
				(0.16)	(0.17)	(0.02)
Minority 3q				0.009	0.009	-0.011*
				(0.19)	(0.19)	(0.09)
Minority 4q				0.045***	0.045***	0.012
				(<0.01)	(<0.01)	(0.12)
$\mathbb{1}[SBA]\times$Minority 2q						0.007
						(0.42)
$\mathbb{1}[SBA]\times$Minority 3q						0.040***
						(<0.01)
$\mathbb{1}[SBA]\times$Minority 4q						0.065***
						(<0.01)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16935	16935	16935	16935	16935	16935
R^2	0.068	0.285	0.289	0.066	0.283	0.287

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

Table 7: SBA Home Loan Denial and Income Inequality

This table presents OLS estimates from the regression of SBA home loan denial (*SBA Denial*) for a given home disaster loan application on the county income inequality as measured by the *Gini* index and various controls and fixed effects. *Gini* is an index that measures the income inequality in the county, *Gini Xq* is the Xth quartile of the *Gini* with the first quartile (e.g., lowest income inequality share) as the omitted category, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *VerifiedLoss* is the loss of the applicant as a result of the disaster as verified by SBA officials. *HMDA-RecentND* is the denial rate for applications of home loan refinancing in the county in the most recent year in which there was no disaster. *Subprime* 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)	(3)	(4)	(5)	(6)
zGini	0.034***	0.028***	0.028***			
	(<0.01)	(<0.01)	(<0.01)			
Gini 2q				0.032**	0.017**	0.016*
				(0.01)	(0.01)	(0.06)
Gini 3q				0.063***	0.037***	0.030***
				(<0.01)	(<0.01)	(<0.01)
Gini 4q				0.091***	0.066***	0.066***
				(<0.01)	(<0.01)	(<0.01)
zPerCapitaIncome		-0.010**	-0.002		-0.009*	0.000
		(0.03)	(0.68)		(0.09)	(0.95)
zln(Population)		0.012***	0.003		0.015***	0.006
		(<0.01)	(0.45)		(<0.01)	(0.10)
zVerifiedLoss		-0.075***	-0.067***		-0.074***	-0.066***
		(<0.01)	(<0.01)		(<0.01)	(<0.01)
zHMDA-RecentND	0.024***	0.020***	0.017***	0.025***	0.022***	0.018***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zSubprime			0.008			0.011*
			(0.18)			(0.07)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1207081	1207081	811133	1207081	1207081	811133
R^2	0.022	0.039	0.041	0.022	0.039	0.040

p-values in parentheses

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

Table 8: 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 3), and county income inequality as measured by the *Gini* index (columns 2 and 5). Columns (1) and (2) are home loans and columns (3) and (4) are business loans. *NPD* represents the continuous version of each measure, with a higher measure representing a higher need for price discrimination. *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.

	Home		Business	
	(1)	(2)	(3)	(4)
NPD	Minority	Gini	Minority	Gini
zln(Amount)	-0.036***	-0.037***	-0.019***	-0.019***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zln(Maturity)	0.033***	0.033***	0.020***	0.020***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zPerCapitaIncome	-0.004***	-0.007***	-0.003**	-0.005***
	(<0.01)	(<0.01)	(0.04)	(0.01)
zln(Population)	0.007***	0.012***	0.008***	0.010***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zNPD	0.008***	0.002*	0.006**	0.003
	(<0.01)	(0.09)	(0.02)	(0.17)
State FE	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes
Observations	727993	727993	168431	168431
R^2	0.047	0.046	0.054	0.054

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

Table 9: 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)	(3)	(4)
zMinority	-0.033		-0.116	
	(0.93)		(0.71)	
Minority 2q		-0.556		-0.664
		(0.31)		(0.20)
Minority 3q		-1.027		-1.047
		(0.22)		(0.14)
Minority 4q		-0.488		-0.614
		(0.68)		(0.54)
zPerCapitaIncome	-0.214	-0.202	-0.224	-0.147
	(0.56)	(0.58)	(0.26)	(0.49)
zln(Population)	-0.426	-0.238	-0.220	-0.122
	(0.10)	(0.31)	(0.34)	(0.53)
zVerifiedLoss	0.195*	0.155	0.056*	0.048*
	(0.10)	(0.11)	(0.07)	(0.08)
State FE	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes
Observations	781319	781319	148806	148806
R^2	0.519	0.538	0.591	0.609

p-values in parentheses

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

Table 10: Economic Significance

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

	Minority 1q	Minority 2q	Minority 3q	Minority 4q	Total
Home Loans					
Actual Loans:					
Loan Application	310,228	315,773	281,615	341,052	1,248,668
Average Loan Amount ($)	$42,751.86	$41,391.15	$31,141.33	$33,908.52	
Point Estimates	-	2.4%	4.4%	9.1%	
Counterfactual loans:					
Additional Approved	-	7,579	12,391	31,036	51,005
Additional Amount ($Mn)	-	$313.68	$385.87	$1,052.38	$1,751.93
Business Loans					
Actual Loans:					
Loan Application	71,176	67,272	60,184	78,057	276,689
Average Loan Amount ($)	$70,021.64	$70,133.80	$73,435.61	$68,985.61	
Point Estimates	-	2.4%	4.9%	8.6%	
Counterfactual loans:					
Additional Approved	-	1,615	2,949	6,713	11,276
Additional Amount ($Mn)	-	$113.23	$216.56	$463.09	$792.89
Grand Totals:					
Total Additional Approved	-	9,193	15,340	37,749	62,282
Total Additional Lending	-	$426.92	$602.44	$1,515.47	$2,544.82

A Appendix

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%	-

Table A.1: Loan Details

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

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