



POVERTY SOLUTIONS

UNIVERSITY OF MICHIGAN

Poverty Solutions at the University of Michigan
Working Paper Series

#4-19

December 2018

Disaster Lending: “Fair Prices, but “Unfair” Access*

Taylor A. Begley, Umit G. Gurun, Amiyatosh Purnanandam, Daniel Weagley

This paper is available online at the Poverty Solutions Research Publications index at:
poverty.umich.edu/publications/working_papers

Any opinions, findings, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the view of Poverty Solutions or any sponsoring agency.

Disaster Lending: “Fair” Prices, but “Unfair” Access*

Taylor A. Begley^a

Umit G. Gurun^b

Amiyatosh Purnanandam^c

Daniel Weagley^d

First Draft: March 21, 2018

This Draft: December 3, 2018

Abstract

The use of risk-insensitive loan pricing by the Small Business Administration’s disaster loan program leads to significantly higher loan denials in areas with greater need for price discrimination: high minority share, high subprime share, and high income inequality areas. Even though these borrowers are often the intended targets of government programs such as disaster lending, they end up with lower availability of credit in this program compared to private markets. Our findings highlight the importance of using market prices as a mechanism to allocate credit across borrowers, a feature that is often absent from government lending programs around the world. Applicants that would likely receive a loan at a higher interest rate under a risk-sensitive pricing mechanism are instead denied credit altogether. 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 to marginal borrowers.

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

JEL Classification: G21, G28, H81, H84

*We are grateful to Sugato Bhattacharyya, Geoffrey Booth, Bill Cready, Rohan Ganduri, John Griffin, Peter Haslag, Uday Rajan, and seminar and conference participants at Emory, Georgia Tech, Johns Hopkins, Koc University, Washington University in St. Louis, and the 2018 Red Rock Finance Conference for helpful comments on the paper. A previous version of this paper was entitled “Disaster Lending: The Distributional Consequences of Government Lending Programs.”

^aOlin Business School, Washington University in St. Louis; email: tbegley@wustl.edu.

^bUniversity of Texas at Dallas; email: umit.gurun@utdallas.edu.

^cRoss School of Business, University of Michigan; email: amiyatos@umich.edu.

^dGeorgia Institute of Technology; email: daniel.weagley@scheller.gatech.edu.

1 Introduction

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

The typical goal of many government lending programs, including the disaster lending program that we study, is to alleviate frictions in access to credit for marginal borrowers by providing them credit in the time of crisis. Given this focus, it is reasonable to expect that marginal borrowers are better served by government lending programs compared to private markets. However, there is an opposing force at work here. Governments face pressure to minimize taxpayer losses while conducting these programs. Indeed, the SBA’s mandate is to break-even on the loans it makes under the disaster lending scheme. Therefore it extends credit to only those borrowers who are expected to provide nonnegative rate of return at the

¹We focus on the disaster-relief loan program because of data availability. The application of our work is much broader. 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.

SBA’s fixed interest rate. Some high risk borrowers are likely to be creditworthy only at a higher interest rate. By fixing the price of credit, these borrowers are now likely to be denied credit altogether. Thus marginal borrowers may face greater loan denial rates relative to a risk-sensitive pricing mechanism, which would provide them access to credit at higher interest rates.² Which of these two forces dominate? Are marginal borrowers getting better or worse outcomes in terms of access to credit in these programs compared to private markets? This is the central question we study in this paper.

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. Similar to a typical mortgage application, SBA loan officers screen loan applications for creditworthiness using a variety of documentation for income, employment, and assets. Despite the subsidized nature of the program, the SBA are vigilant to avoid fraud and to generally be good stewards of taxpayer dollars. This includes denying applicants whose credit profile cannot justify the risk-insensitive, subsidized program borrowing rate. For higher-risk borrowers, their lower expected future payments cannot be offset by charging a higher interest rate. Thus, borrowers who may be sufficiently creditworthy at a higher interest rate are simply denied credit. Since these loans provide aid and access to credit for borrowers at a time of acute need – after natural disasters – denial is likely particularly costly to these higher-risk borrowers.

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

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

and denied applications for these government loans.

We test for the effect of risk-insensitive loan pricing by comparing the loan denial rates of applicants from areas with a higher need for price discrimination (NPD) to loan denial rates of applicants from areas with lower NPD. Areas with greater dispersion in credit quality, and those with greater mass in the “marginal” portion of the credit quality distribution have a higher need for risk-based pricing to receive credit. We use three proxies for NPD in our tests: areas with higher share of minority population, areas with a large share of subprime borrowers based on FICO scores, and areas with higher income inequality. Our hypothesis is that the combination of borrower screening for credit quality and the inflexibility of prices may lead to higher denial rates for applicants from these marginal areas. Alternatively, government program’s—which often have explicit goals to reach and support such populations—may be better equipped to provide credit in these areas, which would lead to a relatively lower denial rate in these areas.

To credibly evaluate these questions and hypotheses, we need a reasonable benchmark. In particular, our goal is to compare outcomes of the government-run, fixed-price (SBA) scheme to potential private-market or government-insured lending where the price is flexible. When examining the denial rates in the SBA’s scheme, it is important to account for a baseline level of denials that occur as a result of credit rationing. That is, in lending markets where there is asymmetric information, we expect there will be a baseline level of rationing (Stiglitz and Weiss, 1981) even with risk-sensitive pricing.³ Also, prior work has shown lower access to credit for minorities even in private markets (see, e.g., Munnell, Tootell, Browne, and McEneaney, 1996). We examine whether there is *excess* credit rationing of these groups in the SBA’s risk-insensitive pricing program compared to lending with risk-based loan pricing. We use the denial rate in the private home mortgage market as our baseline risk-sensitive pricing counterfactual. This comparison group captures the baseline rationing including any

³The 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.

potential biases that persist in those markets. Specifically, the private-market denial rate, obtained from the Home Mortgage Disclosure Act (HMDA) database, captures variation in denial rates due to observable and, importantly, unobservable differences in the credit quality distribution across counties.

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 toward borrowers who are already home owners. We also use Federal Housing Administration (FHA) loans as another counterfactual. FHA loans are issued by private banks, but insured by the government. Despite government insurance, FHA loans do not follow a fixed-price, risk-insensitive pricing regime. The borrower pool in the FHA loan program is of lower average credit quality than the pool of conventional borrowers and so makes a natural comparison group for our SBA applicants who reside in areas with high NPD. Because FHA and SBA exhibit similarities with respect to incentives, constraints, and target borrower population, comparing the denial rates across these two programs allows us to tease out the difference in credit access that arises due to lack of risk-based pricing.

We primarily focus on the minority share of the applicant’s county as our key NPD measure. Minority share captures both hard and soft information about the borrower pool in ways beyond what is captured by subprime share and income inequality. For example, Bayer, Ferreira, and Ross (2016) show that minority borrowers default at a higher rate even conditional on observables like credit score. This can be potentially due to unobserved credit risk factors such as lower levels of wealth, higher employment volatility, or weaker access to informal financing networks like friends and family, among other things. Thus, we would expect higher interest rates in high-minority-share areas in private markets since the interest rate can be adjusted based on the borrower’s “true” credit quality. It is precisely these borrowers that are most likely to be denied credit under the SBA’s program since, by construction, its rates are inflexible. Additionally, the use of minority share 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) and the Equal Credit Opportunity Act (1974). These are intended to ensure private lenders provide fair access to credit across borrowers of different race, religion, gender, etc. In contrast to steering private market behavior to serve government objectives, we are able to examine how the government’s own direct lending to its citizens fares on this dimension.

We find that the SBA program denies loan applications at a significantly higher rate in counties with a greater need for price discrimination, and this differential exists even after controlling for the HMDA private-market denial rate. The result holds for each of the three proxies of NPD we use: subprime share, minority share, and income inequality of the county, but the results are strongest for counties with higher minority population share. The result is not explained by the 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 3.3 percentage points higher denial rate. With the average denial rate in our sample at 46%, these results are economically significant. These relationships are robust across different sample periods, they are not driven only by certain natural disasters (e.g., hurricane versus flooding), and they hold for both large and small disasters. In sum, these results provide evidence that the loans in this scheme are not reaching borrowers in high minority areas at the same rate as low minority areas even after accounting for baseline differences in denial rates using the HMDA data.

We next collapse our loan-level data to county-year denial rates. Using these data and the HMDA denial rates for the same county (one year prior to the disaster), we estimate the difference in denial rate across the different programs (SBA vs. risk-sensitive pricing programs) for counties with different NPD. We find that a one-s.d. increase in minority share corresponds to a 2.7 pps higher denial rate under the SBA program relative to the risk sensitive HMDA loans. Similar results hold when we compare denial rates in the SBA

program to FHA loans that are government insured, but with flexible pricing. Interestingly, in these tests, we find no evidence that the FHA loan applicants are denied at a higher rate in areas with greater need for price discrimination. For counties in the top quartile of minority share, the within-county estimates indicate a denial rate that is 8pps higher than the denial rate in the low minority share counties after controlling for the corresponding FHA loan denial rate.

These results paint a clear picture. Despite some concerns and issues surrounding the behavior of private markets in providing “fair” access to credit, risk-sensitive private market and government insured loan programs grant loans to a significantly larger fraction of borrowers in higher 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, the SBA’s risk-insensitive pricing program fares worse in achieving this goal compared to its flexible pricing counterparts.

An alternative explanation of our result is the possibility of taste-based discrimination. If the SBA program’s loan officers are prejudiced against minorities (beyond any potential bias in the private market), we would expect relatively higher denial rates in higher-minority-share areas. Becker (1957) argues that profit motivations can eliminate such discrimination in the marketplace. While there is a clear mandate that the SBA is to strive to be faithful stewards of tax dollars, their incentives to do so may be weaker than the profit motive in private markets. We investigate whether taste-based discrimination could be driving the results 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 minority performance should be relatively better conditional on getting the job. 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 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 the 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 44,000 additional homeowners (about 4% of the size of the program) would have received loans, which adds up to a grand total of about \$1.5 billion. The economic importance of this number is amplified in light of the setting, post-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. 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 including the perception of fairness. 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 such as areas with higher minority populations.

Our work relates to government intervention in setting prices in a number of contexts, such as the labor market, health insurance market, or rental markets, to name a few (see Stigler (1946) and Bundorf et al. (2012) for example). 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, where risk-insensitive products are usually associated with government-sponsored enterprises (GSEs): 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. 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 the GSEs uniform pricing policies and how they affect 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 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 to individuals, where borrowers use loans to repair or replace real estate and personal property beyond what is covered by home insurance.

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

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

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

⁴The formula for statutory rates is provided in Section 7 of the Small Business Act.

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 the overall budgetary costs (Congressional Budget Office (1997)). This focus on screening combined with the inflexibility in interest rates may lead to greater denials of borrowers of marginal credit worthiness than if the SBA were allowed to adjust interest rates based on borrower credit quality. We discuss this idea further in the next section.

3 Research Design

The role of price in allocating resources 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 (i.e., price discriminate), more borrowers will have access to credit. Fixed-price lending programs (with screening), 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, the borrower is simply denied credit rather than charged a higher rate commensurate with their risk.⁵ The importance of risk-sensitive pricing in allocating credit to high-risk borrowers motivates our key hypothesis: areas with a higher fraction of applicants with marginal credit quality have higher denial rates due to risk-insensitive pricing.

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

⁵In our setting it is when the fixed rate the SBA charges plus the subsidy of the program exceeds the expected loss rate on the disaster loans.

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 since the SBA prices its loans at a subsidized rate that is below the market rate for all borrowers.⁶ 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 are excess denials in SBA lending compared with the private-market benchmark. Our empirical tests are aimed at teasing out this excess denial by exploiting variation across areas that differ in terms of the fraction of the population that falls between the private-market and SBA threshold (i.e., variation in the share of applicants with marginal credit quality).

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 private lenders also ration credit at higher rates in such markets. We need to account for this effect. Our setting is attractive because we are able to observe the credit allocation decision in the private lending market for the same areas. Specifically, we observe the approval/denial decision of applications for home mortgage loans made to nearly all a private lenders in the U.S. For every county, we are able to obtain data on denial rates for all borrowers in the HMDA data set for non-disaster years. Our primary analysis controls for the denial rate in the HMDA database for all refinancing loans made in that county in the most recent non-disaster year. 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 isolate the effect of the *NPD* variable using the following regression model estimated with all SBA loans:

⁶Our 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.

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

$deny_{i,c,t}$ is an indicator variable equal to one if loan application i , originated from county c in year t , was denied. $NPD_{c,t}$ is the need for price discrimination in county c at time t . We use three proxies for need for price discrimination: the minority share, the subprime share, and the income inequality (Gini coefficient) of the application county. These three proxies should capture the relative mass of applicants in the county credit quality distribution between the private-market risk-sensitive threshold and the SBA risk-insensitive threshold. For most of our analysis, we focus on minority share because it is empirically the strongest predictor of loan denial. $HMDA\ Denial_{c,t}$ is the private-market denial rate for county c in the most recent non-disaster year for a disaster in year t . This variable will capture the baseline credit rationing in the home mortgage market. $X_{i,c,t}$ includes county- and loan-level control variables, which we discuss in greater detail in Section 4.

We include state fixed effects (ζ_s) to separate out the effect of any state-by-state differences in the implementation of SBA disaster loans. As noted earlier, these loans come under the federal program, and therefore they have the same terms for all borrowers irrespective of where the disaster strikes. However, there may be a concern about differences in the implementation at the state level, which we absorb with state fixed effects. We also include a fixed effect that is *disaster-type* \times *year* specific (denoted $\delta_{d,t}$). This fixed effect, by construction, soaks away variations that are specific to a certain type of disaster in a given year (e.g., hurricanes in 2005). Inclusion of disaster-type fixed effects in the model allows us to control for differences in lending policies or borrower needs or characteristics across different types of disasters. By interacting this 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 statewide differences and time-varying disaster-type differences in SBA’s lending policies.

In addition to including $HMDA\ Denial_{c,t}$ as a control variable, we also use it as an outcome variable in a difference-in-differences research design. For those tests we compare the relative sensitivity of county-level denial rates to NPD for private-market loan applications versus SBA applications. We discuss this test more fully in the results section.

In some tests, we use the denial rate of Federal Housing Administration (FHA) program loans as our counterfactual measure of loan denial instead of the broader HMDA denial rate. The FHA denial rate is a good counterfactual for our study for a number of reasons. First, FHA loans are also insured by the government, so the FHA program will have 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 to a risk-sensitive loan program. Third, the borrower pool in the FHA loan program is typically composed of more marginal-quality borrowers.

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 relative performance of approved loans. Specifically, better default performance (i.e., lower default rates) in high-NPD (e.g., high-minority) areas would be evidence consistent with taste-based discrimination.

4 Data and Sample

We obtained the data on SBA Disaster individual loans through a Freedom of Information Act request. A key feature that distinguishes our data from the publicly available disaster data is that we have loans that were denied in addition to those that were approved. Our final data set includes around 1.2 million loan applications from 1991 to 2015. These data

include the state and county of the applicant, the applicant’s verified loss as a result of the disaster (e.g., property damage), the disaster description (e.g., Hurricane Andrew), the loan approval or denial decision (*SBA Denial*), and default (i.e., chargeoff) data on approved loans.

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

In Panel B of Table 1, we list the top ten disasters in terms of number of loan applications in our sample. Hurricane Katrina, is the largest disaster, with over 200,000 applications. While some of the largest disasters cluster around 2004-2005, there is clearly variation in the timing of disasters over time. This variation allows us to separate 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 varies 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.⁷ We also use the denial rate for the subsample of HMDA that are made through the FHA program.

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

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

Table 2 presents summary statistics for the variables used in our regression analysis. All dollar amounts are adjusted to year 2000 dollars. There is substantial variation in the subprime share, minority share, Gini, income, and population of the counties in the sample.

⁷The results are similar using contemporaneous year or averages of two or three prior years.

The SBA denial rate of 46% is considerably higher than the average HMDA denial rate of 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 estimate regression equation (1). We standardize all continuous independent variables to have mean zero and unit standard deviation, and we cluster the standard errors at the county level.

Table 3 presents the results. Columns (1)-(3) present the results using subprime share as the NPD proxy, and columns (4)-(6) present the results using minority share.⁸ In columns (1) and (4), we present results for the base specification controlling only for state and disaster-year fixed effects. We find that a one-standard-deviation higher subprime share is associated with an increase of 3.8 percentage points (p -value<0.01) in the loan denial rate. Similarly, a one-standard-deviation higher minority share is associated with a denial rate that is 4.6 percentage points higher. These results suggest that areas with greater NPD experience significantly higher loan denial rates.

We next include controls for per capita income, population, verified loss, and the HMDA denial rate. The HMDA denial rate is the denial rate in the most recent year without a disaster as described in Section 4. The underlying identifying assumption is that conditional on the HMDA denial rate, there is no remaining unobserved credit rationing that would occur

⁸The number of observations is smaller when subprime share is included because we only have subprime share data from 1999 onwards.

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

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

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

5.2 Difference-in-Differences: SBA versus HMDA

As an additional way to contrast the decision making between government and private lending programs, we present a simple difference-in-differences estimation for SBA versus HMDA lending across areas with different racial composition. We construct a data set at the level of county-disaster-year and compute the respective SBA denial rate. 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 as the dependent variable. We then estimate the following regression specification:

$$\begin{aligned} denial\ rate_{i,p,c,t} = & \alpha + \delta \mathbb{1}[SBA]_{i,p,t} + \psi Minority_{c,t} \\ & + \theta(\mathbb{1}[SBA]_{i,p,t} \times Minority_{c,t}) + \Gamma X_{i,p,c,t} + \epsilon_{i,p,c,t} \end{aligned} \quad (2)$$

In this specification, $\hat{\delta}$ represents the average difference in risk-insensitive SBA and risk-sensitive HMDA denial rates. The estimate of interest is $\hat{\theta}$, which indicates the differential sensitivity in denial rates to minority share between the SBA and HMDA lenders. $\hat{\theta} > 0$ indicates that the relationship between minority-share of the population and denial rates is even stronger in the government-directed SBA program as compared with the private-market HMDA counterpart.

Table 4 presents the results. The results in column (1) indicate that a one-standard-deviation increase in minority share is associated with a denial rate that is 2.7 percentage points higher in the pooled sample of HMDA and SBA denial rate observations. In column (2), we include the SBA dummy variable, which shows the relatively higher average denial rate for SBA loans (21pps higher, p -value < 0.01). There is still a significant relationship between minority share and denial rates after controlling for the level difference in denial rates across SBA and HMDA loans. In column (3), we include the interaction between the

SBA dummy variable and minority share. The coefficient on minority share, which now captures the relationship between minority share and loan denials in the private market, is only 0.013 (p -value < 0.01). The private market does deny loans to higher minority areas at a greater rate. Of particular interest is the coefficient on the interaction between SBA status and minority share, which is $\hat{\theta} = 0.027$ (p -value < 0.01). Thus, a one-standard-deviation increase in minority share increases the likelihood of denial by about three times as much for risk-insensitive SBA loans as compared with private-market loans.

The difference between the SBA and private market is even more stark when examining the quartiles of minority share. Results are presented in columns (4)-(6). In column (6), we see that for the private market, the difference in denial rate between the highest quartile and lowest quartile minority share areas is not significant. The coefficient on the highest quartile dummy is only 0.012 (p -value = 0.12). For the SBA, on the other hand, the relationship between minority share and relative denial rates is monotonically increasing. The highest quartile minority share areas have a relative denial rate that is 6.5 (p -value < 0.01) percentage points higher than the low minority quartile areas. In sum, a higher minority share corresponds to higher denials in both government-directed and private markets, but the effect is much larger in the risk-insensitive, government-directed lending program.

5.2.1 Federal Home Administration Program

We next compare the denial rates in the SBA disaster loan program to the denial rates in the Federal Home Administration (FHA) loan program to further tease out the risk-insensitive loan channel. By comparing SBA loans to FHA loans, we minimize any concerns about potential differences between the SBA and private market lenders and potential concerns about differences in the borrower pool between the SBA and HMDA. The U.S. government's FHA loan program provides insurance against default risk for private lenders that make loans that fit the FHA guidelines. This program has similar objectives and constraints as the SBA.

The pool of FHA borrowers is likely riskier than the general population and may better represent the pool of SBA applicants. The important difference between the two programs is that the FHA loans are not restricted to a particular, risk-insensitive lending rate as are the SBA loans. We run the same difference-in-differences analysis as in Table 4, but with the FHA denial rate instead of the HMDA denial rate.

Table 5 presents the results. A similar pattern emerges as in the previous tests, except the difference between the SBA and the market benchmark are even more striking. Examining the results in column (3), we see the coefficient estimate on $zMinority$ is not statistically different from zero. This indicates there is no significant relationship between minority share and loan denial in the FHA loan program for the times and counties in our analysis. In other words, this government-sponsored risk-sensitive loan program is providing access to credit across the spectrum of borrowers. This non-relationship may be expected for a government program that is not only highly sensitive to the issue of fair credit access, but also has the flexibility to change prices.

The SBA program displays an even more significant relationship between minority share and loan denial when compared with the FHA loans. The coefficient on the interaction between *Minority* and the SBA dummy in column (3) indicates that SBA's relative denial rates increase by 3.5 percentage points with a one-standard-deviation increase in a county's minority share. 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 8 percentage points more likely to be denied a loan than applications from low minority share counties relative to the corresponding denial rates in the FHA program.

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 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 difference-in difference tests (regression equation 2) to the minority regressions except with Gini as the NPD cross-sectional variable of interest. By construction, higher Gini areas have a greater dispersion in credit quality and, consequently, a greater need for price discrimination in lending markets. Thus a positive relationship between Gini and SBA denial rates would further support the risk-insensitive channel of loan denial. These tests also reduce concerns that 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. 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 2.5 percentage points higher for SBA loans relative to FHA loans. There is no relationship between Gini and FHA denial rates. Column (3) indicates that Gini and minority share have independent explanatory power for denial rates in the pooled regression, with the effect of minority being about twice as large. In column (4) we include both Gini and minority share plus each variable’s interaction with the SBA dummy. We find that each has an independent relationship with SBA denial rates. The coefficient on minority share drops from 0.035 (column 3 of Table 5) to 0.03 (p -value < 0.01), and the coefficient on Gini drops from 0.025 to 0.011 (p -value = 0.02). 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, and this is not being driven

by some unique unobserved characteristics related to minority share and denial rates.

5.4 Discrimination and Potential Alternative Explanations

In this section, we first examine whether the results may be driven by taste-based discrimination, and then discuss potential concerns about violations of a key assumption in our tests. The key underlying assumption in our main tests is that differences between the pool of SBA applicants and the pool of private-market applicants does not vary systematically according to NPD (after controlling for other important covariates).

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, 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 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:

Is the credit quality of high-minority areas more sensitive to natural disasters relative to 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 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.

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

If the credit quality of high-minority areas are more-negatively impacted, we should see a positive and significant coefficient on minority share ($\hat{\zeta} > 0$). Table 8 presents the results. We find negative point estimates on the minority share, and they are economically and statistically insignificant. This test does not support the hypothesis that the credit quality of high-minority areas has differential sensitivity to natural disasters relative to low-minority areas.

Alternative sources of funding:

Another concern may be the that low-NPD areas have a 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.⁹ Together, this will lead to a relative *decrease* in the average applicant credit quality in the *low*-NPD areas compared to the counterfactual private market applicant pool. As a result, the relative denials (SBA compared with the private market) should be *higher* in the low-NPD areas if this is the case, which works in the opposite direction of our findings.

Lack of paperwork or banking history:

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

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 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

⁹Additionally, 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.

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. Table 9 shows the computation.

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

6 Discussion & Conclusions

We document a substantially higher denial rate of applications for SBA disaster loans in counties with a greater need for price discrimination. 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. Despite these applicants often being the intended recipient of government assistance programs (and also a focus of government regulation in private-market lending), our results show that those 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.

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 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 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.

References

- Adelino, Manuel, Antoinette Schoar, and Felipe Severino, 2016, Loan originations and defaults in the mortgage crisis: The role of the middle class, *The Review of Financial Studies* 29, 1635–1670.
- Bayer, Patrick, Fernando Ferreira, and Stephen L Ross, 2016, The Vulnerability of Minority Homeowners in the Housing Boom and Bust, *American Economic Journal: Economic Policy* 8, 1–27.
- Becker, Gary, 1957, *The Economics of Discrimination* (The University of Chicago Press).
- Bundorf, M Kate, Jonathan Levin, and Neale Mahoney, 2012, Pricing and welfare in health plan choice, *American Economic Review* 102, 3214–48.
- Hurst, Erik, Benjamin J Keys, Amit Seru, and Joseph Vavra, 2016, Regional redistribution through the US mortgage market, *American Economic Review* 106, 2982–3028.
- Kulkarni, Nirupama, 2016, Are Uniform Pricing Policies Unfair? Mortgage Rates, Credit Rationing, and Regional Inequality, *Working Paper* .
- Lindsay, Bruce R, 2010, *SBA Disaster Loan Program: Overview and Possible Issues for Congress* (DIANE Publishing).
- Munnell, Alicia H, Geoffrey MB Tootell, Lynn E Browne, and James McEneaney, 1996, Mortgage lending in Boston: Interpreting HMDA data, *American Economic Review* 25–53.
- Rose, Nancy L, 2014, *Economic Regulation and Its Reform: What Have We Learned?* (University of Chicago Press).
- Stigler, George J, 1946, The economics of minimum wage legislation, *American Economic Review* 36, 358–365.
- Stiglitz, Joseph E, and Andrew Weiss, 1981, Credit rationing in markets with imperfect information, *American Economic Review* 71, 393–410.

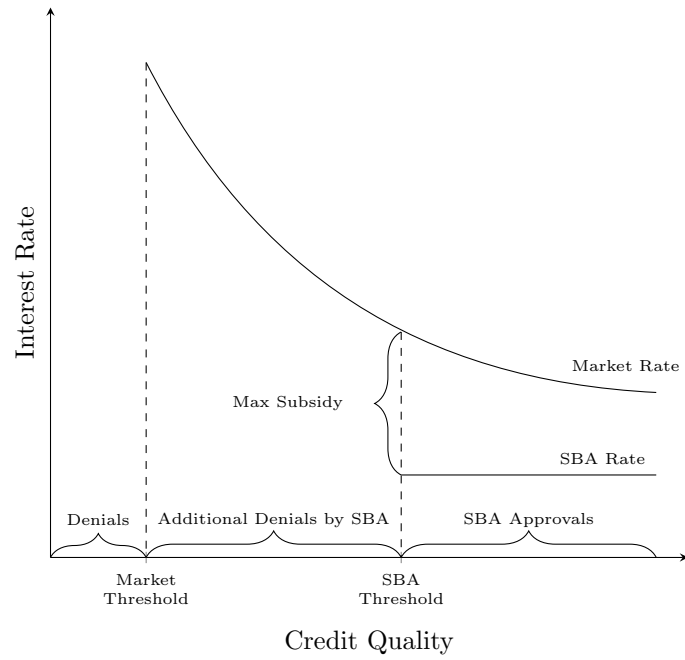


Figure 1: Credit Rationing

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

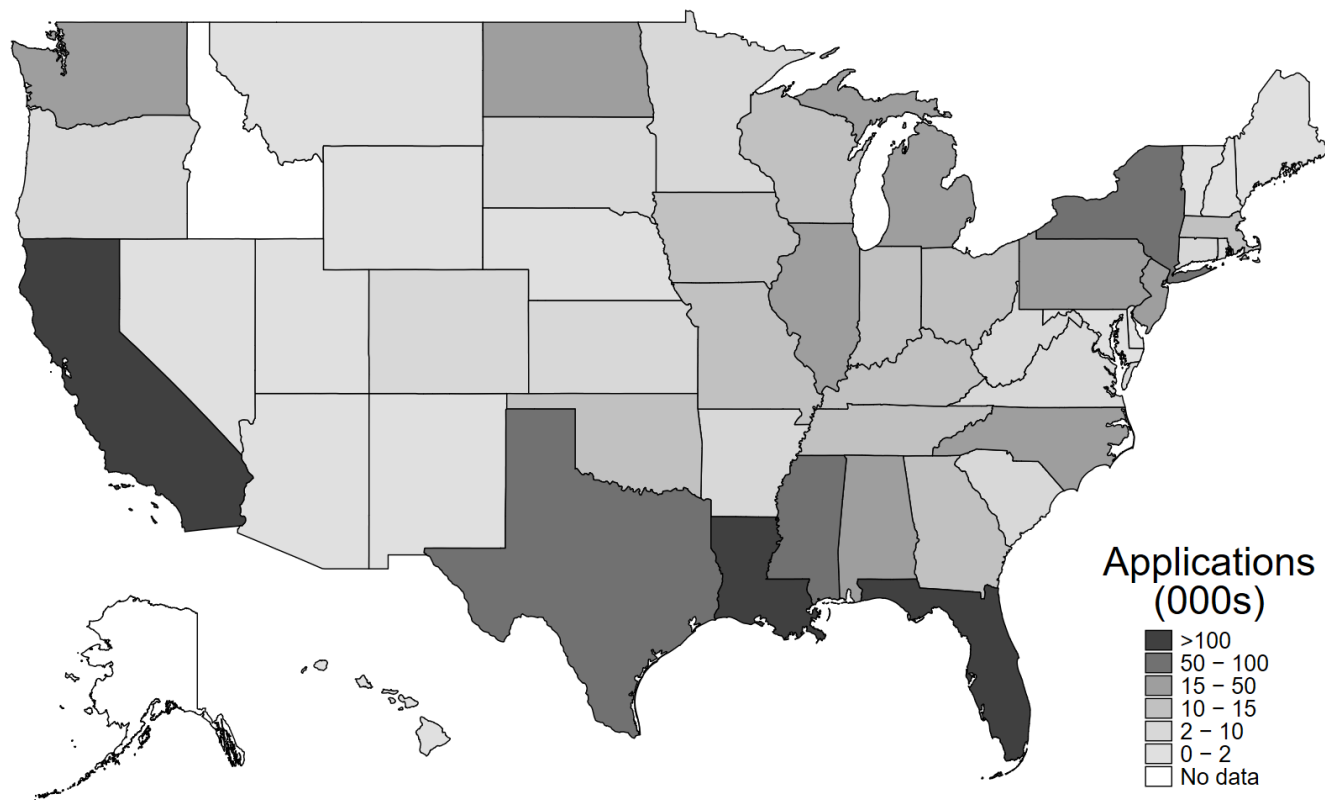


Figure 2: Geographical Distribution of Total Applications

This figure presents the number of disaster loan application during the sample period of 1991-2015 for each state.

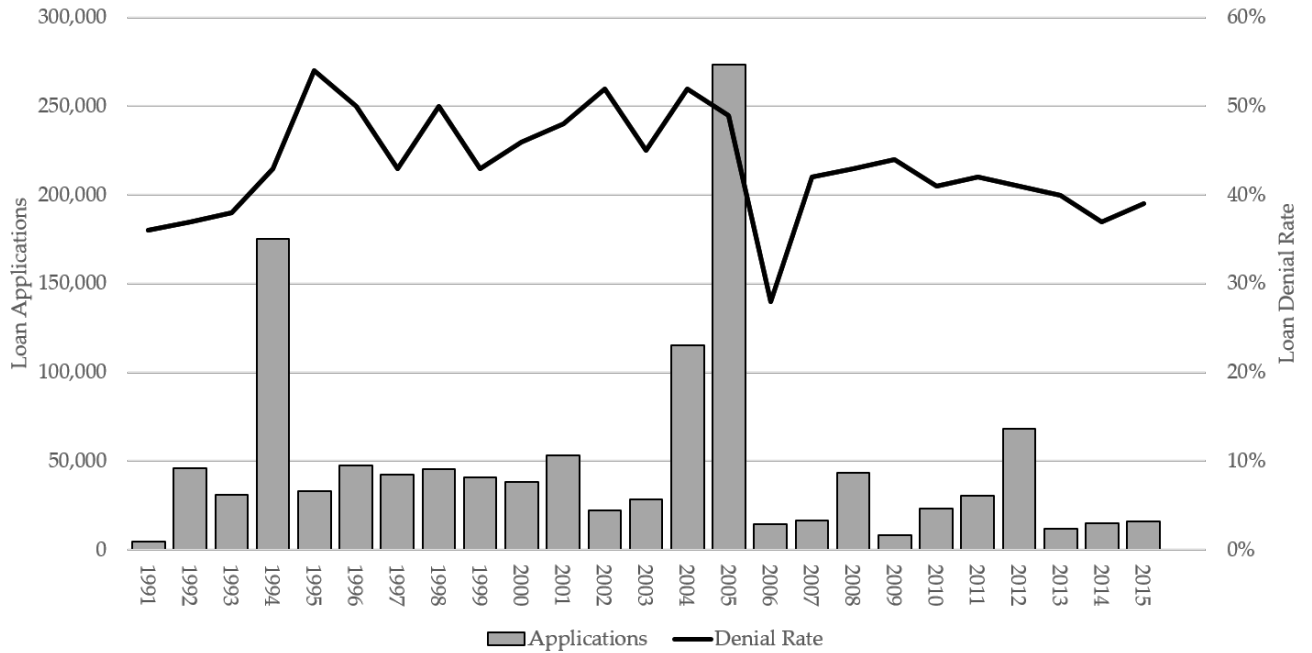


Figure 3: Applications and Denials Over Time

This figure presents the annual number of 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.

<i>Panel A: Disaster Types</i>			
		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%

<i>Panel B: Ten Largest Disasters</i>			
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 $\ln(\text{Population})$ are the county-level per capita income and log of population at the time of the disaster, and *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. For the sample of approved/denied application (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
<i>County Statistics:</i>								
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
$\ln(\text{Population})$	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
<i>SBA Loans (Application Sample):</i>								
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
<i>SBA Loans (Default Sample):</i>								
Amount (000)	32.74	41.79	0.01	8.40	17.10	40.00	561.90	727,993
Maturity	214.84	128.55	1.00	96.00	192.00	360.00	963.00	727,993
Default	0.08	0.27	0.00	0.00	0.00	0.00	1.00	727,993

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

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

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

p-values in parentheses

33

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

Table 4: 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.

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

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 *X*th quartile of the *Minority* with the first quartile (e.g., lowest minority share) as the omitted category, *PerCapitaIncome* and $\ln(\text{Population})$ 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)	(5)	(6)
zMinority	0.027*** (<0.01)	0.027*** (<0.01)	0.013*** (<0.01)			
$\mathbb{1}[SBA]$		0.209*** (<0.01)	0.209*** (<0.01)		0.209*** (<0.01)	0.181*** (<0.01)
$\mathbb{1}[SBA] \times \text{zMinority}$			0.027*** (<0.01)			
Minority 2q				-0.007 (0.16)	-0.007 (0.17)	-0.011** (0.02)
Minority 3q				0.009 (0.19)	0.009 (0.19)	-0.011* (0.09)
Minority 4q				0.045*** (<0.01)	0.045*** (<0.01)	0.012 (0.12)
$\mathbb{1}[SBA] \times \text{Minority 2q}$						0.007 (0.42)
$\mathbb{1}[SBA] \times \text{Minority 3q}$						0.040*** (<0.01)
$\mathbb{1}[SBA] \times \text{Minority 4q}$						0.065*** (<0.01)
zPerCapitaIncome	-0.028*** (<0.01)	-0.028*** (<0.01)	-0.028*** (<0.01)	-0.031*** (<0.01)	-0.031*** (<0.01)	-0.031*** (<0.01)
zln(Population)	-0.013*** (<0.01)	-0.013*** (<0.01)	-0.013*** (<0.01)	-0.009*** (<0.01)	-0.009*** (<0.01)	-0.009*** (<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 5: SBA versus FHA: 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 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 represent the SBA denial rate, and their interaction.

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

denial rate is the county denial rate for either SBA home loans or the FHA denial rate, which is the denial rate for applications of FHA loans in the county in the most recent year in which there was no disaster. $\mathbb{1}[SBA]$ is an indicator equal to one if the observation represents the SBA denial rate and zero if the observation represents the FHA denial rate. *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. *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	0.020*** (<0.01)	0.018*** (<0.01)	-0.000 (0.99)			
$\mathbb{1}[SBA]$		0.277*** (<0.01)	0.277*** (<0.01)		0.277*** (<0.01)	0.244*** (<0.01)
$\mathbb{1}[SBA] \times zMinority$			0.035*** (<0.01)			
Minority 2q				-0.015** (0.01)	-0.014** (0.02)	-0.018** (0.03)
Minority 3q				-0.004 (0.59)	-0.007 (0.37)	-0.031*** (<0.01)
Minority 4q				0.027*** (<0.01)	0.022*** (<0.01)	-0.019* (0.06)
$\mathbb{1}[SBA] \times \text{Minority 2q}$						0.007 (0.56)
$\mathbb{1}[SBA] \times \text{Minority 3q}$						0.047*** (<0.01)
$\mathbb{1}[SBA] \times \text{Minority 4q}$						0.080*** (<0.01)
zPerCapitaIncome	-0.019*** (<0.01)	-0.021*** (<0.01)	-0.021*** (<0.01)	-0.021*** (<0.01)	-0.022*** (<0.01)	-0.022*** (<0.01)
zln(Population)	-0.015*** (<0.01)	-0.010*** (<0.01)	-0.010*** (<0.01)	-0.011*** (<0.01)	-0.006** (0.03)	-0.006** (0.03)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16528	16528	16528	16528	16528	16528
R^2	0.044	0.324	0.328	0.044	0.323	0.327

p-values in parentheses

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

Table 6: SBA Home Loan Denial and Income Inequality: County Diff-in-Diff

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

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

denial rate is the county denial rate for either SBA home loans or the FHA denial rate, which is the denial rate for applications of FHA loans in the county in the most recent year in which there was no disaster. $\mathbb{1}[SBA]$ is an indicator equal to one if the observation represents the SBA denial rate and zero if the observation represents the FHA denial rate. *Gini* is an index that measures the income inequality in the county, *Gini Xq* is the *X*th quartile of the *Gini* with the first quartile (e.g., lowest income inequality share) as the omitted category, *Minority* represents the nonwhite share of the county population, *Minority Xq* is the *X*th 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. *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)
zGini	0.013*** (<0.01)	-0.000 (0.99)	0.008*** (<0.01)	0.003 (0.34)
zMinority			0.014*** (<0.01)	-0.002 (0.67)
$\mathbb{1}[SBA]$	0.277*** (<0.01)	0.278*** (<0.01)	0.277*** (<0.01)	0.277*** (<0.01)
$\mathbb{1}[SBA] \times zGini$		0.025*** (<0.01)		0.011** (0.02)
$\mathbb{1}[SBA] \times zMinority$				0.030*** (<0.01)
zPerCapitaIncome	-0.025*** (<0.01)	-0.025*** (<0.01)	-0.022*** (<0.01)	-0.022*** (<0.01)
zln(Population)	-0.005* (0.06)	-0.005* (0.06)	-0.010*** (<0.01)	-0.010*** (<0.01)
State FE	Yes	Yes	Yes	Yes
Disaster-Year FE	Yes	Yes	Yes	Yes
Observations	16528	16528	16528	16528
R^2	0.323	0.325	0.324	0.329

p-values in parentheses

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

Table 7: 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). $\ln(\text{Amount})$ is the log of the loan amount, $\ln(\text{Maturity})$ is the log of the loan maturity in months, *PerCapitaIncome* and $\ln(\text{Population})$ 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*** (<0.01)	0.008*** (<0.01)		
zGini			0.006*** (<0.01)	0.002* (0.09)
zln(Amount)		-0.036*** (<0.01)		-0.037*** (<0.01)
zln(Maturity)		0.033*** (<0.01)		0.033*** (<0.01)
zPerCapitaIncome		-0.004*** (<0.01)		-0.007*** (<0.01)
zln(Population)		0.007*** (<0.01)		0.012*** (<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: 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 *X*th 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 (0.56)	-0.202 (0.58)
zln(Population)	-0.426 (0.10)	-0.238 (0.31)
zVerifiedLoss	0.195* (0.10)	0.155 (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: 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
<i>Actual Loans:</i>					
Loan Application	301,411	302,150	301,138	302,382	1,207,081
Average Loan Amount (\$)	\$43,276.99	\$41,840.68	\$30,860.16	\$36,258.10	
Point Estimates	-	2.1%	4.4%	8.3%	
<i>Counterfactual loans:</i>					
Additional Approved	-	6,345	13,250	25,098	44,693
Additional Amount (\$Mn)	-	\$265.49	\$408.90	\$910.00	\$1,584.38

A Appendix

Loan Name	Eligible Borrowers	Borrowing Limit	Interest Rate Cap	Term Cap
Personal Property	Homeowners	\$40,000	4 or 8%*	30 years
	Renters			
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	\$2M ⁺	4%	-
	Small agricultural cooperative			
	Most private nonprofit organizations			

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.



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