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

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Abstract. We find the Small Business Administration's disaster-relief home loan program denies significantly more loans in areas with larger shares of minorities, subprime borrowers, and higher income inequality. We find that risk-insensitive loan pricing, a feature present in many regulated and government-run lending programs, is an important driver of these disparities in access to credit. The differences in denial rates are disproportionately high compared with private-market lending and government-insured risk-sensitive loan pricing programs. Thus, despite ensuring "fair" prices, the use of risk-insensitive pricing may lead to "unfair" access to credit.

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1. Introduction

Prices play a central role in the efficient allocation of resources in market-based economies. Credit markets are no different. Nearly all theoretical and empirical work in the banking literature is grounded in the idea that capital is more efficiently allocated when lending rates reflect the credit risk of borrowers, with riskier borrowers paying higher interest rates on their loans. However, a number of lending programs conducted by government agencies and development banks around the world violate this principle and charge rates that do not vary according to credit risk. These lending programs typically offer borrowers a subsidized interest rate without (or with limited) risk-based pricing. With a fixed price (i.e., lending rate), all borrowers who receive credit do so at the same interest rate. Policymakers often debate the costs and benefits of risk-insensitive pricing policies both in government-run programs and private markets—including the ongoing debate on the need for interest rate caps in some lending markets.[1]

Although such risk-insensitive lending programs seem "fair" in the sense that they treat all borrowers equally in terms of pricing, they may end up being "unfair" to lower-quality borrowers who would only be deemed creditworthy under a risk-sensitive pricing mechanism. In this paper, we study the effect of risk-insensitive pricing in government lending programs on the allocation of credit using an important U.S. government lending program: disaster-relief home loans administered through the Small Business Administration (SBA). Our main results show that the SBA's fixed-price lending program provides lower access to credit for marginal and underserved populations. Furthermore, these disparities in access to credit are greater than those found in counterfactual private-market risk-sensitive pricing schemes.[2]

The typical goal of many government lending programs, including the disaster lending program that we study, is to alleviate frictions in access to credit for marginal or "underserved" borrowers. Given this focus, it is reasonable to expect that marginal borrowers would have better access to credit through government lending programs compared with private markets. To that end, the programs often include subsidized, risk-insensitive lending rates. However, there is typically an opposing force limiting the government's ability to provide credit: Governments face pressure to minimize taxpayer losses.[3] The combination of responsible tax dollar stewardship with a risk-insensitive lending rate creates a difficult tension. The inability to charge higher, risk-appropriate interest rates to lower credit quality applicants raises the expected cost of lending to them. Thus, borrowers who are only creditworthy at a higher interest rate may be denied credit altogether if the government lender is unwilling or unable to bear the expected loss that comes from charging the artificially lower risk-insensitive rate.

We develop a stylized model that compares denial rates between a risk-sensitive lending market and a subsidized, risk-insensitive government lending program.

Informational frictions cause some borrowers to be denied credit even in the risk-sensitive market in line with Stiglitz and Weiss (1981).[4] In the government lending program, the level of credit rationing depends not only on the informational frictions faced by the lenders, but also on the extent of the government's subsidy and the interest rate they charge. We find that borrowers in communities with more dispersed credit quality have higher loan denial rates in a risk-insensitive program when the level of subsidy is sufficiently low. In practice, whether the design of the (risk-insensitive) SBA program yields relatively higher denial rates in such communities remains an open empirical question that our paper tackles. Specifically, our empirical tests estimate whether and to what extent marginal borrowers face greater loan denial rates with risk-insensitive pricing compared with a risk-sensitive program where the interest rate takes into account the borrowers' credit risk, allowing higher-risk borrowers to access credit, albeit at a higher rate.

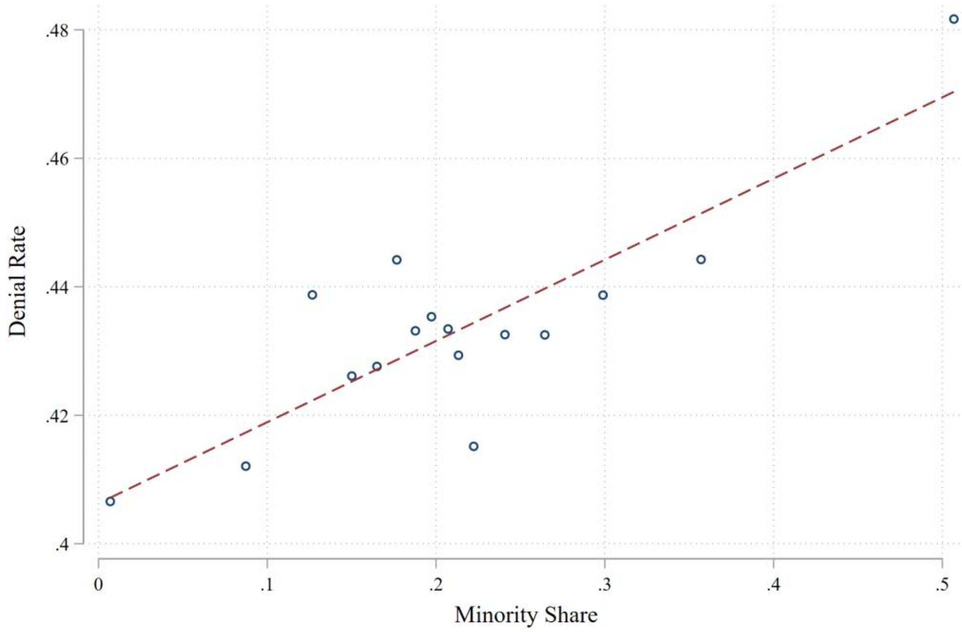
The objective of the SBA disaster loan program is to provide timely access to credit for households and businesses that are victims of natural disasters such as hurricanes, fires, and earthquakes. The loans are given at a highly subsidized rate that is the same for all borrowers who qualify for approval, irrespective of credit quality. We study the SBA disaster-relief *home* loan program using data obtained through a Freedom of Information Act request. The screening process for disaster-relief households is similar to a typical mortgage application (e.g., credit score, income, etc.). These data cover more than a million loan applications following natural disasters across the United States between 1991 and 2015. In contrast to most publicly available databases of government lending programs, our data contain both approved and denied applications for these government loans.

We test for the effect of risk-insensitive loan pricing on credit allocation decisions by comparing the loan denial rates of applicants from areas with a higher need for price discrimination (NPD) to loan denial rates of applicants from areas with lower NPD. We define high-NPD areas as those with a greater mass in the "marginal" portion of the credit quality distribution. As we show in our model, the risk-insensitive program is likely to deny credit to more borrowers in this category as the lenders face greater uncertainty about their true credit risk. Motivated by prior work in the literature on mortgage lending, we use two main proxies for NPD in our tests: areas with a larger share of minority population and areas with a larger share of subprime borrowers based on FICO scores (Smith 1995, Charles and Hurst 2002, Ziliak et al. 2011, Bayer et al. 2016).[5] To summarize, we hypothesize that the combination of borrower screening for credit quality and the inflexibility in setting prices leads to higher denial rates for applicants from these high-NPD areas. Alternatively, government programs, which often have explicit goals to reach and support such higher-risk and underserved areas, may be better equipped to provide credit in these areas. In that case, we would expect a relatively lower denial rate in the high-NPD areas.

We primarily focus on the minority share of the applicant's county as our key NPD measure. Minority share has been shown to capture both hard and soft information about the borrower pool in ways beyond what is captured by measures such as the share of subprime borrowers in an area. Bayer et al. (2016) show that minority borrowers default at a higher rate even conditional on observables like credit score. The higher conditional default rate can potentially be due to unobserved credit risk factors such as lower levels of wealth, higher employment and income volatility, or weaker access to informal financing networks like friends and family, among other things (Smith 1995, Charles and Hurst 2002, Ziliak et al. 2011). Additionally, the Federal Housing Finance Agency includes the minority population as a key criterion in designating an area as "underserved."[6] The use of minority share also allows us to document the disparate impact (i.e., heterogeneity in consequences) of the risk-insensitive interest rates across demographic groups, which is important in light of Fair Lending Laws.[7] Although a number of papers have examined the effectiveness of government interventions in private lending markets on credit access for minorities, we are the first paper to examine how the government's *own* direct lending to its citizens fares on this dimension.

We begin our analysis by documenting a strong positive correlation between NPD and county-level SBA loan denial rates. The relationship is summarized in Figure 1, which is a bin scatter plot of loan denial rates as a function of the minority share of the population while controlling for disaster × year and state fixed effects. In regression analysis, we find borrowers in areas with higher minority share and areas with a higher fraction of subprime borrowers have significantly higher denial rates in the SBA disaster lending program. Of these two proxies for NPD, the minority share of the population correlates more strongly, both economically and statistically, with the denial rate. We find a one-standard-deviation increase in minority-share of the population is associated with a 3.4-percentage-point higher denial rate, even after controlling for income, population, and the extent of losses incurred in the disaster. With the average denial rate in our sample at 42%, these results are economically significant. Although applicants in these areas may be the target of government lending programs, these results provide evidence that the government's own lending program does not reach marginal borrowers at the same rate as other groups during a time of crisis.

Figure 1. (Color online) Minority Share of the Population and SBA Loan Denial Rates



Note. This figure presents a binned scatter plot of the county-level SBA loan denial rate as a function of the minority share of the population while controlling for disaster event fixed effects and state fixed effects.

What is the economic reason for the relative lack of credit access for applicants in high-minority areas? Attributing these differences to the SBA's risk-insensitive pricing scheme faces an empirical challenge: we must separate differences in denial rates due to risk-insensitive pricing from differences that would occur even under a risk-based pricing scheme. Differences may arise even in a risk-based pricing scheme because of baseline differences in credit risk or levels of credit rationing due to asymmetric information in line with our theoretical model. Therefore, to tease out the effect of risk-insensitive pricing, we need a reasonable counterfactual benchmark for the baseline risk-sensitive denial rate.

We use home loan application decisions in the risk-sensitive mortgage market obtained from the Home Mortgage Disclosure Act (HMDA) data set to form our counterfactuals. In particular, we use home improvement loan applications through the Federal Housing Administration (FHA-HI) program as our primary risk-sensitive benchmark.[8] The FHA-HI loans are similar to the SBA disaster loans on a number of dimensions. They are both aimed at home repair and improvements, have similar collateral requirements, and have the same seniority.[9] The borrowers in the FHA-HI program also have a similar income distribution and receive loans of similar average magnitude as the borrowers in the SBA program. The FHA-HI counterfactual also allows us to examine variation in denial rates across risk-insensitive and risk-sensitive lending programs within the same area and around the same time as the disaster loans. Thus, the FHA-HI benchmark incorporates baseline credit quality, credit rationing, and any potential biases that may be present in the local market at a particular time.[10] A key difference, however, between FHA-HI loans and SBA home loans is that FHA-HI loans do not follow a fixed-price, risk-insensitive pricing scheme. These qualities of the FHA program make it a plausible counterfactual risk-sensitive lending program, allowing us to examine differences in credit access in the SBA disaster program that arises due to risk-insensitive pricing.

To summarize, there are two offsetting forces at play when we compare the denial rate across the FHA-HI program and the SBA program. The higher subsidy provided by the SBA program allows more people to be included in the program, whereas risk-insensitivity excludes some marginal borrowers altogether. In the end, there are two open empirical questions. (a) Whether on average the denial rate is higher in the SBA program or not? (b) Are marginal borrowers more likely to be denied in the SBA program or not? Our results show that on average both programs have similar denial rates, that is, the higher subsidy of the SBA program offsets the additional denial that arises due to its risk-insensitive nature. To tease out the distributional effects, we estimate differences in loan denial rates across risk-insensitive (SBA) and risk-sensitive (FHA-HI) lending programs for each county-year for which there are SBA loan applications.[11] We find that a one-standard-deviation increase in minority share corresponds to a 4.2-percentage-point higher denial rate under the SBA program relative to the risk-sensitive FHA loans. Examining across quartiles of minority share, we find applicants from counties in the top quartile of minority share experience an SBA denial rate that is approximately 10.2 percentage points higher than the SBA denial rate in the low-minority-share counties after differencing out the corresponding county-level baseline FHA-HI loan denial rate. We find similar results across a variety of subsamples that highlight the robustness of the results. Specifically, we find similar results when constraining the sample of SBA loans to those requiring collateral or restricting the SBA sample to loans less than $25,000 to match the cap on FHA-HI loans. Furthermore, we find similar results when we compare denial rates in the SBA program to FHA refinancing loans (not just home improvement) or all mortgage refinancing applications in the HMDA database.

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

To provide some context on the economic importance of our results, we use our main estimates to conduct a back-of-the-envelope calculation of the additional credit that would have been extended if the SBA program allowed for risk-sensitive pricing. Our calculation suggests that about 90,000 additional homeowners would have received loans, which adds up to a total of about $2.9 billion in loans. The economic importance of this number is amplified by the setting since the marginal value of credit is especially high in the aftermath of a natural disaster.

Potential threats to our identification strategy would entail unobserved factors that drive differences across loan programs that systematically vary with our NPD measures. Through a number of strategies, we present evidence that factors including taste-based discrimination or potential systematic differences in the loan pools across high- and low-NPD areas across the SBA and counterfactual loan groups are unlikely to drive our results.

Our paper provides important insights into policy discussions on the costs and benefits of government-assisted lending programs. Specifically, our results show that policymakers need to carefully consider the distributional consequences of the disaster lending program: a program that is intended to help marginal borrowers in times of distress, such as in the wake of hurricanes, floods, and pandemics. Our paper is related to several strands of literature including studies on government intervention into markets and, specifically, credit markets, studies on whether price discrimination can lead to unfair pricing across groups of individuals, and the literature on the supply of (private market) credit in the wake of natural disasters, among others. Our paper is the first one to study the implications of risk-insensitive pricing on minorities and other marginal borrowers, a finding that has important implications for regulations on fair access to credit across different demographics of society. Furthermore, our study is the first to analyze the effectiveness of government lending programs in reaching these borrowers as compared with the private lending market. After presenting and discussing our results, we discuss the contribution of our paper in the context of the existing literature in more detail in Section 8.3.

In terms of policy decisions, our model provides some key insights into the design and implementation of the disaster loan program. The current SBA program uses uniform pricing with a heavy subsidy, whereas programs such as FHA use risk-sensitive pricing with a relatively smaller subsidy. Using our stylized model, we run a counterfactual analysis to show how a blend of these two programs can lead an improvement in distributional outcomes. Our counterfactual study shows that an interest rate that is structured as a discount to the prevailing risk-sensitive market rate may work as a better mechanism in terms of access to credit and distributional fairness. Such a mechanism still provides a subsidy to borrowers hit by the disaster, but it allows the program to differentiate across borrowers with varying levels of credit risk, thereby expanding access to marginal communities.

2. SBA Disaster Loan Program

2.1. Program Objectives

The SBA Disaster Loan Program provides loans to individuals and businesses who are victims of disasters with a disaster declaration by the President or the SBA. More than 1.9 million loans totaling more than $47 billion have been approved by the SBA since its inception (Lindsay 2010). Our main analysis focuses on loans made to individuals (i.e., not businesses). Borrowers use these loans to repair or replace real estate and personal property beyond what is covered by home insurance.

Two of the key frictions that the SBA Disaster Lending Program aims to overcome are timing (pressing need for credit for which the private markets may not have the capacity) and negative externalities that result from lost jobs and income for individuals and small businesses. Consider the following excerpt from the Congressional Justification Report (Small Business Administration 2020):

> Returning small businesses to normal operations, preserving jobs, and helping families rebuild their homes after a disaster are critical to ensuring that local economies recover as quickly as possible. The SBA deploys disaster assistance resources immediately, effectively, and efficiently to disaster survivors to preserve jobs and help return small businesses to operation.

The speed of aid is critical after a disaster. Delays in providing funding can quickly lead to substantial depreciation of capital. For example, replacing a roof or removing water from a basement needs to be done in a timely manner to prevent mold or further damage to a home. Banks are typically much slower at processing such applications and may be dealing with postdisaster logistical challenges themselves (e.g., damage to their branch or shortage of employees). Thus, the SBA plays an important role in recovery.

The SBA is not a profit-maximizing institution, as evidenced by the subsidized interest rates on the disaster loans. However, the SBA must balance the objective of lending to borrowers in need (and any accompanying externalities) against the budgetary costs incurred by increasing capital availability at subsidized rates. Said differently, there is a strong emphasis on being a good steward of taxpayer dollars as shown by the fact that the SBA explicitly screens applicants based on their creditworthiness. The tradeoff facing the SBA is highlighted in the Office of the Inspector General's (OIG) review of the SBA's performance surrounding Superstorm Sandy (Office of the Inspector General 2016):

> We recognize that borrowers in this program are disaster survivors in need of assistance and that SBA disaster loans are unexpected debts. However, the program is designed with the expectation that these loans are ultimately repaid. Borrowers with an unsatisfactory credit history are more likely to default and therefore, pose a greater risk to taxpayer dollars … . Because SBA utilizes taxpayer funds to lend to disaster survivors, it is also our responsibility as a creditor to establish a reasonable assurance that disaster loans will be repaid. Accordingly, our loan decisions are based on a balance between our role as a provider of disaster assistance and our responsibility to protect the government's interests and taxpayer dollars.

Anecdotal evidence indicates there is significant scrutiny of the SBA disaster loan program's performance in both its efficiency in allocating capital and overall budgetary costs. For example, a 1997 congressional budget office report raised concerns about the SBA disaster loan program's budgetary costs and suggested increasing the interest rate on loans to reduce these costs (Congressional Budget Office 1997, pp. 135–136).

2.2. Loan Underwriting

In the wake of a disaster, the SBA processes loan applications, performs inspections, makes lending decisions, contracts with borrowers, and then disburses funds. The SBA loan officers, who are made up of both permanent and temporary workers, assess an applicant's creditworthiness when determining whether to approve a loan. The lending decision is based on a number of factors that largely mirror the typical mortgage application process: an acceptable credit history, an ability to repay loans, and collateral (if available). Requested documentation includes items such as prior tax filings and employment records.

During the loan review process, an appraiser will verify the applicant's loss, and the amount of loss will cap the size of the loan. The loan officers' primary responsibilities are to collect and verify facts (taking care to avoid fraud) and ensure the application is properly submitted. The underwriting criteria that drive loan approval are clearly defined in the SBA's Standard Operating Procedures (Small Business Administration 2015) and leave very little discretion to the loan officer with respect to making any independent evaluation of credit quality beyond the procedures outlined by the SBA.[12] Finally, the application approval decision is subject to the same fair lending laws as private market lenders (e.g., the Equal Credit Opportunity Act) and cannot be explicitly driven by an applicant's race, color, national origin, or gender.

Although projecting loan performance is a driving influence in the screening process, the SBA does not price loans differentially according to applicant risk. The loan interest rate is determined by a statutory formula based on the government's cost of borrowing. For individuals seeking home loans, there are only two possible interest rates: a lower rate for borrowers who do not have "credit available elsewhere," based on the applicant's credit score, cash flow, and assets (Small Business Administration 2015), and a higher rate for borrowers who do have credit available elsewhere. The interest rates are calculated for each disaster given the government's current cost of borrowing.[13] For both types of borrowers, the rate is typically lower than the prevailing private-market interest rate on a 30-year fixed-rate mortgage. For example, for Hurricane Harvey in 2017, the respective SBA rates (1.75% and 3.5%) were both below the Freddie Mac average rate of around 3.9% (Figure IA.1 in the online appendix presents the fact sheet for Hurricane Harvey). Thus, it is in the interest of those seeking credit to apply for these loans, and this minimizes selection bias concerns in the pool of applicants. Importantly, for applicants of marginal creditworthiness, the interest rate cannot be increased to a point in which the risk-return tradeoff is sufficient for approval. Instead, such loans are simply denied.

3. Model

As discussed in the previous section, because the SBA disaster loan program must balance the two objectives of providing assistance to the affected borrowers while still minimizing the cost of the program to the taxpayers, it is not ex ante clear whether the program will reject more or fewer loans than the private risk-sensitive market. We develop a simple model in this section to derive conditions under which the SBA program is more (or less) likely to reject loans as compared with the risk-sensitive benchmark. We also use our model to run counterfactual experiments that can inform policy design.

The model borrows some of the essential ingredients of canonical credit rationing models to analyze the tradeoff the SBA faces in its lending program. We consider a continuum of borrowers who need to invest one dollar at $t = 0$ in a project (e.g., repair their home). The borrower puts in his own equity of e and borrows the remaining amount $1 - e$ from a lender (e.g., the SBA). The project has a random payoff at time $t = 1$ given by $\tilde{R} \sim N(\mu, \sigma_u)$. The lender does not have knowledge of this distribution, but it observes a signal f (e.g., FICO score) that correlates with the quality of the borrower's average payoff μ and its variance σ_u. Specifically, the lender can observe the average payoff (μ), but it does not observe the riskiness of the borrower's payoff, σ_u, as in Stiglitz and Weiss (1981). We assume a risk-free rate of 0% without any loss of generality.

The lender has a pricing schedule $p(f)$, equal to one plus the promised interest rate at $t = 1$, where observationally riskier borrowers pay a higher price ($p'(f) < 0$). Following Stiglitz and Weiss (1981), we assume that the borrowers make an optimal decision based on the pricing of the loan and their private information about the riskiness of the project's payoffs. Therefore, conditional on a FICO score of f, the borrower with a random payoff of $R(f)$ takes the loan only if the following condition holds:

$$E[max(\tilde{R(f)} - p(f), 0)] \geq e. \tag{1}$$

The random payoff $\tilde{R(f)}$ completely captures the default risk of the borrower in the model. We assume that $\tilde{R(f)} \sim \mathcal{N}(\mu(f), \sigma_u(f))$, with $\mu'(f) > 0$ and $\sigma'(f) < 0$. These conditions capture the idea that as the borrower's FICO score deteriorates, the project is expected to be less attractive with lower mean and more variance in the payoff, similar to the real world.

Noting that $\tilde{R(f)} = \mu(f) + \sigma_u(f)Z$ where Z is a standard normal random variable, we get the following equation as the participation condition for a borrower with score f:

$$E[max(\tilde{R(f)} - p(f), 0)] \geq e \Rightarrow \int_{-\infty}^{\infty} (\mu(f) + \sigma_u(f)Z - p(f))^+ \phi(z) dz \geq e, \tag{2}$$

where $\phi(z)$ is the probability density function of a standard normal random variable. Therefore, the borrower takes the loan only if

$$\sigma_u(f)\phi\left(\frac{p(f) - \mu(f)}{\sigma_u(f)}\right) + (\mu(f) - p(f))\left[1 - \Phi\left(\frac{p(f) - \mu(f)}{\sigma_u(f)}\right)\right] \geq e. \tag{3}$$

Lenders anticipate this participation behavior and require that the following breakeven condition hold for them to lend to borrowers at FICO level f ($\Phi\left(\frac{p(f)-\mu(f)}{\sigma_u(f))}\right)$ is the default probability of borrower f):

$$1 - e = E\left[\left(1 - \Phi\left(\frac{p(f) - \mu(f)}{\sigma_u(f)}\right)\right)p(f) \mid \sigma_u > \sigma_u^*\right]. \tag{4}$$

The condition states that the lender will lend to borrowers with a FICO score of f if they breakeven with their pricing schedule $p(f)$ conditional on the pool of borrowers they attract based on the participation equation. As the FICO score deteriorates, the lender increases the price to breakeven, but beyond a level, f^*, the breakeven condition will fail, and the lender will stop lending altogether. This point corresponds to the risk-sensitive lender's lending threshold. Borrowers below the critical value of f^* are rationed even with risk-sensitive pricing.

As discussed earlier, the SBA program has dual objectives of providing credit to borrowers in need and being good stewards of taxpayer dollars by minimizing excessive losses. We model this "modified budget constraint" by assuming that the SBA breaks even up to a subsidy level s. Thus, the breakeven constraint for the SBA is as follows:

$$1 - e = E\left[\left(1 - \Phi\left(\frac{p(f) - \mu(f)}{\sigma_u(f)}\right)\right)p(f) \mid \sigma_u > \sigma_u^*\right] * (1 + s). \tag{5}$$

The condition states that the SBA also attempts to break even, but it has a weaker budget constraint compared with the private market. Therefore, the SBA values the expected payoff conditional on participation by a slightly higher amount, which is given by $(1 + s)$ in the model. This can be set to one with $s = 0$, in which case the SBA behaves in a similar manner as a private bank.

We introduce a pricing schedule, $p(f) = a - bf$, to calibrate the model and generate numerical solutions. f can vary from -1.5 to $+1.5$, with an average value of zero. The lender offers a rate of a% to prime top-quality borrowers, which we characterize as those with $f > 0$. As the borrower's f-score goes down, the borrower pays a greater rate at a slope of b. A larger b denotes higher higher risk-sensitivity. In the SBA lending market, the rate is fixed at a subsidized level for every borrower ($b = 0$) and the fixed rate is denoted by r_{dl}, which is below a%.

We parametrize the mean payoff of the project as a linear function $\mu(f) = \mu_0 + \mu_1 * f$ with both μ_0 and μ_1 as positive numbers. We ensure $\mu_0 > 1$ to capture the idea that the average borrower ($f = 0$) has a positive NPV project. We parameterize $\sigma(f) = 0.25e^{-f}$ such that it decreases with f. The parameter values for the base case estimation are provided in Table 1.

We estimate the denial rate based on the borrowers' participation choice and the bank's and SBA's break-even constraint as derived in the model and present the denial rates for different scenarios in Table 2. We purposefully calibrated the model to make the unconditional average denial rate roughly equal across the two groups, which is consistent with the average denial rates across the two programs we analyze in empirical exercises later in the paper (SBA and FHA-HI). The first row of the table presents the estimation results for the base case scenario with a subsidy of 2.5% for the SBA program. The market-based pricing schedule denies credit to 45.62% of borrowers in this economy. Using identical assumptions except for the subsidy and the use of risk-insensitive pricing, the disaster lending program denies credit to 46.21% of the borrowers, giving us an excess denial rate of 0.6% in the model. The denial rates are roughly similar for the two programs for the base case: the risk-insensitive pricing aspect of the disaster lending program lowers the acceptance rate for riskier borrowers, but the opposing force of the SBA subsidy increases the acceptance rate for this group of borrowers.

We now introduce a riskier group of borrowers for whom the volatility of payoff is higher than the base case scenario. This group has higher uncertainty about their labor income, wealth, or other financial sources; that is, this group represents the marginal borrowers of the economy. In our calibration exercise, we characterize the variance of their payoff by assuming: $\sigma(f) = 0.50e^{-f}$. This group of borrowers has a higher need for price discrimination (NPD) and will be the focus of our empirical tests. We compare the denial rate for this group of borrowers across the two programs. The SBA denial rate is 64.62% and considerably higher than the market denial rate of 60.06%.

Our model makes it clear that the level of excess denial in the SBA market depends on the level of subsidy and the extent of risk-insensitive pricing. If the level of subsidy s in our model is sufficiently high, then the SBA denial rate can in fact be lower than the risk-sensitive market. We show that result in a counterfactual analysis where we vary the subsidy parameter s in Figure 2, which plots the excess denial rate (the denial rate in the disaster lending program minus the corresponding rate for the risk-sensitive program) as a function of the subsidy.[14] At $s = 0$, the SBA behaves exactly like a private lender, recovering the entire amount lent under the disaster lending program in expectation. Excess denial is highest in this scenario. As s increases, the SBA approves more (negative NPV) loans and the excess denial rate decreases. For a sufficiently high subsidy, the excess denial rate falls below zero. In this scenario, the SBA lending program provides "excess" credit to the high-risk borrowers because of the large lending subsidy.

Our model shows that the level of excess denial in the SBA disaster loan program is not ex ante clear but rather is an open empirical question. We develop our empirical tests in light of the intuition derived from the model. After presenting our key empirical findings, we conduct some counterfactual analysis to analyze how a policy change in the design of the disaster lending program might affect outcomes.

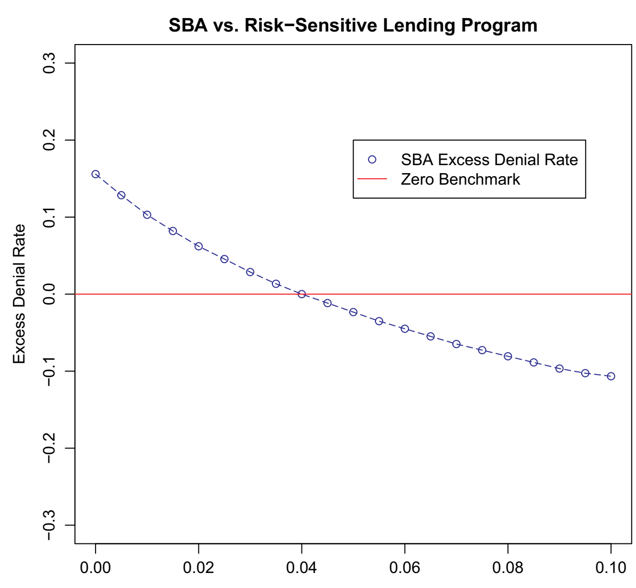
Table 1. Model Parameters: Base Case

Parameters	Definition	Values
a	Interest rate for prime borrowers	0.08
b	Risk-sensitivity factors	0.08
r_{dl}	Fixed rate for disaster lending	0.02
e	Owner's equity	0.10
s	SBA subsidy	2.5%
μ_f	Average project payoff for borrower f	$1.25 + 0.5 * f$
σ_f	Volatility of payoff	$0.25 * exp(-f)$
$\sigma_f(H)$	Volatility of payoff for group H borrowers	$0.50 * exp(-f)$

Table 2. Estimation Results: Denial Rate

Case	Group	Market	Disaster	Excess
Base case	Average risk group	45.62%	46.21%	0.60%
Group H	High NPD group	60.06%	64.62%	4.56%

Figure 2. (Color online) Relationship Between the Excess Denial Rate in the Disaster Lending Program as the Level of Subsidy Increases



Notes. The borrowers face a pricing schedule, $p(f) = a - bf$, based on the signal (f) of their quality (e.g., FICO score). There is a lower bound of a on the interest rate. For this group of marginal borrowers, we set $\sigma(f) = 0.50e^{-f}$ with a lower bound of 0.5.

4. Research Design

4.1. Measures of the Need for Price Discrimination

We use two main proxies for the need for price discrimination in our initial tests: the minority share and the subprime share (credit score below 660) of the county population.[15] These proxies aim to capture the relative mass of applicants in the credit quality distribution for a county between the private-market risk-sensitive threshold and the SBA risk-insensitive threshold.

For most of our analysis, we focus on minority share. The use of this variable as our main proxy for NPD is motivated by a large literature on racial differences in lending markets, which has shown evidence of observable and unobservable differences in credit quality across groups. In particular, the minority share of the population is strongly correlated with credit scores and has also been shown to be strongly related to other important drivers of mortgage credit quality including wealth and volatility of income and employment. Moreover, high-minority areas have historically been a priority for legislation such as the Fair Housing Act, so examining how the government's own SBA lending program fares against a private-market benchmark is of additional interest.

4.2. Empirical Specification

Our first tests regress county-year-level denial rates in the SBA program on NPD and other controls including state × year and disaster-type × year fixed effects. This test examines whether, on average, there are differences in SBA disaster loan denial rates across high- and low-NPD areas. The motivation for these tests is to provide baseline facts on which areas receive greater access to credit. Although it is important to document this fact in itself, a positive correlation between an area's *NPD* and SBA loan denial rate is not fully conclusive about the relationship between the SBA's risk-insensitive pricing scheme and loan denial rates. This correlation may also capture baseline heterogeneity in factors such as overall average credit quality or the information environment (leading to higher rationing) that would lead to the same outcome in private markets where pricing is flexible. Thus, an ideal research design to separate these effects would compare the denial rate in the disaster lending program to the denial rate for identical applicants under risk-sensitive loan pricing. While such a counterfactual is unobservable, we can observe some close substitutes.

Our main empirical specification compares the SBA denial rate to a plausible counterfactual risk-sensitive loan program within county × year across areas with varying degrees of *NPD*. For each county-year observation in the SBA data, we create a corresponding observation based on the county's counterfactual risk-sensitive denial rate in the most recent nondisaster year. Thus, for each county × year in the SBA loan data set, we have an observation for each of the two loan programs: one with the SBA denial rate and one with the private-market (risk-sensitive) denial rate as the dependent variable. We then estimate the following regression specification with observations for county c, loan program p, and year t:

$$denial\ rate_{p,c,t} = \alpha + \delta \mathbb{1}[SBA_{p,c,t}] + \theta(\mathbb{1}[SBA_{p,c,t}] \times NPD_{c,t}) + \zeta_{c,t} + \epsilon_{p,c,t}, \tag{6}$$

where $NPD_{c,t}$ is the proxy for need for price discrimination in county c at time t, which we standardize to have zero mean and unit standard deviation; $\mathbb{1}[SBA_{p,c,t}]$ is an indicator equal to one if the denial rate is for the SBA program; and $\zeta_{c,t}$ indicates county × year fixed effects, which allow us to exploit within-county-year variation in denial rates across the SBA and counterfactual programs. These granular fixed effects account for any unobserved county × year heterogeneity that would similarly drive denial rates across programs. The county × year fixed effects also absorb any variation across counties in disaster type. In this specification, $\hat{\delta}$ represents the average difference in risk-insensitive SBA and risk-sensitive private-market denial rates. The estimate of interest is $\hat{\theta}$, which indicates the differential sensitivity in denial rates to NPD between the risk-insensitive SBA program and the risk-sensitive counterfactual. The expression $\hat{\theta} > 0$ indicates that the relationship between NPD and denial rates is stronger in the government-directed SBA program compared with the private-market counterpart.

4.3. Counterfactual Loan Programs

The ideal counterfactual loan program would consist of the same set of borrowers in the same financial condition applying for the same type of loan, only replacing the risk-insensitive pricing scheme with a risk-sensitive pricing scheme. We use credit allocation decisions in the private mortgage market to approximate this ideal, with a particular focus on applicants to a government-insured lending program. We describe our counterfactuals in more detail below along with their relevant strengths and challenges.

Our main counterfactual denial rate is the denial rate for the FHA-HI program using data from HMDA. Several factors make the FHA-HI denial rate a plausible counterfactual. First, FHA-HI loans are insured by the government, so the FHA-HI program shares some similar incentives and constraints as the SBA. Second, FHA-HI loans are priced by the private-market lenders that issue them, so we are comparing a risk-insensitive loan program (SBA) to a risk-sensitive loan program (FHA-HI). Third, proceeds of FHA-HI loans are required to be "used only to finance property improvements that substantially protect or improve the basic livability or utility of the property," which is similar to the use of SBA loans to improve damaged property. It is reasonable to assume that a borrower who needs financing for roof repairing or basement flooding does so soon after the need arises, which reduces concerns about loan application timing. Fourth, FHA-HI borrowers are of similar average income (year 2000 dollars) at $59,000 compared with the income of SBA borrowers of $52,000 shown in Collier et al. (2020). Fifth, the average loan size is similar across the two programs with an average size of $33,470 in the FHA-HI program and $32,740 in the SBA disaster loan program (year 2000 dollars). Sixth, both types of loans are junior to the primary mortgage. Seventh, the average denial rate is similar across the two programs at 43% in the FHA-HI loan program and 42% in the SBA loan program. Eighth, the two programs have similar threshold loan values for which they start to require available capital to be collateralized. For every county, we obtain data on denial rates for the FHA-HI applicants for the most recent nondisaster year and use this as our baseline counterfactual denial rate.

As alternative counterfactuals, we consider refinancing applications to the FHA program and all refinancing applications in the HMDA data set (rather than exclusively FHA loans) for a given county and time. This broader set of applications includes loans that are held on banks' balance sheets, sold to other financial institutions, or securitized through the government sponsored enterprises (Fannie Mae and Freddie Mac), and alleviates concerns that any particular quirks or distortions unique to the FHA market drive our results.

The inclusion of county-year fixed effects and the program indicator variable (SBA or FHA-HI) ensures that our results cannot be explained away by any unobserved factors that similarly drive credit quality across counties or fixed differences in denial rates across the SBA and the risk-sensitive program. Any remaining threat to our identification has to come from unobserved differences between the SBA and the counterfactual program across counties, that systematically varies with the level of *NPD*. We discuss some of these concerns and our empirical strategy to address them here.

4.3.1. Changing Applicant Pool. One concern for our identification strategy relates to the potential for a *disproportionate* worsening of the applicant pool in the SBA program relative to the counterfactual program in high-*NPD* areas relative to low-*NPD* areas. We consider three channels through which this could affect the interpretation of our empirical tests: (1) a disproportionate negative shock to creditworthiness from the natural disaster itself; (2) disproportionate loan application timing in the counterfactual program; and (3) disproportionately poor understanding of the SBA application process. We discuss these in turn.

4.3.1.1. Differential Shock to Creditworthiness. One concern related to our identification strategy is that borrowers may experience a decline in their creditworthiness during the disaster period. In this case, the private-market benchmark may underestimate the counterfactual denial rate for the disaster lending market. If a postdisaster deterioration is similar across areas with varying levels of *NPD*, then our empirical strategy is unaffected because we are estimating the incremental denial rate for high-*NPD* areas as compared with relatively low-*NPD* areas. The remaining concern is that the credit quality of high-*NPD* disaster loan applicants falls disproportionately as compared with the corresponding difference for the low-*NPD* areas. We examine this issue directly by examining relative changes in creditworthiness following the disaster across counties with different levels of *NPD*.

4.3.1.2. Differential in Strategic Loan Application Timing Between the SBA and Our Counterfactual. The second potential concern is whether there is greater scope for application timing in the counterfactual loan programs than in the SBA program. Because disasters are plausibly unpredictable and the window for application is relatively short, the SBA program does not lend itself to "timing" the market in the sense of waiting until you reach some optimal credit quality before applying. In nondisaster settings, it may be the case that mortgage loan applicants engage in market timing, such as waiting to apply until their credit score or downpayment is sufficiently large. If such timing were to both (1) affect loan denial rates and (2) occur at a disproportionately higher rate in high-NPD areas relative to low-NPD areas, then this would present problems for the interpretation of our results. In the context of our main test in regression (6), this would mean that, relative to our ideal counterfactual, any disproportionate timing in the FHA market for high-NPD areas would lead to denial rates that would be biased downward relative to low-NPD areas and bias our difference-in-differences estimates upward.

Our focus on FHA home improvement loans as the base case counterfactual reduces such timing concerns. These loans are used to repair houses and make them "more livable and useful" such as fixing a leaking roof or flooded basement.[16] As such, there is often less room for discretion and the cost to waiting, for example, for an improvement in FICO score can be significant.

Second, we examine these premises through the lens of prior literature to evaluate whether it is likely that there is significant timing in mortgage applications and, if so, whether individuals in high-NPD areas are better at timing their application. First, there is a large literature showing that, on average, households do not seem to behave optimally in terms of mortgage product choice or timing the market (Campbell and Cocco 2003, Campbell 2006, Keys et al. 2016). Furthermore, recent empirical work has shown that the majority of borrowers suboptimally choose their mortgage contract and application timing and that those with less financial sophistication are worse at such timing (Agarwal et al. 2016, 2017). Although it is plausible that some timing may influence our results, given the results in the prior literature and the economic magnitudes of the estimates we find, it seems unlikely that mortgage market timing explains our results.

4.3.1.3. Do Applicants Understand the SBA Loan Program's Design? There may be concerns that applicants to the SBA program may not understand the program and apply without any strategic considerations. This alone is not a serious threat to our identification unless applicants understand the counterfactual loan program much better and only apply when they know they are likely to be approved. The result would be a relatively homogeneous denial rate between low- and high-*NPD* areas in the counterfactual program, whereas yielding a greater high- vs. low-NPD disparity in the SBA program where everyone applies.

Although we cannot directly measure applicants' understanding of the SBA program, we can provide some evidence that SBA applicants have a grasp of the details of the program by exploiting an institutional feature of the SBA program relating to collateral requirements. The SBA allows for unsecured borrowing up to a certain dollar amount (e.g., $25,000 in 2014) above which loans are subject to the SBA's collateral requirement.[17] If applicants do not understand the application process and loan program requirements, then we expect the distribution of loans to be somewhat smooth around the collateral thresholds. Alternatively, if applicants know how this aspect of the program works and pledging collateral is costly, we expect a "bunching" of loans just below the threshold.

Figure IA.2 in the online appendix presents the empirical distribution of loans under $30,000 separately for above- and below-median minority areas (our main measure of NPD). As mentioned above, the collateral requirement threshold for loans was $10,000 from 1991 to 2007, increased to $14,000 in 2008, and then increased to $25,000 in 2014. The sharp increases in the number of loans right below the collateral threshold indicate that applicants have some familiarity with the program requirements for approval, and patterns are similar for both above- and below-median minority share of the population. These results support the idea that applicants are aware of how the SBA program works and that there are not meaningful differences in this knowledge across high- and low-NPD areas.

4.3.2. Differences in Collateral and Loan Size. Could differences in the collateral requirements and loan size for the SBA disaster program and the FHA-HI loan program drive our results? The differences in collateral requirements are slight. Neither program requires collateral on loans below a certain threshold. The FHA-HI program requires collateral to be pledged, if it is available, on loans above $7,500. Similarly, the SBA program requires available collateral to be pledged on loans greater than $10,000 from 1991 to 2007, $14,000 in 2008, and $25,000 from 2014 onward. We address lingering concerns about whether these differences differentially affect high- versus low-NPD areas by constraining the sample of SBA loans to only those loans that are likely to be above the SBA's collateral threshold and rerun our main test. We discuss the results of this test in Section 6.[18] A related concern is that the FHA-HI loans are limited to a maximum of $25,000, whereas SBA home loans can be up to $200,000 dollars. In a robustness test, we constrain the sample of SBA loans to conform to this lower limit to address this concern.

4.3.3. Taste-Based Discrimination. A final concern relates to potential taste-based discrimination (Becker 1957) by the SBA loan officers. Our empirical specification is based on the difference in denial rate between the SBA program and the FHA-HI loans. Our goal in this paper is not to assess the level of taste-based discrimination in general. As long as the level of discrimination remains similar across the two programs, our results relating risk-insensitive pricing to excess denial rate remains well identified. If the SBA officers deny credit to minorities based on prejudice at a disproportionately higher rate than the FHA or other counterfactual programs, then this behavior may explain our results. In the case of taste-based discrimination, applicants from high-minority areas who receive credit under the disaster loan program must be of better credit quality than applicants from low-minority areas because high-minority area borrowers have to cross a higher hurdle to get the loan. We directly test this idea by comparing the ex post default rates of approved loans across high- and low-minority areas. We discuss the details of this test later in the paper as we present the analysis.

A second way we examine this channel is by testing whether disparities in credit access are amplified in areas of higher racial animus. For example, Dougal et al. (2019) find that historically black colleges and universities pay higher underwriting fees when issuing bonds, with the largest effects in geographies with higher degrees of racial animus. We use their measures to test whether these factors are present in the SBA program.

5. Data and Sample

We obtained the data on SBA Disaster home loans through the Freedom of Information Act. A key feature that distinguishes our data from the publicly available disaster data are that we have loans that were denied in addition to those that were approved. Our final data include around 1.2 million 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 3, 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," including tornadoes, severe thunderstorms, hail, and flooding, represents nearly one-third of the applications. The table reveals variation in the denial rate across different types of disasters, but it is broadly in the range of 40%–50%. Panel B lists the top ten disasters in terms of number of loan applications in our sample. Hurricane Katrina is the largest disaster with more than 200,000 applications. Figure IA.3 in the online appendix 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.

We obtain data on private-market mortgage lending from the Home Mortgage Disclosure Act (HMDA) data for the years 1990–2015. These data include the vast majority of home purchase and refinancing loan applications and lending decisions in the United States. We focus on FHA home improvement applications. We compute the county-level denial rate for FHA home improvement (FHA-HI) loans during the most recent year in which the county did not experience a disaster as our main counterfactual private-market denial rates.[19] We match this rate to the relevant SBA loan applications by county and year. We alternatively use FHA refinancing loans and the broader HMDA denial rate in some of our tests. The latter includes loans not only through the FHA program, but also those held on banks' balance sheets, sold to other financial institutions, or securitized through government-sponsored entities.

Table 3. Disaster Summary Statistics

Panel A: Disaster types		
	Applications	Denial rate
Hurricane	571,357	48%
Severe weather	432,938	44%
Earthquake	175,986	43%
Tropical storm	55,784	49%
Fire	12,603	45%

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

Notes. 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 for the ten largest disasters (by loan application count) in the sample.

During the course of the analysis, we use three different explanatory variables to capture the *Need for Price Discrimination* (*NPD*). The motivation for these proxies are discussed in Section 4. Our first measure is the fraction of the minority population in the county from the Census. The second *NPD* measure is the percentage of individuals with Equifax subprime credit scores (<660) in a county, which is only available from 1999 onward from the St. Louis Federal Reserve (FRED) database. For robustness, we use the level of income inequality in the area as a third *NPD* measure. Such areas have borrowers on both extremes of the income distribution, and thus the underlying credit dispersion is likely to be higher. We use the county-level Gini index for 1990, 2000, and 2010 from the U.S. Census and American Community Survey data to measure income inequality. We assign the 1990 Gini measure for disasters during 1991–1999, the 2000 Gini for disasters during 2000–2009, and the 2010 Gini for disasters during 2010–2015.

Finally, we use county population from the U.S. Census, county-level per capita income from the FRED, and verified losses incurred by the borrower as assessed by SBA appraisers from the SBA database. Table 4 presents summary statistics, with all dollar amounts adjusted to year-2000 dollars.

6. Results

6.1. SBA Denial Rate Across Areas

We begin our analysis by documenting a strong positive relationship between the denial decision by the SBA and the need for price discrimination (NPD) in the disaster-struck county. Figure 1 shows this relationship in a binned scatter plot of SBA denial rate as a function of the minority share of the county's population. We include state and disaster-event × year (e.g., hurricanes in 2004) fixed effects to flexibly absorb variation in denial rates across states and disaster types over time.

We further examine this relationship with regression analysis. Because our key explanatory variables (*NPD*) are county specific, we collapse the loan-level data to a county-level denial rate.[20] We regress the average county-level loan denial rate on county-level NPD

Table 4. Summary Statistics

	Mean	Standard deviation	Minimum	p25	p50	p75	Maximum	Count
County characteristics								
Subprime	0.33	0.08	0.17	0.27	0.33	0.39	0.52	4,171
Minority	0.22	0.18	0.01	0.07	0.17	0.33	0.81	6,266
Gini	0.43	0.04	0.36	0.41	0.43	0.46	0.53	6,266
Per capita income (000)	33.15	15.77	11.40	20.02	30.25	42.98	82.77	6,266
ln(Population)	11.35	1.38	9.12	10.30	11.12	12.28	14.69	6,266
FHA-HI Denial	0.42	0.31	0.00	0.17	0.40	0.61	1.00	6,266
SBA loans (all applications, county-level)								
SBA denial	0.42	0.25	0.00	0.28	0.42	0.55	1.00	6,266
SBA denial (Collateral)	0.39	0.28	0.00	0.22	0.37	0.50	1.00	5,582
SBA denial (below $25k)	0.45	0.27	0.00	0.29	0.45	0.59	1.00	5,849
Verified Loss (000)	38.75	43.29	2.40	12.59	24.26	45.35	234.58	6,266
Amount (000)	29.46	31.92	0.13	10.50	19.59	35.94	333.68	5,819
SBA loans (approved loans, loan-level)								
Amount (000)	32.74	41.79	0.01	8.40	17.10	40.00	561.90	727,901
Maturity	214.84	128.56	1.00	96.00	192.00	360.00	963.00	727,901
Default	0.08	0.27	0.00	0.00	0.00	0.00	1.00	727,901

Notes. 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, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *FHA-HI Denial* is the county-level denial rate for applications for home improvement loans insured by the Federal Housing Administration in the year prior to the disaster. For the sample of loan applications (All applications, county-level), *SBA Denial (x)* is the county-level denial rate for home disaster loan applications where *x* denotes whether subsampled based on applications being above the collateral threshold or with verified losses of less than $25k, *VerifiedLoss* is the county-level average loss of the applicant as a result of the disaster as verified by SBA officials, and *Amount* is the county-level average SBA loan amount. For approved loans (Approved loans, loan-level), we report statistics on the loan *amount*, the *maturity* in months and whether the loan was charged-off (*Default*).

(subprime share and minority share). 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 5 presents the results. Columns (1) and (2) present the results using subprime share as the NPD proxy, and columns (3) and (4) present the results using minority share.[21] In columns (1) and (3), we present results for the base specification controlling only for state × year and disaster-event × year fixed effects. We find that a one-standard-deviation higher subprime share is associated with an increase of 2.2 percentage points ($p < 0.01$) in the loan denial rate. Similarly, a one-standard-deviation higher minority share is associated with a denial rate that is 3.2 percentage points higher. We next include controls for per capita income, population, and verified loss, which is the average amount of loss as determined by SBA appraisers across disaster loan applications within the county-year. Columns (2) and (4) show that including these controls slightly increases the coefficient estimates on the NPD measures.

In column (5), we present estimates that include both the subprime share of the county and the minority share of the county. We find that the minority share of the county remains highly economically and statistically significant while subprime share is insignificant. This suggests that the minority share of the population may capture both the measured credit quality of the area as well as other unmeasured credit quality factors (with respect to credit score). As suggested by prior literature, the unmeasured factors may include lower wealth, lower income, and more volatile employment that have been shown to characterize higher-minority areas. Minority share may, therefore, better capture the size of the mass of borrowers of marginal credit quality in an area. For this reason, and for its policy relevance related to fair lending laws, we use minority share as our main proxy of *NPD* throughout the remainder of the paper. Our results are qualitatively similar when using subprime share as the proxy for *NPD*, and in Section 6.3, we show our results hold for other proxies of NPD.

These results thus far establish a new and important fact: the government's own lending program does not reach marginal borrowers, who are often the intended recipients of government programs, at the same rate as other groups. What could be the possible mechanism behind this result? We next examine whether the SBA program's lack of risk-sensitive pricing (i.e., charging riskier, marginal borrowers a relatively higher rate to enable a loan to be made) plays a role in the higher denial rates in high-NPD areas.

6.2. Within-County Differences: SBA vs. FHA-HI Denial Rates

In this section, we analyze the within-county differences in denial rates between the risk-insensitive SBA program and the risk-sensitive FHA home improvement (FHA-HI) program across areas with different racial

Table 5. SBA Loan Denial and Need for Price Discrimination

	Subprime		Minority		Both
	(1)	(2)	(3)	(4)	(5)
zSubprime	0.022***	0.027***			0.007
	(0.007)	(0.009)			(0.010)
zMinority			0.032***	0.034***	0.034***
			(0.005)	(0.006)	(0.009)
zSubprime × *zMinority*					−0.004
					(0.006)
zPerCapitaIncome		0.015		−0.001	0.008
		(0.010)		(0.007)	(0.010)
zln(Population)		−0.008		−0.014***	−0.020***
		(0.006)		(0.005)	(0.007)
zVerifiedLoss		−0.019***		−0.028***	−0.017***
		(0.006)		(0.006)	(0.006)
State × year fixed effects	Yes	Yes	Yes	Yes	Yes
Disaster × year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	4,097	4,097	6,162	6,162	4,097
R^2	0.247	0.250	0.238	0.244	0.254

Notes. This table presents Ordinary Least Squares (OLS) estimates from the regression of then SBA home loan denial rate (*SBA Denial*) for a given county-year on measures of need for price discrimination (*NPD*) and various controls and fixed effects. *NPD* is measured by the *Subprime* (FICO < 660) share of the county population (columns (1) and (2)) and *Minority* race share of the county population (columns (3) and (4)). Both measures are included in column (5). *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *VerifiedLoss* is the county-level average loss of the applicants as a result of the disaster as verified by SBA officials. *Subprime* data are only available from 1999 onward (thus the smaller sample sizes). *Disaster × year fixed effects* are fixed effects for each disaster type and year combination (e.g., hurricanes in 2004), and each regression includes *State × year* 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. Standard errors in parentheses.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

composition, our main measure of NPD. To do so, we estimate Equation (6) by regressing county × year denial rates (SBA or FHA-HI) on an indicator for the SBA loan program and its interaction with the minority-share of the population. We also include county × year fixed effects to flexibly account for any time-varying local changes in creditworthiness. These fixed effects also absorb the main effect of the minority share of the population (which does not vary within county × year). The estimates reveal whether the difference in denial rates within county × year across SBA and FHA-HI lending is greater for high-minority areas.

Column (1) of Table 6 presents the main result. The coefficient on the SBA dummy indicates the SBA program and FHA-HI programs have similar overall denial rates. The main coefficient of interest is the interaction between the SBA dummy variable and the minority share of the county, which is economically and statistically significant. A one-standard-deviation increase in minority share corresponds to a 4.2-percentage-point higher denial rate in the SBA program compared with the FHA-HI program.[22] Column (2) shows that the excess denial rate increases monotonically as we move from the lowest to the highest quartile of minority share. These estimates are statistically significant and economically large. In the highest quartile of minority share areas, the SBA denies loans at a rate that is 10.2 percentage points higher than in the lowest quartile areas (relative to the FHA-HI denial rates). In sum, in the risk-insensitive SBA lending program, applicants from high-minority areas are denied credit at a much higher rate relative to the government-insured lending program with risk-sensitive rates.

In Table IA.3 of the online appendix, we examine the relationship between NPD and FHA denial rates by running regressions similar to those in Table 5. We find that the relationship between minority share of the population and FHA denial rates to be about one-third the magnitude and statistically less significant with a point estimate of 0.01. The relationship between subprime share and denial rates is statistically and economically insignificant. Despite the FHA also being a government-subsidized lending program, these results suggest the FHA's ability to adjust prices is an important feature in providing more "fair" access to credit.

In columns (3) and (4) of Table 6, we reconstruct the county-level denial rates using only the SBA disaster loans with values that are likely to be above the threshold at which collateral is required to be pledged if available (described in Section 4.3.2). We find very similar results. In columns (5) and (6), we run the same tests but only including loans below $25,000 as that is the maximum loan amount in the FHA-HI program. This test will ensure that our results are not being driven by SBA loans with much larger values than our counterfactual loan program. The point estimate on the interaction of

Table 6. Differential Denial Rates Across SBA Loans and Comparison Loans by Minority Share

	All loans		Collateralized		Below 25k	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}[SBA]$	0.006	−0.043***	−0.025***	−0.067***	0.025***	−0.033**
	(0.005)	(0.013)	(0.006)	(0.015)	(0.006)	(0.013)
$\mathbb{1}[SBA] \times zMinority$	0.042***		0.035***		0.047***	
	(0.005)		(0.006)		(0.006)	
$\mathbb{1}[SBA] \times Minority\ 2q$		0.035**		0.033*		0.043**
		(0.016)		(0.018)		(0.017)
$\mathbb{1}[SBA] \times Minority\ 3q$		0.055***		0.047***		0.063***
		(0.016)		(0.018)		(0.017)
$\mathbb{1}[SBA] \times Minority\ 4q$		0.102***		0.088***		0.120***
		(0.016)		(0.018)		(0.017)
County × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,532	12,532	11,217	11,217	11,741	11,741
R^2	0.509	0.508	0.491	0.490	0.511	0.510

Notes. For each county-year in the SBA data set, we compute the home loan denial rate and append an additional observation to the data set with the FHA home improvement (FHA-HI) denial rate as the comparison group. This table presents OLS estimates from the regression of county-level loan denial rates (SBA or relevant comparison group) for disaster-affected counties on the minority share of population in the county, whether the observation represents the SBA denial rate, and their interaction.

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

denial rate is the county-year denial rate for either SBA home loans or the comparison group denial rate. Columns (1) and (2) uses all SBA loan applications (aggregated ot the county level); columns (3) and (4) restricts SBA applications to those loans above collateral threshold; and columns (5) and (6) restricts SBA applications to those with loan amount below \$25k. For the comparison group loans, the denial rate is for applications in the county in the year prior to the 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 comparison group denial rate. *Minority* represents the nonwhite share of the county population (its main effect is absorbed by the fixed effects), *Minority Xq* is the *X*th quartile of *Minority* with the first quartile (e.g., lowest minority share) as the omitted category (their main effects are absorbed by the fixed effects). Each regression includes county × year fixed effects. 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. Standard errors in parentheses.

$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

SBA and minority share indicates that a one-standard-deviation increase in minority share corresponds to a 4.7-percentage-point ($p < 0.01$) increase in denial rate.

As alternative counterfactuals, we consider all FHA refinancing loans and all refinancing applications in the HMDA data set (including FHA loans) for a given county and time. This broader set of applications includes loans that are held on banks' balance sheets, sold to other financial institutions, or securitized through government-sponsored enterprises or private securitization. Results are presented in Table IA.4 of the online appendix. We find similar results. In sum, these results provide further evidence that the SBA program, with risk-insensitive interest rates, denies relatively more credit in areas with higher-*NPD* than lending programs with risk-sensitive (market) pricing and show that the disparity in lending outcomes is not driven by the specific choice of counterfactual risk-sensitive lending program.

6.3. Alternative Measures 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 when there is a higher need for price discrimination, we examine the county's Gini index (income inequality) and subprime share of the population. By construction, higher Gini areas have a greater dispersion in credit quality and, consequently, a greater need for price discrimination in lending markets. Subprime share, as described earlier, captures the portion of the population with marginal observable credit quality.

Table 7 presents the results. We reproduce the main result using minority share in column (1) for comparison. We find similar results using the two alternative measures of NPD. A one-standard-deviation increase in income inequality is associated with a denial rate that is 1.8 percentage points higher for SBA loans relative to FHA loans (column (2)). A one-standard-deviation increase in subprime is associated with a denial rate that is 2.0 percentage points higher for SBA loans relative to FHA loans (column (3)). In column (4), we present all three measures of NPD and find that minority share (our main NPD measure) dominates the other measures.

7. Alternative Explanations

Our identification strategy relies on the idea that within the same county × year, outcomes in the FHA-HI provide a plausible risk-sensitive lending counterfactual

Table 7. Alternative Measures of Need for Price Discrimination

	(1)	(2)	(3)	(4)
$\mathbb{1}[SBA]$	0.006	0.009*	0.029***	0.022***
	(0.005)	(0.005)	(0.007)	(0.007)
$\mathbb{1}[SBA] \times$ zMinority	0.042***			0.047***
	(0.005)			(0.008)
$\mathbb{1}[SBA] \times$ zGini		0.018***		−0.006
		(0.006)		(0.008)
$\mathbb{1}[SBA] \times$ zSubprime			0.020***	−0.001
			(0.007)	(0.008)
County × year fixed effects	Yes	Yes	Yes	Yes
Observations	12,532	12,532	8,342	8,342
R^2	0.509	0.505	0.510	0.514

Notes. For each county-year in the SBA data set, we compute the home loan denial rate and append an additional observation to the data set with the respective FHA-HI denial rate. This table presents OLS estimates from the regression of county-level loan denial rates (SBA or FHA-HI) for disaster-affected counties on whether the observation represents the SBA denial rate, its interaction with the variable measuring need for price discrimination in the county, and county-year fixed effects (which absorb the main effects of the need for price discrimination variable).

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

denial rate is the county-year denial rate for either SBA home loans or FHA-HI loans. For FHA loans, the denial rate is for applications in the county in the most recent year in which there was no disaster. $\mathbb{1}[SBA]$ is an indicator equal to one if the observation represents the SBA denial rate and zero if the observation represents the FHA denial rate. *Minority* represents the nonwhite share of the county population, *Gini* is an index that measures the income inequality in the county, *Supbrime* represents the share of the county's population with FICO score greater than 660. Each regression includes county × year 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. Standard errors in parentheses.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

denial rate. Our empirical strategy accounts for both baseline differences in denial rates across the lending programs and time-varying unobserved heterogeneity across counties. However, as discussed in Section 4.3, there are potential threats to our identification strategy. If SBA loan officers are more likely than private lenders to engage in taste-based discrimination against minority borrowers, then our results could simply be explained by such biases. Also, if the SBA borrower pool in high-NPD areas becomes especially worse in terms of creditworthiness at the time of disaster compared with the corresponding change for low-NPD areas, then our results could be explained by this change, not the lack of risk-sensitive pricing. We address these and other potential concerns below.

7.1. Taste-Based Discrimination and Racial Animus

We now consider the alternative explanation that taste-based discrimination (i.e., prejudice) against minority borrowers is driving the results. A detailed assessment of taste-based discrimination in these markets is beyond the scope of our work. Although it is hard to empirically assess this important question with observational data, we can test one specific prediction that arises from taste-based discrimination 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, if borrowers in higher-minority-share areas need to cross a higher hurdle to obtain credit, the approved loans in these areas should have a lower default rate under this hypothesis. We estimate an OLS default model with minority and income inequality as the explanatory variables, and Table 8 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.

Along this line of inquiry, we examine if the documented disparities in credit access are related to the racial animus of the state's population. We follow Dougal et al. (2019), who use racial animus rankings

Table 8. Taste-Based Discrimination: Ex Post Loan Performance

	(1)	(2)	(3)	(4)
zMinority	0.013***	0.007***		
	(0.002)	(0.002)		
zGini			0.005***	0.002
			(0.001)	(0.001)
zln(Amount)		−0.035***		−0.035***
		(0.002)		(0.002)
zln(Maturity)		0.033***		0.033***
		(0.003)		(0.003)
zPerCapitaIncome		−0.005***		−0.008***
		(0.001)		(0.002)
zln(Population)		0.007***		0.011***
		(0.002)		(0.001)
State × year fixed effects	Yes	Yes	Yes	Yes
Disaster × year fixed effects	Yes	Yes	Yes	Yes
Observations	727,901	727,901	727,901	727,901
R^2	0.039	0.053	0.039	0.053

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

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

according to five different methods. We use their measure of *HighAnimus* defined as states ranking in the top ten highest degrees of animus for each measure. As an alternative measure, we also compute the sum of the five rankings (*SumOfRanks*). We use the negative of *SumOfRanks* so both have the interpretation of larger values representing higher animus.

To test the hypothesis that racial animus is driving our results, we include a triple-interaction of *SBA* × *Minority* × *RacialAnimus* in our main tests (as well as the individual interactions between *RacialAnimus* and *SBA* and *Minority*, respectively). A positive coefficient on the triple-interaction term would mean that the sensitivity of SBA denial rates to *Minority* (relative to our counterfactual lending environment) is disproportionately higher in states with higher degrees of racial animus. Table IA.5 in the online appendix presents the results. The triple interaction term is negative, but statistically insignificant. This shows that the magnitude of SBA's higher denial rate in high minority areas remains similar across states with different levels of racial animus. These results do not support the idea that the disparities are driven by taste-based discriminatory behavior of individual loan officers at the local level. Instead, the results are consistent with features of the SBA program (e.g., the risk-insensitive lending rate) leading to systematically higher denial rates in high-minority areas.

7.2. Differential Sensitivity to Disaster

We discuss and provide evidence in Section 4.3.1 that differences in applicants' understanding of the SBA program and differential loan application timing are unlikely to fully explain our results. We now consider whether the relative creditworthiness of high-*NPD* areas is more damaged by natural disasters relative to low-*NPD* areas. That is, does the underlying credit quality of high-*NPD* areas disproportionately drop following natural disasters? If the credit quality distribution shifts more for high-*NPD* areas, then our predisaster FHA counterfactual may not fully capture relative credit quality.

We examine changes in the credit quality distribution from pre- to postdisaster across high- and low-NPD counties to address this potential concern. We examine changes in the subprime share and changes in mortgage delinquency rates from before to after the disaster. Specifically, for subprime share, we test whether the change in subprime share of the population (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:

$$Subprime_{c,t+1} - Subprime_{c,t-1} = \zeta Minority_{c,t} + \delta_{d,y} + \Sigma_{state} + \Gamma X_{c,t} + \epsilon_{c,d,t}. \quad (7)$$

If the credit quality of high-minority areas is more negatively impacted (which could feed back into denial rates), we should see a positive and significant coefficient on minority share ($\hat{\zeta} > 0$). Table 9 presents the results. Column (1) shows that the empirical estimates are statistically insignificant. In columns (2) and (3), we extend the horizon to two years and three years and find no significant relationship. Thus, these tests do not support the hypothesis that the credit quality of high-minority areas has a differential sensitivity to natural disasters relative to low-minority areas.

To further examine whether high-minority areas' creditworthiness suffers a disproportionate shock, we collect data from the Consumer Financial Protection Bureau on 30–60 days and 90 days county-level mortgage delinquency rates. Strengths of these data are their higher frequency (monthly rather than annual) and the sharp measurement of the local area's ability to service mortgage debt. Since the data series begins in 2008, it covers the final eight years of our sample.

We start by plotting delinquency rates from 3 months prior to disaster to 12 months after disaster for low-, medium-, and high-minority share areas in Figure IA.5 of the online appendix. We find very similar trends across the three groups. Next, we follow a similar

Table 9. Differential Sensitivity: Relative Changes in Subprime Share

	$Subprime_{t+\tau} - Subprime_{t-1}$		
	$\tau = 1$ (1)	$\tau = 2$ (2)	$\tau = 3$ (3)
zMinority	0.024	0.052	0.045
	(0.089)	(0.127)	(0.180)
zPerCapitaIncome	−0.172	−0.189	−0.185
	(0.112)	(0.163)	(0.198)
zln(Population)	−0.095	−0.135	−0.170
	(0.081)	(0.096)	(0.129)
zVerifiedLoss	0.008	−0.015	−0.025
	(0.019)	(0.026)	(0.022)
State × year fixed effects	Yes	Yes	Yes
Observations	5,616	5,354	5,229
R^2	0.514	0.537	0.538

Notes. This table presents OLS estimates from the regression of change in subprime share of the county population 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. In columns (2) and (3), we examine longer periods after the disaster, replacing subprime share in $t+1$ with subprime share in $t+2$ and $t+3$, respectively. *Minority* represents the nonwhite share of the county population, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *VerifiedLoss* is the loss of the applicant as a result of the disaster as verified by SBA officials. *Subprime* is the share of the population with FICO below 660, and these data are only available from 1999 onward (thus smaller sample sizes in the regressions). Each regression includes state×year 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 and year. Standard errors in parentheses.

$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

framework to the regressions in Table 9 with the dependent variable being the change in the delinquency rate from a month prior to the disaster to 6, 12, or 18 months after the disaster date. If high-minority areas were to experience disproportionate shocks to their creditworthiness, we would expect the coefficient on *Minority* to be positive and statistically significant. Table 10 presents the results and shows that across both delinquency measures and all time horizons, high-minority areas do not have a disproportionate increase in mortgage delinquency. These tests further support the hypothesis that high and low minority areas have similar sensitivities to natural disasters.

7.3. Time Periods, Disaster Size, and Disaster Types

In Table IA.6 of the online appendix, we estimate our baseline regressions on subperiods of our sample (roughly equally divided by observations).[23] We find that our results are present in all period subsamples. The stability of the results shows that the effects are not driven by a particular political party in power or portion of the housing boom and bust cycle. We also find that the effect is not concentrated in just the large (one of the top 25) or small disasters, as both subsamples exhibit a significant relationship between minority share and relative denial rates in the SBA program (results also in Table IA.6 in the online appendix). We also look at whether a single type of disaster is driving our main results by re-estimating our baseline regression, excluding each of the five types of disasters one at a time. Table IA.7 in the online appendix shows that no single disaster type is driving our results.

7.4. Other Financial Factors and Business Loans

In the Section A of the online appendix, we discuss other financial factors that could be important such as FEMA assistance, private-market funding, and baseline ability to apply. We argue that these are unlikely to overturn our results. As part of this analysis, we run similar tests examining denial rates for SBA disaster loans to businesses and find very similar results.

8. Discussion and Conclusion

8.1. Economic Significance

In this section, we provide some context on the economic importance of our results by providing an estimate of the credit that would have been extended if all counties were in the lowest minority-share quartile. To do this, we multiply the number of loan applications in the second, third, and fourth quartiles of minority share by the difference in approval rates between these counties and the lowest quartile counties. We use the estimates in column (2) of Table 6 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

Table 10. Differential Sensitivity: Relative Changes in Delinquency Rates

	30- to 60-day delinquency rate			90-day delinquency rate		
	(1) +6 mo	(2) +12 mo	(3) +18 mo	(4) +6 mo	(5) +12 mo	(6) +18 mo
zMinority	−0.03	−0.03	−0.07	−0.05	−0.07	−0.05
	(0.05)	(0.05)	(0.05)	(0.04)	(0.06)	(0.07)
zPerCapitaIncome	0.05**	0.05**	0.04	−0.06**	−0.07**	−0.04
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
zln(Population)	0.03	−0.03	0.01	0.07	0.04	−0.11
	(0.07)	(0.08)	(0.07)	(0.07)	(0.09)	(0.11)
zVerifiedLoss	−0.05	−0.07*	0.00	0.04	0.08	0.00
	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.07)
State × month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	479	479	479	479	479	479
R^2	0.62	0.62	0.68	0.80	0.88	0.88
$\overline{Y}$	−0.05	−0.12	−0.19	0.09	0.09	0.03
Average delinquency rate	3.24	3.24	3.24	3.35	3.35	3.35

Notes. This table presents OLS estimates from the regression of change in county-level mortgage delinquency rates from the month before the disaster until 6, 12, and 18 months after the disaster on the minority share of population in the county and various controls and fixed effects. Columns (1)–(3) use the 30 to 60 days delinquency rate, and columns (4)–(6) use the 90 or more days delinquency rate. The sample is from 2008 onward (when delinquency data are available). *Minority* represents the nonwhite share of the county population, *PerCapitaIncome* and *ln(Population)* are the county-level per capita income and log of population at the time of the disaster, *VerifiedLoss* is the loss of the applicant as a result of the disaster as verified by SBA officials. Each regression includes state × month fixed effects. We report the average change ($\overline{Y}$) and average delinquency rate below each regression. 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. Standard errors in parentheses.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

"missing" loans. The calculation suggests that about \$2.87 billion of additional loans would have been granted under conditions where the price is flexible and based on the riskiness of the borrower. In terms of the number of loans, our estimates show that about 90,216 more homeowners would have had access to credit during these critical postdisaster time periods. Although denied SBA applicants may still qualify for some FEMA assistance, the FEMA size limits and aims of that program mean this assistance cannot fully substitute for SBA loans.[24] Billings et al. (2022) provide evidence on how the relative lack of access to government funds in the wake of natural disasters for financially constrained households leads to adverse future financial outcomes. Combined with their findings, our results show that the lack of access to disaster loans can impose a significant cost on borrowers in the high NPD areas.

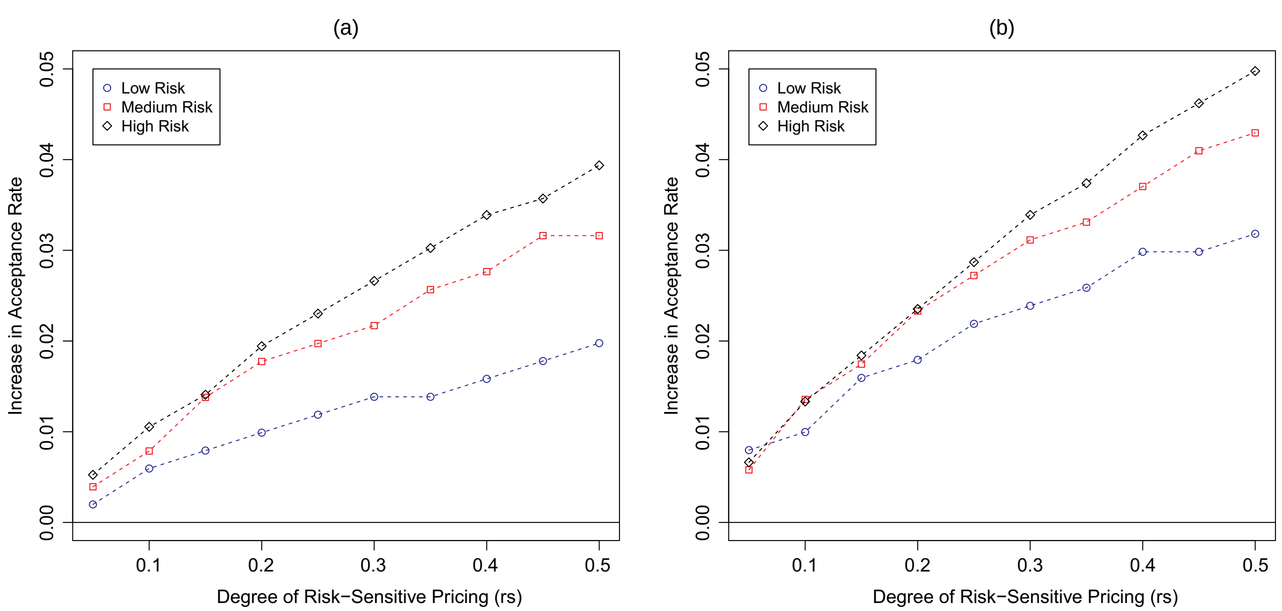
8.2. Counterfactual Policies

We now run counterfactual analyses to shed light on policy recommendations for the design of disaster loan contracts using the model developed in Section 3. For this analysis, we keep the same parameter values as in the base case presented earlier. We also keep the subsidized nature of the disaster lending rate but now allow for risk-sensitive pricing. Specifically, we set the disaster lending rate at the base case rate r_{dl} plus a fraction of the corresponding market-based rate for the borrower's given risk. Thus, the pricing is given by $r_{dl} = r_{dl}^{base} + r * rs$, where r is the risk-sensitive rate that the market would charge for the borrower and rs is a factor that determines the extent of risk-based pricing in the disaster lending program. At $rs = 0$, the program is risk insensitive as in the base case. We vary this parameter from 0 to 0.5 for our analysis.

We consider three sets of borrowers depending on the dispersion in their credit quality: high risk ($\sigma_f = e^{-f}$), medium risk ($\sigma_f = 0.5e^{-f}$), and low risk ($\sigma_f = 0.25e^{-f}$). We compute the improvement in acceptance rates as the program moves from risk-insensitive to the proposed risk-sensitive scheme. We set the subsidy level at $s = 0.03$ and plot the improvement in acceptance rate for each of the three group of borrowers in Figure 3(a). As the pricing becomes more risk-sensitive, every group benefits in terms of higher access to credit, but the slope is steepest for the highest risk group (Group H). Therefore, a risk-sensitive pricing model bridges the gap in denial rate across the group of borrowers. Next, we change the subsidy parameter to a lower value, $s = 0.01$, and repeat the exercise. The results are plotted in Figure 3(b). With a lower subsidy, the slopes of all three lines are steeper relative to those with a higher subsidy. When the subsidy of the SBA lending program is low, a move toward risk-sensitive pricing benefits the most marginalized group even more. For instance, in the extreme case of a grant (i.e., 100% subsidy), everyone gets the loan and there is no benefit in terms of access to credit with a move toward risk-based pricing.

One limitation of our stylized model is that we do not compute the borrower's utility from obtaining a loan.

Figure 3. (Color online) Improvement in Acceptance Rate Across Borrower Type with Varying Levels of Risk-Sensitive Pricing



Notes. This figure presents the increase in acceptance rate for high risk ($\sigma_f = e^{-f}$), medium risk ($\sigma_f = 0.5e^{-f}$), and low risk ($\sigma_f = 0.25e^{-f}$) borrowers with different levels of risk-sensitive pricing (rs) where the pricing is given by $r_{dl} = r_{dl}^{base} + r * rs$. rs is a factor that determines the extent of risk-based pricing in the disaster lending program. In (a), the subsidy is "high" at 3%. In (b), the subsidy is "low" at 1%. (a) High subsidy ($s = 0.03$). (b) Low subsidy ($s = 0.01$).

Absent such richness in the model, we cannot compare the benefit that an approved borrower derives from getting the concessional loan with the cost a denied borrower incurs from a rejected loan. Intuitively, the high- or medium-risk borrowers who end up obtaining a loan under the SBA risk-insensitive program are the biggest beneficiaries: they obtain credit at a rate much lower than the market rate. For the low-risk borrowers, the benefit in terms of interest rate differential is lower since their market rate is also low. We leave a more detailed structural modeling of these issues for future research.

8.3. Related Literature

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

Our paper is also related to literature which studies the effects of regulation in private credit markets such as the effect of 19th century usury laws on access to credit (Benmelech and Moskowitz 2010) and the effect of an interest rate ceiling on access to credit in Chile (Cuesta and Sepulveda 2018). Although these papers also find an adverse impact of credit market regulations on the quantity of credit, our paper is the first one to study the implications of risk-insensitive pricing on minorities and other marginal borrowers, a finding that has important implications for regulations on fair access to credit across different demographics of society. Furthermore, our study is the first one to analyze the effectiveness of government lending programs in reaching minority borrowers and, more generally, marginal borrowers compared with the private market.

Relatedly, much prior work notes that certain government-provided credit subsidies may increase aggregate welfare in the presence of information frictions (Stiglitz and Weiss 1981; Smith 1983; Gale 1990, 1991). Recent papers, such as Bachas et al. (2021) and Mullins and Toro (2017), show that small business lending is highly responsive to federal loan guarantees. Similarly, Brown and Earle (2017) study the SBA program and find that access to credit has large effects on employment. Howell (2017) shows that federal grants affect both innovation as well as future fundraising for small firms. We contribute to this debate by studying a government program that affects millions of people when, perhaps, they need government intervention the most.

Our paper is also related to the literature on costs of price discrimination and how it contributes to unfair prices. In the foreign exchange derivatives market, for example, Hau et al. (2021) show that unsophisticated borrowers face discriminatory, higher prices. In mortgage markets, Bartlett et al. (2022) analyze loan rejection rates and document that unsophisticated and impatient borrowers face worse borrowing conditions and show that fintech lenders are less likely to discriminate than traditional lenders. In contrast to these studies, our paper shows important costs when price discrimination is not allowed. Specifically, although risk-insensitive pricing may mitigate some potential downsides of price discrimination, we show that this benefit comes at the cost of a higher denial rate for marginal borrowers.

A number of recent papers examine the benefits of financial inclusion or costs of financial exclusion. Célerier and Matray (2019) show that an increase in bank-branch supply leads to greater financial inclusion for low-income households, and this leads to greater household wealth accumulation and financial security. Relatedly, Buchak and Jørring (2016) find banks are less likely to discriminate on race when competition increases. Stein and Yannelis (2020) find the establishment of the Freedman's Savings Bank increased financial inclusion for minorities and document positive effects of inclusion on a number of important outcomes. Appel and Nickerson (2016) and Aaronson et al. (2021) find a negative long-term effect of "redlining" on home prices. These papers examine the longer-run effects of disparities in access to finance, whereas we examine how the structure of a lending program can lead to such disparities.

Finally, our paper is also related to the empirical literature investigating private lending activity following a natural disaster. Morse (2011), for example, uses natural disasters to investigate whether payday lenders ease credit constraints for poor residents. Collier et al. (2020) study how firms use credit and insurance protection in their effort to recover after natural disasters. Billings et al. (2022) show how the relative lack of access to government funds in the wake of natural disasters can be costly for the affected population. Berg and Schrader (2012) analyze whether bank relationships improve credit access following aggregate shocks using a volcanic eruption in Ecuador to identify an exogenous increase in loan demand. Cortés (2014), Chavaz (2016) and Cortés and Strahan (2017) study whether response to credit demands by borrowers hit by natural disasters vary by lender size, scope, and local competition structure. In particular, Cortés and Strahan (2017) show that it is the smaller banks that help smooth the credit demand shocks. Collier and Ellis (2021) estimate demand elasticities for borrowers after a disaster and highlight the degree of their price sensitivity.

8.4. Conclusions

We document a substantially higher denial rate for SBA disaster loan applications in counties with a greater need for price discrimination. Applicants in high-minority-share areas are denied access to government-provided credit at a disproportionately higher rate relative to the private lending market. This disparity occurs despite these applicants often being the intended recipient of government assistance programs and a focus of government regulation in private-market lending.

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.

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

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Endnotes

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

[2] We focus on the home loan disaster lending program because of data availability. The application of our work, however, is much broader. For example, the SBA disaster lending scheme is used to help small businesses fight the adverse economic consequences of the COVID-19 pandemic. Furthermore, the World Bank's International Bank for Reconstruction and Development lent more than 500 billion dollars between 1946 and 2017, interest rates on some of these loans do not vary across countries within the same year. Also, the U.S. government alone currently has more than 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.

[3] The SBA explicitly state, "Our loan decisions are based on a balance between our role as a provider of disaster assistance and our responsibility to protect the government's interests and taxpayer dollars" (Office of the Inspector General 2016, p. 12).

[4] Just as in a market setting with a price ceiling, it naturally follows that there is likely to be excess, unmet demand. At a broad level, our work relates to one of the oldest debates in economics about the tradeoffs 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 (Bundorf et al. 2012).

[5] In robustness tests, we report results with other NPD measure including the local levels of income inequality and housing cost burden.

[6] The FHFA considers census tracts to be underserved if they fall below income thresholds and/or above minority population thresholds.

[7] Fair access to credit for minority borrowers has been one of the central themes of U.S. banking regulation over the past fifty years with regulations such as the Fair Housing Act (1968), the Equal Credit Opportunity Act (1974), and the Community Reinvestment Act (1977). These regulations are intended to ensure private lenders provide fair access to credit across borrowers of different race, religion, gender, and so on.

[8] See https://www.hud.gov/program_offices/housing/sfh/title.

[9] FHA-HI loan proceeds are used to finance property improvements that "substantially protect or improve the basic livability or utility of the property."

[10] For example, Munnell et al. (1996) and Dougal et al. (2019) show that minorities have lower access to credit in private markets. Dobbie et al. (2018) find bias in UK consumer lending against immigrants and older applicants as a result of misalignment of incentives between loan officers and their employer.

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

[12] For example, a recent SBA loan officer job posting describes the duties of the job as, "Applying accepted financial procedures to analyze financial resources to determine an applicant's ability to repay requested loans … Review all pertinent facts needed to make eligibility determinations, Ensure loan files contain all pertinent documentation … Process loan applications on web-based computer system."

[13] 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%. Table IA.1 in the online appendix provides more details. The formula for statutory rates is provided in Section 7 of the Small Business Act. In untabulated tests, we confirm that those applicants that are classified as having credit available elsewhere default at a lower rate.

[14] We only plot the sensitivity analysis for the higher risk borrower group because they are the focus of our analysis.

[15] We also use the county income inequality (Gini coefficient) an as additional measure for robustness.

[16] See https://www.hud.gov/program_offices/housing/sfh/title/sfixhs. Although funds can be used for basic items such as built-in appliances, all luxury items such as swimming pools or outdoor fireplaces are prohibitied.

[17] The SBA's Standard Operating Procedure states, "SBA policy establishes collateral requirements based on a balance between protection of the Agency's interest as a creditor and as a provider of disaster assistance" (Small Business Administration 2015, p. 127).

[18] We do not observe loan amounts on denied applications, but we do observe verified loss. We regress loan amounts on verified losses for loans for which we have these data and find the average loan is about 75% of the verified loss. Thus, our "collateralized" sample is constrained to the sample of applications with verified loss at least 33% above the SBA collateral threshold.

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

[20] In the online appendix, we present results for similar tests using loan-level data in Table IA.2. We find the coefficients of interest are somewhat larger in magnitude and remain highly statistically significant.

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

[22] In untabulated tests, we estimate the regression with various sets of fixed effects (only year, only county, and year and county fixed effects). We find the estimate of the coefficient of interest remains similar (0.040, 0.044, and 0.044, respectively), and that the p value remains below 1% in all specifications. The R^2 increases with each specification from 0.072 to 0.179 to 0.221, respectively. The stability of the coefficients combined with the significant increases in R^2 provide further support that omitted variables are unlikely to be driving our results (Oster 2019).

[23] Figure IA.4 in the online appendix presents the time series of applications and denial rates during the sample.

[24] FEMA's aid is capped at only $35,500 in 2019 (it was lower in previous years), and FEMA explicitly states that their aid is "intended to meet basic needs and help you get back on your feet. FEMA is not empowered to make you whole" (https://www.fema.gov/press-release/20210318/fact-sheet-frequently-asked-questions-about-fema-individual-assistance). FEMA aid is only to make the home "safe, sanitary and fit to occupy" (https://www.fema.gov/assistance/individual/housing).

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