Loan Guarantees and Incentives for Information Acquisition*

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Abstract

To address credit constraints in small-business lending markets, policymakers frequently use loan guarantees, which insure lenders against default. Guarantees affect loan prices by altering the effective marginal cost of lending but may create a moral hazard problem, weakening lenders' information-acquisition incentives. I quantify these channels using data from the SBA 7(a) Loan Program. Guarantees benefit borrowers, on average, but redistribute surplus from low- to high-risk borrowers. Fixing government spending, an alternative policy with a 50% guarantee and a subsidy leads to an increase in borrower surplus and 0.1 percentage point (1.1%) decline in the program's default rate.

Keywords: loan guarantees, information acquisition, small business lending

JEL Codes: G21, G28, L15

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1. Introduction

Small businesses are a major source of employment growth in the United States. They are responsible for a sizable share of private-sector jobs, employing 47.3 percent of the workforce across 30.7 million small businesses as of 2016.[1] Given their large contribution to employment and the substantial attention paid to them by the media and general public, governments tailor policy to foster small-business growth. One common piece of the policy agenda, both in the United States and elsewhere, involves expanding access to capital. Many small businesses face large up-front costs, including real estate and machinery, and find it difficult to obtain start-up funding and capital required for ongoing operational expenses. Since small firms are typically unable to access institutional debt markets or equity financing (Mills & McCarthy, 2014) and rely disproportionately on traditional bank lending, governments frequently transmit small-business policy through this channel.

Access to credit by small businesses is further constrained by information asymmetries, which are prevalent in lending markets. Recent empirical work examines the role of asymmetric information in consumer (Einav *et al.*, 2012, 2013; Cuesta & Sepulveda, 2021; Kawai *et al.*, 2022) and commercial lending (Crawford *et al.*, 2018; Wang, 2020; Ioannidou *et al.*, 2022). This body of work highlights how asymmetric information and market power can influence policy transmission. However, understanding the source of asymmetric information is also critical when considering the impact of counterfactual market structures or policies, as agents may adjust their information-acquisition practices in response to such variation. Government intervention is common in small-business lending markets to relax credit constraints on these businesses and realize employment externalities.[2] Accounting for equilibrium responses – along the information-acquisition margin in particular – is potentially important to consider when evaluating policy interventions in small-business lending

[1] "2019 Small Business Profile." U.S. Small Business Administration Office of Advocacy. Available at https://advocacy.sba.gov/wp-content/uploads/2019/04/2019-Small-Business-Profiles-US.pdf.

[2] The degree of asymmetric information is potentially larger in small-business credit markets than in others. New businesses lack a long repayment history and use funds to complete heterogeneous projects. Thus, lenders leave many decisions to the discretion of loan officers. Frequently, officers rely on "soft" information when deciding whether to approve a loan and what interest rate to offer (Wang, 2020). Liberti & Petersen (2019) provides a discussion of "hard" vs. "soft" information.

and other selection markets. Ignoring these effects could lead to misleading conclusions about the efficacy of interventions, especially if policymakers are concerned with their distributional impact.

This paper makes three contributions. First, I quantify the effect of government guarantee programs on lenders' information acquisition in small-business lending markets. Guarantees are a common form of intervention, and they act as insurance against ex-post default risk: governments agree to cover a pre-specified portion of the remaining loan balance in the event of default. This, in turn, could affect lenders' incentives to acquire information and create a moral hazard problem. This paper provides a novel estimate of the magnitude of the moral hazard effect and shows that guarantees increase borrower surplus by a modest amount, on average, but that gains accrue to high-risk borrowers at the expense of their safer counterparts. Second, I show that an alternative policy design, consisting of a less generous guarantee and a lender subsidy such that expected government spending remains fixed, leads to borrower surplus gains. These gains arise due to lenders facing stronger incentives to gather information, which limits the redistribution from low- to high-risk borrowers. To reach these conclusions, I develop an empirical model of lending that allows for endogenous information-acquisition choices, which is the third contribution of the paper. In doing so, I contribute to the growing literature that examines the interaction of market power and asymmetric information in empirical settings.

Government guarantees are widely-used policy tools. They are frequently applied in small-business lending markets (e.g., SBA 7(a) Program in the United States), as well as in other settings, including mortgage markets under programs administered by the U.S. Federal Housing Administration and Department of Veterans Affairs. Understanding the extent to which guarantees perturb lenders' incentives and the resulting effect on borrowers contributes to the debate over the efficacy of these programs and informs policy design. The impact of guarantees is driven by two channels. First, they alter the effective marginal cost of lending. Default is less costly to lenders when guarantees are generous, exerting downward pressure on prices. However, the interaction of market power and adverse selection can counteract this price response. In a market characterized by adverse selection, the marginal borrower is less risky than inframarginal borrowers, constraining a lender's willingness to raise prices (Mahoney & Weyl, 2017; Crawford *et al.*, 2018; Lester *et al.*, 2019). Guarantees alter this disincentive, exerting upward pressure on prices, and could offset the gains that would otherwise accrue to borrowers due to the lower cost of default. I refer to the price effects resulting from the change in effective marginal cost as the *guarantee pass-through*. Its magnitude depends on the probability of default, the extent of adverse selection (i.e., correlation of price responsiveness and propensity to repay), and borrowers' willingness to pay for funds.

Second, government guarantees affect lenders' incentives to acquire information. Increasing guarantees brings lenders' payoffs under repayment and default closer to one another, which could create a moral hazard problem, decreasing the marginal value of information.[3] I refer to this as the *information effect*. This unintended consequence is welfare-improving for high-risk borrowers but harms those that are low risk, which benefit from lenders having precise information. Policymakers have debated the potential for moral hazard in loan guarantee programs, including in the United States Senate Budget Committee in 2014,[4] but there is no consensus on the magnitude of these effects. This paper provides a novel estimate of this magnitude.

The combination of the two channels described above implies that an increase in the generosity of guarantees need not benefit all borrowers. Determining the direction and magnitude of the impact is an empirical question, and alternative policy arrangements may lead to higher borrower surplus. In this paper, I answer three questions. First, what is the impact of increasing the generosity of guarantees on prices, borrower surplus, and lender profits? Second, how do guarantees affect borrowers across the distribution of risk? Third, does an alternative policy design lead to higher borrower surplus? Understanding the separate impact of the guarantee pass-through and the information effect is crucial for evaluating alternative policy designs. For example, a strong information effect suggests that a policy that leaves

[3]This idea is similar to the "lazy bank hypothesis" set forth by Manove *et al.* (2001) in their analysis of collateral's effect on lender behavior, but government guarantees do not affect borrower incentives.

[4]An excerpt from this debate reads: "The guarantee takes a substantive risk away from the bank making the loan (indeed, that is the whole point of the SBA loan guarantee) and very well could provide incentives for some banks to cut corners through the underwriting process. This is what economists call moral hazard and could have manifested itself with lenders being less than careful in their decisions to extend SBA loans." See https://www.budget.senate.gov/chairman/newsroom/press/sessions-writes-to-small-business-administration-about-cost-of-loan-program.

lenders more exposed to default risk may benefit borrowers, on average.

I answer these questions using data from the U.S. Small Business Administration's (SBA) 7(a) Loan Program, which is the largest lending program administered by the agency and provides guarantees on small business loans. In 2009 and 2010, Congress enacted two pieces of legislation with components aimed at stimulating small-business lending. The American Recovery and Reinvestment Act of 2009 and the Small Business Jobs Act of 2010 allocated a total of $1.2 billion to increase maximum guarantee rates and reduce guarantee fees (Congressional Research Service, 2019b). This resulted in two discrete time periods during which government guarantees were higher. Using the temporal variation induced by these policy changes, I provide evidence of a strong lender-side response to the guarantee incentives.

Higher guarantees induce both a spike and sustained increase in lending activity, and lenders offer contracts with more generous terms: lower interest rates, larger amounts, and longer maturities. In the guarantee expansion (SBA Recovery) period, average interest rates are 4.2 basis points lower than in the baseline (1% of the mean rate), average loan amounts are $56 thousand higher (10% of the mean amount), and average loan terms are between 4 and 5 months longer (3% of the mean term), all economically and statistically significant changes. In the high-guarantee period, there is also a lower correlation between loan prices and ex-post default, indicating a decline in the precision of risk pricing when guarantees become more generous.

The descriptive evidence by itself illustrates the aggregate impact of the guarantee policy changes, but it is unfit to quantify the magnitude of the moral hazard problem, the resulting mispricing of risk, and its effect on borrower surplus. Moreover, it does not allow us to examine alternative policy designs. For these purposes, I develop a model of small-business lending with guarantees. Borrowers are differentiated by observable characteristics, as well as ex-ante unobservable risk and price responsiveness. Lenders choose the precision of information to acquire, given the known distribution of borrowers, and receive noisy signals of risk. The precision of these signals governs how closely price offers match borrower risk.

I estimate the primitives of the model using loan-level data from the SBA 7(a) program. With the estimates in hand, I examine the impact of guarantee-rate changes on equilibrium prices, borrower surplus, and lender profits. Average prices and price dispersion fall, while borrower surplus and lender profits increase with the generosity of guarantees, but the magnitudes are modest. These results suggest that lenders and borrowers benefit from generous guarantees, on average, but there are heterogeneous effects across the distribution of risk. High-risk borrowers (i.e., those in the bottom quintile of the utility of repayment) receive $1,500 more surplus per loan under the baseline guarantee of 90% than under a guarantee of 50%, while their low-risk counterparts (i.e., in the top quintile) receive $500 less. If the program intends to expand credit to the most credit-constrained borrowers, then the outcomes suggest it is successful in that aim. That said, the gains come at the expense of lower-risk borrowers in the 7(a) program, and the information effect plays a sizable role in this outcome. This latter point suggests that alternative policies that limit bank moral hazard could lead to better outcomes for low-risk borrowers and potentially borrower surplus gains.

A natural choice is a hybrid policy with a less generous guarantee and a subsidy. The smaller guarantee strengthens incentives for lenders to acquire information about borrowers, offsetting some of the distortion toward high-risk borrowers. The subsidy decreases the cost of lending to all borrowers, inducing downward pricing pressure. I find that a program with a guarantee of 50% and a subsidy such that expected spending is fixed generates approximately $1,200 more borrower surplus per loan over the baseline guarantee of 90% with no subsidy. It also reduces the distortion toward high-risk borrowers. The resulting change in the composition of borrowers that accept loans leads to a 0.1 percentage point (1.1%) decline in the program's default rate. These findings suggest that a combination of policy instruments can be used to reduce the impact of bank moral hazard, increase borrower surplus, and limit default.

1.1. Related Literature

This paper contributes to the empirical analysis of asymmetric information and contract design. Seminal work by Chiappori & Salanie (2000) develops a test for asymmetric information using auto insurance plan selection, and similar ideas have been applied to empirically analyze other markets characterized by asymmetric information, including health insurance (e.g., Starc, 2014) and lending (e.g., Einav *et al.*, 2012, 2013; Crawford *et al.*, 2018; Cuesta & Sepulveda, 2021; Wang, 2020; Ioannidou *et al.*, 2022; Kawai *et al.*, 2022; Bosshardt *et al.*, 2023; Yannelis & Zhang, 2023). This paper builds upon the strand of work that analyzes the endogenous collection of information, in this case focusing on potential moral-hazard effects of government guarantee policies in a market with variable screening costs. I incorporate ideas from the theory literature (Stiglitz & Weiss, 1981; Manove *et al.*, 2001) and empirical literature on screening soft information (Panetta *et al.*, 2009; Wang, 2020) to microfound the information structure of the contract designer (i.e., the lender) and apply this framework to analyze loan guarantee systems.

In quantifying the effect of guarantees on information acquisition, this paper contributes to the study of bank moral hazard. A large theoretical literature examines bank moral hazard and incentives for ex-ante screening (e.g., Gorton & Pennacchi, 1995) and ex-post monitoring (e.g., Holmstrom & Tirole, 1997). Empirical work has examined moral hazard in the context of loan securitization (e.g., Keys *et al.*, 2010; Rajan *et al.*, 2015). This paper builds on the ideas presented in the empirical work but focuses on the heterogeneous impact of bank moral hazard across the distribution of borrowers. The ideas underlying the distributional impact of moral hazard are related to the findings of Nelson (2022) and Jansen *et al.* (2023), as well as the literature studying guarantees of government-sponsored enterprises in mortgage markets, including Jeske *et al.* (2013) and Gete & Zecchetto (2018). Assessing the distributional impact of government policy is particularly notable in the context of small-business loan guarantee programs, as the policies are designed with the goal of expanding credit to riskier borrowers that have limited outside funding options.

Finally, this paper relates to work examining the efficacy of guarantees. Gale (1990) and Gale (1991) provide a theoretical basis for the study of these programs. Recent work has examined the interventions empirically to estimate the elasticity of credit supply with respect to the guarantee rate (Bachas *et al.*, 2021) and quantify the extent of market power held by lenders in these government programs (Cox *et al.*, 2022). Other papers have explored the effect of guarantees on entrepreneurship (Lelarge *et al.*, 2010), lenders' incentives to collect collateral (Ioannidou *et al.*, 2018), small-business employment growth (Brown & Earle, 2017), and firm-level performance and productivity (Gonzalez-Uribe & Wang, 2021).

2. Institutional Background

The empirical analysis in this paper focuses on the SBA 7(a) Loan Program, the SBA's main loan guarantee program, which was established in 1953. The program intends to provide financing to small businesses that have "sufficient cash flow to repay the loan but may not have the necessary collateral or history required by a bank's lending policy" (Office of the Comptroller of the Currency, 2015). To be eligible for a 7(a) loan, businesses must satisfy size standards set by the SBA and pass a *credit elsewhere test*. This test does not rely on a quantifiable metric; it states that SBA guarantees are available only to borrowers that would be unable to obtain a loan without them.[5] This stipulation motivates my decision to model lenders with monopoly power in Section 4. Competition among lenders is limited to those within the 7(a) program and, typically, a borrower is approved for a guarantee with a single lender. Only 282 of 51,153 borrowers approved for an SBA guarantee between 2009 and 2011 were approved with more than one lender during that same period.

Funds obtained through 7(a) loans must be used for an allowed purpose. For example, they may be used to purchase real estate or manufacturing equipment, to make capital improvements, or to acquire or start businesses. Borrowers cannot take out additional SBA-backed funds to refinance an existing loan in the 7(a) program (Office of the Comptroller of the Currency, 2015). In the fiscal year 2018, the SBA guaranteed 60,353 loans, worth approximately $25.4 billion (Congressional Research Service, 2019a). While only a small subset of the 30 million small businesses in the U.S. receive loans through the program, these firms tend to be particularly credit constrained, as evidenced by their passage of the credit elsewhere test.

The lending process for guaranteed loans varies depending on whether the lender participates in the preferred lending program. Preferred lenders apply to be part of the program, and their regional SBA field office decides whether they have a competent performance record and can adequately judge borrower risk.[6] Preferred lenders are

[5] See 13 CFR 120.101 and SOP 50 10 5(E). The credit elsewhere test requires that the lender review available resources of any individual who owns at least a 20% stake in the firm and must identify a deficiency in the borrower's profile, such as lack of sufficient collateral, that renders the borrower unable to receive funds absent a guarantee.

[6] For more information, see SOP 50 10 5(E): Lender and Development Company Loan Programs, U.S. Small Business Administration Office of Finance.

granted autonomy in issuing loans (D'Acunto *et al.*, 2017). They must submit an application to the SBA for an eligibility review but are otherwise responsible for the final credit decision (Office of the Comptroller of the Currency, 2014). Thus, preferred lenders are able to adjust their information acquisition practices.

For non-preferred lenders, the guarantee approval process is more structured. The lender submits an application to the SBA, which includes, for example, business information, expected use, current and projected financial information, and names of firm ownership.[7] The SBA reviews the application and then chooses whether to approve the guarantee. After the SBA approves a guarantee, the loan can be canceled prior to disbursement (Dilger, 2016). If the borrower and lender instead proceed, the borrower must pay the required guarantee fees.[8] Once the loan is approved and disbursed, the borrower either repays each period or defaults. In the case of default, the SBA pays the lender the guaranteed percentage of the remaining loan balance.

It is important to note one further feature of the SBA 7(a) program. Banks' pricing is constrained by interest rate caps, which vary by loan size and maturity. For example, during the period of analysis in this paper, a lender issuing a loan of more than \$50,000 with a term of less than seven years may charge a maximum spread on a fixed-rate loan of 2.25% above the Fixed Base Rate. Loans of the same size but with a maturity of more than seven years may be priced up to 2.75% above the Fixed Base Rate.[9] Given this constraint, in addition to the interest rate, banks may choose other contract characteristics to maximize payoffs. In the remainder of the paper, I rely on a loan price that captures the present value of future cash flows, discounted using the zero-coupon Treasury yield curve. This price is a function of both the

[7] See https://www.sba.gov/sites/sbagov/files/files/7a_Loan_Submission_Checklist_Cover_Sheet_H_3.pdf.

[8] Guarantee fees are technically the responsibility of the lender, but they typically pass this expense through to the borrower. For loans with maturity of 12 months or less, the guarantee fee is 0.25% of the guaranteed portion of the loan. For maturities over 12 months, the fee varies by loan amount. During the sample period studied in this paper, for loans of \$150,000 or less, the fee is 2.0%. The fee is 3.0% for loans between \$150,001 and \$700,000, 3.5% for loans between \$700,001 and \$5,000,000. An additional 3.75% is charged for amounts above \$1,000,000. SOP 50 10 5(E): Lender and Development Company Loan Programs, U.S. Small Business Administration Office of Finance.

[9] The Fixed Base Rate is periodically published by the SBA. Before October 1, 2009, it was equal to the prime rate. On October 1, 2009, it became a function of the one-month LIBOR and the average of 5- and 10-year LIBOR swap rates. See https://www.govinfo.gov/content/pkg/FR-2009-09-30/html/E9-23558.htm. This change occurred outside the windows examined in this paper.

interest rate and maturity and provides the present value of a riskless asset with the same cash flows as the loan. Computational details can be found in Appendix C.

Lender incentives are governed by the guarantee rate, and the SBA sets maximum rates nationwide: typically, 85% for loans of $150,000 or less and 75% otherwise. While guarantee rates can vary, and sometimes do in practice, the majority are issued at the maximum level. In the empirical analysis, I exploit exogenous increases in this maximum rate. To stimulate lending to small businesses during the recession, Congress included guarantee increases in two pieces of legislation.[10] The American Recovery and Reinvestment Act of 2009 and Small Business Jobs Act of 2010 temporarily increased the maximum rate to 90% for all loans.[11] The first expansion lasted from March 16, 2009[12] until funding ran out on May 31, 2010, while the second lasted from September 27, 2010 until funding ran out on January 3, 2011 (Congressional Research Service, 2019a). In all expansion periods, guarantee fees were also waived for all new loans. Additionally, the Small Business Jobs Act increased the maximum loan amount from $2 to $5 million (Congressional Research Service, 2019a). These acts provide four plausibly exogenous shocks (i.e., takeup and expiration) to government guarantees, which I leverage in my empirical analysis.

3. Descriptive Evidence

Increasing the generosity of guarantees could lead to changes in loan characteristics through the two channels described in Section 1: the guarantee pass-through and the information effect. The direction and magnitude of these adjustments is an empirical question. In this section, I leverage the variation induced by the 2009 and 2010 legislation to quantify changes to lending practices when guarantee rates are higher. These results serve two main purposes. First, they illustrate the average differences

[10]The changes to the guarantee program were part of a large legislative agenda. To ease concerns about confounding variation, such as changes to the SBA size standards leveraged in Denes *et al.* (2023), I show that the results are robust to examining only the expiration of the high guarantees. The exact date at which the guarantees expired was a function of the total amount of funding and was unrelated to any other programs that were instituted through the two legislative acts of interest.

[11]The SBA did not allow previously-approved loans to be canceled and reapproved at a higher rate.

[12]Note the legislation passed on February 17, but the SBA did not implement the expansion until March 16. See https://www.sba.gov/sites/sbagov/files/2018-06/recov_perform_rptcard_12_2009.pdf.

in characteristics for loans issued under low- and high-guarantee regimes. While understanding these equilibrium differences is useful by itself, the contribution of this paper centers on guarantees' impact on information acquisition and risk pricing. Answering these questions requires a model, so the descriptive results also serve a second purpose: motivating the key components of the model. They provide evidence of the two effects underlying lenders' responses to guarantee-rate changes (i.e., the guarantee pass-through and information effect) and motivate the decision to include both channels when modeling lending decisions with guarantees.

3.1. Data

For the empirical analysis, I rely on a number of data sources. First, I collect publicly-available loan data from the SBA 7(a) Loan Data Reports, which contain loan-level information for all 7(a) loans approved on or after January 1, 1990. From this source, I obtain loan characteristics (e.g., interest rate, term, amount, percent guaranteed), borrower and lender characteristics, and repayment outcomes. The dataset also includes canceled applications which were approved for a guarantee by the SBA but canceled prior to the first disbursement of funds. Cancellations occur automatically if the guarantee fee is not paid to the SBA within 90 days but may also occur if borrowers receive other funding options or close the business.[13] I use these canceled applications as a measure of borrower rejection of a loan offer. For loans that were not canceled, I assign a loan to the default classification if it is listed as charged off as of December 31, 2019. As of this date, only 18% of loans remain outstanding, and I group these loans with those that have been paid in full.

I augment the loan-level data with lender information from the Federal Financial Institutions Examination Council (FFIEC) Bank Call Reports. This dataset contains bank balance sheet information, released at a quarterly frequency. Because I use balance sheet information to capture variation across banks, rather than within bank across time, I consider data from one point in time: December 31, 2010. Specifically, I use these data in the empirical model to capture heterogeneity in banks' lending costs. I match these characteristics to the loan data using the bank name and zip code

[13] Dilger (2016) notes that more loan guarantees are approved annually than disbursed and attributes these cancellations to changes in demand for funds, business ownership, or outside funding options.

and successfully match approximately 80% of loans.[14] The unmatched loans are drawn disproportionately from non-FDIC-insured institutions. While these lenders could face different incentives than their counterparts, they are responsible for a small subset, a maximum of 20%, of SBA loans during the sample period. Furthermore, the main takeaways from the descriptive evidence, using the full dataset, are identical to those from the structural model. This alleviates selection concerns.

To complete the dataset, I obtain one-month LIBOR over time from FRED and demographic data from the U.S. Census Bureau, Bureau of Labor Statistics, and Federal Housing Finance Agency to proxy for borrower characteristics. As with the FFIEC data, I rely on the demographic data to capture cross-sectional variation and therefore obtain demographics from a single point in time: 2010. I merge information on local housing prices, population, and median household income.

	Mean	S.D.	Min.	25th Pct.	Median	75th Pct.	Max.
All Loans							
Interest Rate (Pct.)	5.86	0.57	2.25	5.5	6	6	9.23
Term (Months)	164.35	88.46	7	90	120	244	318
Amount Borrowed ($ Thousands)	557.78	487.28	6.5	200	400	772	2,000
Guaranteed Share	0.86	0.06	0.32	0.85	0.9	0.9	0.9
Acceptance	0.87						
Loan Size $>$ 150,000	0.81						
Preferred Lender	0.71						
Observations	13,994						
Accepted Loans							
Default	0.07						
Observations	12,159						

Table 1: Summary Statistics. This table displays summary statistics for the main sample of loans. The top panel ("All Loans") displays statistics for all loans approved for a guarantee. The bottom panel ("Accepted Loans") includes only loans that were disbursed.

For the main analyses, I restrict to loans of up to $2 million[15] approved within a window of the four exogenous changes to guarantees and trim the price distribution at the 1st and 99th percentile to remove outliers.[16] Also, if multiple loans were issued

[14]This match rate is approximately the same as that in Choi & Lee (2019). This restriction yields a smaller sample for the structural portion (N = 11,664) than for the descriptive (N = 13,994).

[15]The Small Business Jobs Act of 2010 increased the maximum loan amount from $2 to $5 million (Congressional Research Service, 2019a). I exclude these newly eligible loans to standardize the borrower pool over time.

[16]In Appendix A.1, I show that the results are robust to including the price outliers.

to a single borrower between 2009 and 2011, I keep only the first loan to ensure pre-existing relationships do not confound the estimates of information precision. Because these analyses rely on temporal variation, focusing on a small window around events limits confounding factors, like changes to bank lending costs and other macroeconomic fluctuations, that could affect loan characteristics or outcomes. The main specifications examine six-week windows on either side of the exogenous changes, but results are robust to using two-week windows (see Appendix A.1). Additionally, I provide support in Appendix B that changes to guarantee rates are not correlated with variables that determine bank lending costs and Treasury yields, although they are associated with changes to bank stock prices for a subset of the largest U.S. banks. One final restriction relates to a specific feature of the second uptake of the guarantee expansion. A number of loans, whose applications were submitted in the months leading up to the expansion, were held in a queue to wait for higher guarantee rates. Because these applications may have been submitted outside the window around the expansion, I exclude them from the analysis.[17] Summary statistics for the final loan-level dataset are displayed in Table 1.

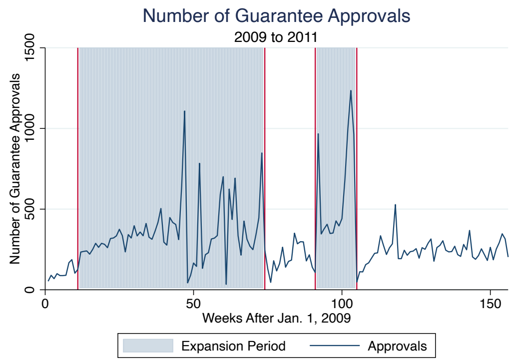
3.2. Lending Activity Over Time

The SBA data clearly illustrate the lenders' response to the guarantee-rate increases. Banks adjust along the extensive margin, and lending activity expands. Figure 1 plots the trend in lending over time. Panel (a) displays total approvals and Panel (b) displays the share of loans issued by preferred lenders. More generous guarantees result in a spike in lending, and higher average amounts of lending persist throughout the period. Furthermore, the bunching around events is correlated with a higher share of preferred lenders. These banks are provided more autonomy in the lending process and are therefore more able to shift loans into the high-guarantee period.

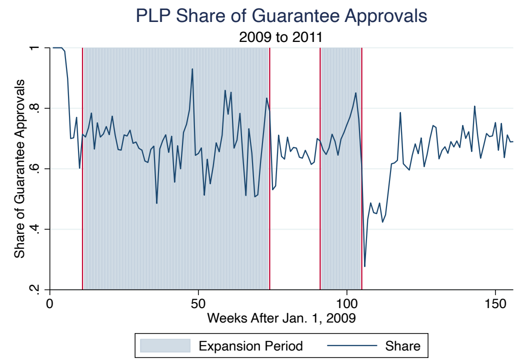
These trends suggest that loans are not necessarily assigned randomly into treatment, and, for this reason, the regression results in the remainder of this section should not be interpreted as causal effects.[18] Instead, I intend for them to describe the

[17] The SBA cleared the queue within one week. I therefore exclude loans issued within seven days of the second expansion. See https://obamawhitehouse.archives.gov/blog/2010/10/05/one-week-later-nearly-2000-small-businesses-approved-sba-loans-due-jobs-act.

[18] Ideally, riskless borrowers – for which guarantees are not valuable – could serve as a control, but it



(a) Approvals



(b) PLP Share

Figure 1: Lending Activity Over Time. This figure displays, from 2009 to 2011, plots of (1) total 7(a) guarantee approvals and (2) share of loan approvals filed by preferred lenders. The red vertical lines signify changes in maximum guarantee rates. The unshaded areas denote the baseline guarantee rates, while the shaded areas denote the expansion period.

equilibrium responses to the policy change, combining the guarantee pass-through, the information effect, and any shift in the distribution of borrowers. The results, and their shortcomings, help motivate the structural model, which allows me to disentangle these three pieces of the observed equilibrium changes.

3.3. Changes to Loan Characteristics

Not only do lenders issue a larger number of loans to capture higher government guarantees; they also offer more generous contract terms. To quantify the extent to which lenders alter loan characteristics in the high-guarantee periods, I estimate specifications which exploit the temporal policy variation:

$$Y_{ijt} = \alpha + \delta \mathbb{I}(t = \text{SBA Recovery}) + \beta X_{it} + \epsilon_{ijt}, \tag{1}$$

where Y_{ijt} is a characteristic of loan i issued by lender j in week t and X_{it} is a vector of borrower covariates: indicators for business type, NAICS code (two-

is difficult to find such borrowers in the 7(a) program. In Appendix A.1, I present results showing incremental changes for observably higher-risk relative to lower-risk borrowers, similar in concept to the analysis of Cuesta & Sepulveda (2021). Higher-risk borrowers experience larger interest-rate and maturity changes. The incremental change in loan amount is negative but noisily estimated.

digit), whether the loan is used for real estate (maturity $>$ 10 years), and event date, corresponding to each guarantee-rate change, as well as controls for zip code demographics, including the change in the housing price index since 2008, median household income, and total population. δ is the coefficient of interest and captures the changes to average loan characteristics during the guarantee expansion period.

Columns (1) – (4) of Table 2 display results of Specification 1. Interest rates decline in the guarantee expansion period, while the average amount borrowed and loan term increase. All of these results are both statistically and economically significant. The average interest rate decreases by approximately 4.2 basis points, the average loan amount increases by \$56 thousand, and the average loan term increases by between 4 and 5 months, all of which are consistent with the relaxation of credit constraints on small businesses. Conditional on observables, lenders are willing to provide financing at lower interest rates, extend larger loans, and allow longer repayment terms when government guarantees are higher.

Furthermore, these results are driven by preferred lenders, who are afforded substantial discretion in the lending process and are better equipped to respond to policy variation.[19] Columns (5) – (8) of Table 2 present results of an adjusted version of Specification 1, including a preferred lender indicator and its interaction with the SBA Recovery indicator, and show that the equilibrium response to the guarantee expansion is large and statistically significant for preferred lenders, while it is small and typically statistically insignificant for non-preferred lenders.[20] In the structural model, I allow for lender-side heterogeneity by preferred status to capture any differences in information acquisition costs due to the program rules.

The lower interest rates, longer maturities, and larger capital outlays suggest that a portion of the gains induced by the guarantees is passed on to borrowers (i.e., the guarantee pass-through is positive), on average. The model presented in Section 4 captures this intensive-margin result by allowing guarantees to shift

[19] In a similar context, D'Acunto *et al.* (2017) find that businesses more likely to be financed by a preferred lender in the SBA loan program exhibit lower rates of employment growth. This points to the real effects of the moral hazard problem I examine in this paper.

[20] To assuage concerns that the differential response could be driven by (1) observable differences between the two groups or (2) a change in the composition of preferred lenders in the high-guarantee period, I conduct a number of robustness tests in Appendix D.

	(1) Interest Rate (Pct.)	(2) Amt. Borrowed ($ Thousands)	(3) Loan Size > 150,000	(4) Loan Term (Months)	(5) Interest Rate (Pct.)	(6) Amt. Borrowed ($ Thousands)	(7) Loan Size > 150,000	(8) Loan Term (Months)
Loans Issued Within 42 Days of Events								
SBA Recovery	-0.0418	56.29	0.0569	4.169	-0.00205	27.12	0.0230	0.759
	(0.0161)	(10.86)	(0.00883)	(0.936)	(0.0220)	(16.72)	(0.0131)	(1.381)
Preferred Lender					-0.0634	-112.60	-0.0809	3.422
					(0.0399)	(18.40)	(0.0199)	(2.511)
SBA Recovery $\times$ Preferred Lender					-0.0449	58.58	0.0599	4.169
					(0.0225)	(20.20)	(0.0184)	(1.892)
Mean Outcome	5.86	557.78	0.81	164.35	5.86	557.78	0.81	164.35
Observations	13,994	13,994	13,994	13,994	13,994	13,994	13,994	13,994
Zip Code Dem. Controls	✓	✓	✓	✓	✓	✓	✓	✓
Business Type FE	✓	✓	✓	✓	✓	✓	✓	✓
NAICS (Two-Digit) FE	✓	✓	✓	✓	✓	✓	✓	✓
Real Estate FE	✓	✓	✓	✓	✓	✓	✓	✓
Event Date FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 2: Changes to Loan Characteristics. Columns (1) - (4) present results of Specification 1, including all loans issued within 42 days of guarantee-rate changes. Columns (5) - (8) present the preferred-lender heterogeneity analysis using an adjusted version of Specification 1. All specifications include controls for zip code level demographics (median household income, total population, change in the housing price index since 2008), as well as fixed effects for business type, NAICS (two-digit), real estate, and event date. Standard errors are clustered by lender.

banks' effective marginal costs of lending. Despite observing gains for borrowers, on average, not all necessarily benefit from higher guarantees. Whether and the extent to which borrowers benefit depends on the magnitude of the information effect, which controls how precisely loan characteristics match the borrower's risk. Measuring the information effect requires a more explicit model of the lending market. However, before turning to the model, I provide descriptive evidence supporting the notion that lenders price risk less precisely when loan guarantees increase in generosity.

3.4. Loan Pricing

The results of Specification 1 are informative of the impact of government guarantees on equilibrium loan characteristics, but they do not allow for analysis of heterogeneous effects across the risk distribution and do not speak to the information channel directly. To examine these two points, I exploit two features of the SBA lending setting: (1) lender pricing decisions are informative of their information structure and belief about a borrower's risk, and (2) observed ex-post repayment outcomes are informative of true borrower risk.[21] Changes in the mapping from borrower default risk to loan price, above what can be explained by characteristics, are suggestive of differences in the lender's precision of information.[22] I examine changes in this mapping during the high-guarantee period and provide evidence that lenders price risk less precisely, which is consistent with a decline in their screening effort.[23]

I rely on a two-stage regression framework. First, I estimate a flexible mapping

[21]These features are frequently present in markets with asymmetric information and are exploited in related ways in Chiappori & Salanie (2000), Rajan *et al.* (2015), and Crawford *et al.* (2018).

[22]It is important to note that a change in the mapping from default to price could also stem from heterogeneity in the guarantee pass-through. A generous guarantee is less valuable when lending to a low- rather than a high-risk borrower. Thus, a change to the guarantee rate should affect prices differently across the distribution of borrower risk. Appendix D provides evidence that the observed changes in price-default mappings are not the result of only this mechanical effect. If changes in the precision of information played no role, the mappings of preferred and non-preferred lenders would move together. The fact that preferred lenders, who are more able to adjust their information acquisition, respond disproportionately suggests the presence of an information effect.

[23]Given the extent of bunching in the high-guarantee period, there may be concern that the decline in precision of risk pricing is driven by lenders rushing to approve loans and that information acquisition would not have changed absent this time constraint. To alleviate this concern, I show in Appendix A.2 that the pricing regression results are robust to restricting to loans issued outside of the one-week window on either side of the policy changes.

from characteristics to prices using loans in both the low- and high-guarantee periods:

$$p_{ijt} = f(M_{ijt}, B_{ijt}) + X_{it}\beta + \epsilon_{ijt}, \tag{2}$$

where p_{ijt} is the loan price offered to borrower i by lender j in week t. To standardize the price across loans, I compute the price as the present-value equivalent for a ten-year loan, the modal loan maturity in the sample, discounting cash flows using the zero-coupon Treasury yield curve, as described in Appendix C. In essence, this measure captures the price of a portfolio of treasuries with the same cash inflows as the loan. This same price is used in the remainder of the paper. I show in Appendix A.2 that the results of the pricing analysis are robust to other specifications of the lenders' choice variable. In particular, to address concerns that the results may be driven by differences in default behavior across maturities, I show that the takeaway is the same when using the interest rate on the left-hand side and controlling for a flexible function of the loan maturity, loan amount, and guarantee.

In Specification 2, f is a flexible function (i.e., quadratic terms and interactions) of M_{ijt}, the guarantee rate, and B_{ijt}, the size of the loan. X_{it} is a vector that includes indicators for business type, two-digit NAICS code, event date, and maturity over 10 years. I also control for zip code demographics using the same covariates as described in Section 3.3. ϵ_{ijt} captures all borrower, loan, and lender characteristics priced into the loan but not observed by the econometrician. This residual could include soft information collected by the loan officer, hard information not included in the SBA dataset, or lender characteristics, including its marginal cost of lending.

The second stage estimates the correlation between the unobserved component of price, ϵ_{ijt}, and borrower default, the observed ex-post loan outcome:

$$\begin{aligned} d_{ijt} = \gamma_1\epsilon_{ijt} + \gamma_2\mathbb{I}(t = \text{SBA Recovery}) + \\ \gamma_3\epsilon_{ijt} \times \mathbb{I}(t = \text{SBA Recovery}) + g(M_{ijt}, B_{ijt}) + X_{it}\delta + e_{ijt}, \end{aligned} \tag{3}$$

where d_{ijt} is an indicator of default, $g(\cdot)$ is quadratic terms and interactions of the guarantee rate and loan size, and X_{it} is the same vector of controls as in the first stage. The coefficient of interest is γ_3, which measures the change in the correlation between default and the price residual during the high-guarantee period. It captures changes in the lenders' precision of risk pricing. A negative coefficient indicates that loan prices are less informative of borrower risk when guarantees are high.

	(1) Default	(2) Charge Off
ϵ	1.990	1.216
	[1.649,2.343]	[1.003,1.452]
$\mathbb{I}(t = \text{SBA Recovery})$	-0.031	-0.027
	[-0.060,-0.002]	[-0.046,-0.008]
$\epsilon \times \mathbb{I}(t = \text{SBA Recovery})$	-0.550	-0.379
	[-0.926,-0.202]	[-0.631,-0.147]
Raw Correlation	0.239	0.213
SD(ϵ)	0.038	0.038
Observations	12,159	12,159

Table 3: Pricing Regression Results. This table presents results for the second stage of the two-stage pricing regression, Specification 3. The first column displays results for an indicator of default on the left-hand side, while the second column displays results for the share of the loan charged off. All specifications include quadratic terms and interactions of the guarantee rate and loan amount and controls for zip code level demographics, as well as fixed effects for business type, NAICS (two-digit), real estate, and event date. Block-bootstrapped (by lender) 95% confidence intervals are displayed in brackets; N=1,000.

Table 3 displays estimates for the second stage. There is a positive correlation between the unobserved components of price and default. Intuitively, lenders observe more than the econometrician and therefore are better able to price borrower risk. The correlation falls substantially during the high-guarantee period, with the coefficient on the price residual falling by between 25 and 30%, indicating a change in the mapping from risk to price. As in Section 3.3, the response of preferred lenders differs from that of their counterparts. Appendix D presents the bootstrap distribution of γ_3 for both types of lenders. Preferred lenders are better able to adjust their pricing function, owing to the greater autonomy provided them by the SBA.

Together, these descriptive results show that lenders respond swiftly to the policy changes. In the high-guarantee period, lenders issue observably more generous loans and price risk less precisely. However, these results are not fit for analysis of compositional changes, changes in information precision, and quantification of the resulting price-risk mismatch. In the remainder of the paper, I present a model of the small-business lending market, describe the estimation procedure, and use the results to inform the design of small-business lending policies.

4. Model and Estimation

The empirical model provides a general framework, in the style of Crawford *et al.* (2018), to study the impact of guarantees on pricing and information acquisition. In this section, I describe each component of the model in detail and discuss identification of the primitives governing borrower and lender decisions.

4.1. Framework

Let borrowers be indexed by i and lenders be indexed by j. Conditional on observables, borrowers are characterized by their propensity to repay, ξ_i^R, and their price responsiveness, α_i, distributed jointly by $F_{\xi^R,\alpha}$. The lender does not observe the borrowers' repayment types, ξ_i^R, but chooses its signal precision and obtains noisy signals, s_{ij}, of the borrowers' risk. Lenders are heterogeneous in the cost they must pay to gain a unit of signal precision and thus choose different optimal information acquisition strategies. Conditional on the signal the lender receives for a borrower, it chooses the loan characteristics to offer, and borrower outcomes (i.e., acceptance and default) are then realized. A more detailed description of the timing of the model is as follows: (1) A set of borrowers i, whose types (risk) and price responsiveness are private information, are paired with a given lender j. (2) Given the guarantee rate, its cost of information acquisition, and knowledge of the distribution of borrowers, lender j chooses the precision of its information and receives signals of the borrower types. Given the signal, lender j offers a loan of price p_{ij} to the borrower. (3) The borrower receives a shock to its value of receiving a loan (analogously, to its outside option), and borrower i chooses whether to accept the loan. (4) If it accepts, the borrower defaults or repays according to its propensity to repay, ξ_i^R.

One key assumption of the model is the existence of lender market power, through the exogenous pairing of borrower i and lender j. The institutional details support this assumption. To receive a loan in the 7(a) program, a borrower must pass the credit elsewhere test, meaning lenders face limited, if any, competition from non-SBA lenders for 7(a) loans. SBA lenders may compete with one another, but I provide evidence that such competition is limited. I observe all loans approved by the SBA for a guarantee and find few instances in which a borrower is approved with multiple lenders. Appendix E provides additional support for this assumption.[24]

4.1.1. Borrower Acceptance and Default

As in Crawford *et al.* (2018), I model the borrowers' acceptance and default decisions using reduced-form rules. In this framework, the baseline level of adverse selection is determined by the correlation of ξ^R and α, rather than by a structural relationship mapping borrower risk to the acceptance decision, as in Stiglitz & Weiss (1981). Suppose businesses have the following utility of loan repayment:

$$u_i^R = X_i^R \beta^R + \xi_i^R, \tag{4}$$

where X_i^R is a vector of borrower covariates that shift the probability of repayment[25] and ξ_i^R is the borrower's private-information propensity to repay. I normalize the utility of default to zero, and borrowers repay if $u_i^R \geq 0$.

One assumption underlying the repayment decision merits further discussion. I impose that default rates do not depend on prices, conditional on observables and ξ_i^R. This assumption is common in the literature on SBA-guaranteed lending (see, e.g., Cox *et al.* (2022)), as well as work on other forms of consumer credit (see,

[24] A number of studies examine the connection between competition and information acquisition (Ruckes, 2004; Hauswald & Marquez, 2006; Avramidis *et al.*, 2022). In these models, information acquisition incentives and competition are negatively related (i.e., incentives are strongest under low competition). The fact that I do not model competition would, therefore, be problematic if (1) competition influences information acquisition and (2) the level of competition varies with the guarantee rate. As discussed, the institutional details of my setting and analyses in Appendix E suggest that strategic considerations are limited and therefore this is not a main concern.

[25] This structure implicitly assumes that the level of collateral is captured by borrower observables, X_i^R. A change in collateral would alter the default payoff and would be indistinguishable from a level shift in the utility of repayment. While some loans in this program are secured with collateral, the program's stated purpose is to expand credit to parties that do not satisfy the requirements of a typical bank lending policy, one of which is sufficient collateral. Thus, the assumption that collateral levels are captured by observables is likely less binding here than in other lending contexts.

e.g., Nelson (2022)). This assumption rules out higher loan payments constraining liquidity, as well as moral hazard. Allowing for moral hazard, or a response of default decisions to changes in loan prices, would temper price effects and could introduce non-monotonicities into the mapping from signals to prices.[26]

The utility borrowers receive from obtaining a loan is a borrower-specific function of covariates, price, and a preference shock:

$$u_{ij}^A = X_i^A \beta^A - \alpha_i p_{ij} + \epsilon_{ij}, \tag{5}$$

where X_i^A is a vector of borrower covariates that shift the probability of acceptance, p_{ij} is the price offered by lender j to borrower i, and ϵ_{ij} is a preference shock, distributed Type I Extreme Value. Adverse selection enters through the correlation of ξ_i^R and α_i, where riskier borrowers may be less price-sensitive than their safer counterparts. In Appendix H.1, I show that the results are robust to a model with a random coefficient on the constant instead of price, which captures a setting where riskier borrowers are more likely to accept loans at all prices.

4.1.2. Lender Information Acquisition and Pricing

The lenders' decision problem proceeds in two stages. First, lenders choose the precision of information to collect about borrowers; this amounts to choosing the joint distribution of signals and borrower risk, denoted F_{s,ξ^R}. Then, lenders receive signals and offer prices to maximize ex-ante expected profits, conditional on the signal. I describe these decisions in reverse order, beginning with the price offers.

At this stage, lenders take as given the precision of information and the joint distribution of borrower risk and price sensitivity, $F_{\xi^R,\alpha}$, in the population. Lender j then receives a noisy signal of borrower i's risk, ξ_i^R, and updates its beliefs using Bayes' rule. I assume the signal has the following structure:

$$s_{ij} = \xi_i^R + \sigma_\gamma(H_{ij})\epsilon_{\gamma,ij}, \tag{6}$$

[26] Depending on the shape of the default function, non-monotonicities could arise if the degree to which expected default is responsive to changes in price is sufficiently different across signal realizations. For a further discussion of these non-monotonicities, see Crawford *et al.* (2018).

where $\sigma_\gamma(H_{ij})$ is the standard deviation of the signal noise for a loan of a lender-borrower pair of type H_{ij} and $\epsilon_{\gamma,ij} \sim F_{\epsilon_\gamma}$ is a mean-zero, symmetrically distributed error. This setup implies that signals for all loans of type H_{ij} have the same precision. In principle, H_{ij} can include borrower and lender covariates. In practice, due to data limitations, I allow the precision to vary only by lender size, guarantee period, and the lender's preferred status. See Section 4.2.1 for further discussion.

The lender sets its price offer to maximize its ex-ante expected payoff, conditional on the signal. Specifically, the lender solves:

$$\max_{p_{ij}} \int P^A(\alpha, p_{ij}, X_i^A) \left[(1-(1-M_{ij})P^D(\alpha, X_i^R))p_{ij} - \zeta_{ij}\right] f_{\alpha|s_{ij}}(\alpha) d\alpha, \tag{7}$$

where $P^A(\alpha, p_{ij}, X_i^A)$ is the probability of acceptance given price sensitivity α at price p_{ij} with observables X_i^A, $P^D(\alpha, X_i^R) = \int_{-\infty}^{-X_i^R\beta^R} f_{\xi|\alpha,s_{ij}}(\xi)d\xi$ is the probability of default for a borrower of type α with observables X_i^R, ζ_{ij} is the marginal cost of lending, and M_{ij} is the guarantee rate. The first-order condition of Equation 7 implies that the optimal price satisfies:

$$p_{ij}^* = \underbrace{\zeta_{ij} \frac{\int \frac{\partial P^A}{\partial p}(\alpha, p_{ij}^*, X_i^A)\, f_{\alpha|s_{ij}}(\alpha)d\alpha}{\int \frac{\partial P^A}{\partial p}(\alpha, p_{ij}^*, X_i^A)(1-(1-M_{ij})P^D(\alpha, X_i^R))\, f_{\alpha|s_{ij}}(\alpha)d\alpha}}_{\text{Guarantee-corrected effective MC}} - \underbrace{\frac{\int P^A(\alpha, p_{ij}^*, X_i^A)(1-(1-M_{ij})P^D(\alpha, X_i^R))\, f_{\alpha|s_{ij}}(\alpha)d\alpha}{\int \frac{\partial P^A}{\partial p}(\alpha, p_{ij}^*, X_i^A)(1-(1-M_{ij})P^D(\alpha, X_i^R))\, f_{\alpha|s_{ij}}(\alpha)d\alpha}}_{\text{Guarantee-corrected captured markup}}. \tag{8}$$

The pricing function captures key features of the risk-based pricing framework of Phillips (2013) and Edelberg (2006), as prices are a function of lending costs, a markup term, and a premium depending on the borrower's risk. It also captures the two channels through which guarantee-rate changes affect prices. The guarantee pass-through enters through a change in the lender's payoff under default, shifting both terms of Equation 8. Note that the form of u_i^R implies no direct effect of prices on default. However, prices do still affect the ex-ante expected default rate, given acceptance, faced by the lender through the risk composition of borrowers willing to accept loans. Equation 8 captures this selection channel through the correlation of ξ_i^R and α_i given signal, s_{ij}. The information effect enters through the joint distribution of risk and price responsiveness, conditional on the signal. If information is more precise, prices are more responsive to changes in the realized signal and vice versa.

With knowledge of the pricing rule, lenders choose the precision of their information ex ante. As discussed, the precision of information varies with H_{ij}, and I assume joint optimization of this precision for all loans of type H_{ij}. Given H_{ij}, lenders know the distribution of borrower observables and the joint distribution of borrower risk and price sensitivity, which determine the expected payoff as well as the marginal benefit of additional information. The lenders then choose how much costly effort to expend collecting more information about the borrowers. This extra effort could be used to obtain "soft" information, such as a subjective measure of trustworthiness, through face-to-face meetings with the borrower or to verify other codifiable information like revenue projections and business plans.

I assume precision is costly to acquire and lenders of type $H_{ij} = \tilde{H}$ pay $\kappa_{\tilde{H}} \cdot \frac{1}{\sigma_\gamma^2}$ to obtain a signal with standard deviation σ_γ. In this specification, $\kappa_{\tilde{H}}$ is a primitive and is invariant to changes in guarantee policy. If lenders must meet with borrowers to acquire information, we would expect the information cost to scale linearly with the number of meetings and the number of meetings to positively correlate with the final precision. Pomatto *et al.* (2023) provide an axiomatic foundation for information acquisition that microfounds this form of cost structure.[27]

To choose the signal precision, lenders maximize expected profit across all pairs of type $H_{ij} = \tilde{H}$. The optimal precision solves

$$\max_{\sigma_\gamma} \sum_{ij \in \mathcal{J}_{\tilde{H}}} \iint P^A(\alpha, p_{ij}, X_i^A)[(1-(1-M_{ij})P^D(\alpha, X_i^R))p_{ij} - \zeta_{ij}] f_{\alpha,s}(\alpha, s; \sigma_\gamma) d\alpha ds - \kappa_{\tilde{H}} \cdot \frac{1}{\sigma_\gamma^2}, \quad (9)$$

[27]Whereas the standard mutual information-based costs in rational inattention models capture the costs of processing information, the function used here instead captures the costs of acquiring information. The axioms set forth by Pomatto *et al.* (2023) ensure monotonicity of costs in precision and imply a constant marginal cost of information. In my setting, these are attractive properties.

where all components of expected profit are defined as in Equation 7, $\kappa_{\tilde{H}}$ is the marginal cost of information, and $\mathcal{J}_{\tilde{H}}$ denotes the set of loans of type $\tilde{H}$. The precision of information affects payoffs through two components. First, it enters through expected default outcomes, as the lender updates its beliefs of borrower risk. Second, it affects lender beliefs over acceptance decisions, through the correlation of price responsiveness and risk. The equilibrium level of information equates the marginal benefit of more precise risk pricing and the cost of acquiring signals of that precision. To examine the extent to which information acquisition responds to guarantee-rate changes, we must estimate the primitives of the model. In the remainder of this section, I describe how I take the model to the data.

4.2. Identification and Estimation

4.2.1. Parameterization

I specify the borrower's utility of repayment as a linear function of borrower observables, X_i^R, which includes a constant, indicators for categories of loan amounts[28], loans with maturity less than or equal to ten years, loans issued in the SBA Recovery period, events (i.e., corresponding to each take-up and expiration of high guarantees), two-digit NAICS, and business type, as well as the same zip code level demographics as in Section 3. [29]

The borrower's utility of acceptance is a function of these same borrower observables. These utilities of repayment and acceptance allow borrower decisions to vary across loan use, as proxied by loan size and maturity category, across time, and across borrower characteristics. The functions also allow a discrete shift in the SBA Recovery period to capture both selection of borrowers into the high-guarantee scheme and the fact that guarantee fees, which are typically passed through to the borrower, were waived whenever guarantees were expanded.

To complete the borrower side, I parameterize the distribution of risk and price

[28]Specifically, I allow for heterogeneity in repayment and acceptance decisions across the following categories (in $ thousands): [$0, $150], ($150, $700], ($700, $1,000], and ($1,000, $2,000]. These categories delineate loan amounts for which the guarantee fees discretely change. Intuitively, these discrete changes in guarantee fees should influence the borrower's utility of loan acceptance.

[29]For computation, I normalize the demographic variables, w_i, as $\frac{w_i - \min_i w_i}{\max_i w_i - \min_i w_i}$.

responsiveness as bivariate normal. This parameterization requires two normalizations. I set $\mathrm{E}[\xi_i^R] = 0$ and $\mathrm{Var}[\xi_i^R] = 1$, so the repayment decision takes the form of a standard probit. The remaining parameters governing the joint distribution are to be estimated. Specifically, the distribution takes the following form:

$$\begin{pmatrix} \xi_i^R \\ \alpha_i \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ \mu_\alpha(X_i^\alpha) \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma_\alpha \\ \rho\sigma_\alpha & \sigma_\alpha^2 \end{pmatrix} \right),$$

where X_i^α groups loans by whether they were issued in the SBA Recovery period and whether they have a maturity of more than ten years (i.e., real estate). Allowing the mean price responsiveness to vary along these dimensions captures changes to the attractiveness of the borrowers' outside options across periods and loan uses.

On the lender side, I assume the marginal cost function is linear and separable in the shifters of lending cost, Z_{ij}, the ongoing guarantee fee, which is a function of the guarantee rate, and an independent shock, ω_{ij}. Specifically,

$$\zeta_{ij} = \beta^Z Z_{ij} + \psi(M_{ij}) + \omega_{ij}, \tag{10}$$

where the shifters of lending cost, Z_{ij}, include loan amount category, event-date indicators, one-month LIBOR, normalized bank-level interest-bearing balances and non-interest-bearing balances, currency, and coin due from depository institutions, as well as bank-state level balances. This allows for cost variation across loan amounts, over time, across banks, and within banks, across states. I provide intuition of the identification of the model in Section 4.2.2, highlighting the role of the cost shifters excluded from borrower decisions in particular. The ongoing fee is 0.55% per year for the guaranteed portion of the loan, and I detail the computation of $\psi(M_{ij})$ in Appendix C. I assume $\omega_{ij} \sim N(0, \sigma_\omega^2)$, where σ_ω is a parameter to be estimated.

Finally, as mentioned above, I assume the lender receives a signal of borrower risk, as specified in Equation 6. The standard deviation of the signal noise takes the form: $\sigma_\gamma(H_{ij}) = \exp(\beta^{\sigma_\gamma} H_{ij})$, where H_{ij} consists of indicators of bank size (Total Assets $<$ \$10B, Total Assets $\in$ [\$10B,\$100B), Total Assets $\geq$ \$100B) interacted with an indicator for preferred lenders, an indicator for the SBA Recovery period, and preferred $\times$ SBA Recovery. This parameterization allows lenders to respond to guarantee-rate changes through the precision of their information; preferred lenders or lenders of different sizes may respond differentially. I assume $\epsilon_{\gamma,ij} \sim N(0,1)$.

4.2.2. Identification

We observe borrower acceptance and default decisions, lender pricing decisions, and observables that vary across both borrowers (e.g., NAICS code and geography) and lenders (e.g., bank balance sheet information). The primitives of interest are the components of the borrowers' utility of repayment and utility of acceptance, and the joint distribution of borrower types, price responsiveness, and signals.

On the borrower side, parameters are informed by variation in default and acceptance rates. Under the location and scale normalizations described above, variation in default rates across borrower covariates pins down the coefficients of the repayment utility function. Similar variation pins down the coefficients on the exogenous shifters of the utility of acceptance (i.e., those entering X_i^A).

Because prices are set with knowledge of s_{ij}, which is not independent of ξ_i^R and α_i, another source of variation is required to recover the joint distribution of risk and price responsiveness, $F_{\xi^R,\alpha}$. I rely on the cost shifters excluded from borrower decisions, as described in Section 4.2.1. The mean price responsiveness is informed by differences in acceptance rates across these cost shifters. The variance of this distribution is pinned down by the extent to which price responsiveness varies across borrowers that differ in their exogenous covariates. Finally, ρ is informed by the correlation between acceptance and default decisions. If borrowers that are unlikely to accept given their covariates are also much more likely to default, then ρ is positive and large in magnitude.

I impose one assumption on ρ, namely, $\rho \geq 0$. This assumption restricts the direction of selection in the market, ensuring that demand is not advantageously selected. Under advantageous selection, prices need not be monotonic in the signals received by lenders. Lenders learn about price responsiveness only through its correlation with risk, ξ_i^R. If advantageous selection is sufficiently strong, then a borrower that is believed to be high risk may receive a lower price offer because its level of risk implies weak demand. A similar, non-advantageous selection assumption is imposed in the consumer lending literature, e.g., Nelson (2022).

The lender-side parameters are informed by variation in prices across lender cost shifters and borrowers' residual risk. Assuming ω_{ij} is an i.i.d. cost shock, the linear parameters of the marginal-cost function are identified by variation in average price across the cost shifters, Z_{ij}. The remaining parameters ($\sigma_\gamma(H_{ij})$ and σ_ω) are informed by two sources of variation: (1) variation in prices across default status and (2) the variance of prices.

The intuition for the separate identification of the standard deviation of the signal noise, $\sigma_\gamma(H_{ij})$, and that of the cost shock, σ_ω, stems from differential pricing across ex-post default outcomes. A similar intuition underlies the analysis in Section 3. Suppose we condition on the borrower covariates, X_i^R and X_i^A, the exogenous cost shifters, Z_{ij}, the lender covariates entering the standard deviation of the signal noise, H_{ij}, and the guarantee rate, M_{ij}. In the remainder of this section, I suppress these conditioning variables for notational convenience.

Define $a_{ij} = 1$ if borrower i accepts the loan from lender j and zero otherwise. Let d_{ij} take the same values for the default decision. Consider two conditional distributions: $p_{ij}|a_{ij} = 1, d_{ij} = 1$ and $p_{ij}|a_{ij} = 1, d_{ij} = 0$. The first is the distribution of price offers for borrowers that default in the end, and the second is the distribution of price offers for borrowers that do not. Note that prices are set at loan origination, while the default outcome is realized ex post. Thus, a given price offer is informative of what lender j believes about borrower i's risk, while the ex-post default outcome is a proxy for that borrower's risk.

To set ideas, first assume there is no variation in lending costs. As prices are decreasing in the signal realization, a decline in the standard deviation of the signal noise results in an increase in the separation of the two conditional distributions. Intuitively, prices respond more to borrower risk, proxied by ex-post default, when information is more precise. It follows that the precision of information is informed by the difference in the location of these two distributions. This simple intuition relies on the lack of variation in lending costs, as part of the difference between the location of the distribution conditional on default and that conditional on repayment could be due to cost shocks. To disentangle variation in marginal costs from the lenders' precision of information, I rely on the facts that (1) I observe not only the locations of the two distributions but also their spread, and (2) the cost shocks are independent of borrower risk. It follows that changes in the variance of cost shocks correspond to changes in the width of both conditional distributions (e.g., an increase in the variance of the cost shocks increases the widths of both the distribution of prices conditional on default and that conditional on repayment). Together, the location and spread of the distributions of price offers across ex-post outcomes pins down the information precision and the variance of lending costs. With the important sources of variation in hand, I next describe the estimation procedure.

4.2.3. Estimation

For each borrower, I observe (a_{ij}, d_{ij}, p_{ij}), where a_{ij} denotes the acceptance decision, d_{ij} denotes the default decision, and p_{ij} is the observed price offer. As described in Appendix C, I compute the price as the present value of a normalized ten-year loan for baseline specifications. However, I examine the robustness of the empirical results to alternative price calculations in Appendix H.2. Let Θ denote the full vector of parameters to be estimated: $\Theta = [\beta^R, \beta^A, \beta^Z, \sigma_\omega, \mu_\alpha, \sigma_\alpha, \rho, \sigma_\gamma(H_{ij})]$. I estimate the model using maximum likelihood. More details on the estimation procedure can be found in Appendix F. I describe the fit of the model in Appendix G.

5. Estimates of Borrower and Lender Primitives

5.1. Borrower-Side Results

Borrower characteristics capture substantial variation in acceptance and default within and across periods. Based only on observables, most borrowers accept loans between 80 and 95 percent of the time, and the rates decline after the policy change, suggesting a difference in borrowers' outside options in the SBA Recovery period. Default probabilities range from close to zero to approximately 20 percent. The borrower covariates again capture variation in repayment across periods, as observably safer borrowers comprise a larger share of loans after the policy change than in the baseline.[30] Within period, borrower observables, including the primary industry

[30]This result highlights the importance of allowing a shift in the risk composition of borrowers in the high-guarantee period when estimating the model. In the counterfactuals, I assume the distribution of borrowers remains fixed, so the guarantee pass-through and information effect recovered in

of the business, the loan amount, and the event date, contribute to heterogeneity in acceptance and default rates. These results reflect differences across the observed covariates in the typical use of the loaned funds or in the level of demand for a particular good or service, among other differences. Figure 9 in Appendix G displays estimates of loan-level acceptance and default probabilities, based solely on observed borrower covariates, in the baseline and SBA Recovery period.

Table 4 lists estimates and standard errors for selected borrower-side primitives. The full set of estimates is presented in Appendix G. The borrowers' utility of repayment has a noisy relationship with the loan amount. Businesses likely complete different types of projects depending on the size of the loan, but these results suggest there is still significant variation in project risk, conditional on the loan amount. One other driver of heterogeneity in default is the expected use of the loan, proxied by categories of loan maturity. Real estate loans, with maturities longer than ten years, default at less than half the rate of other loans. There is also substantial variation in the utility of repayment across time. Loans issued at the height of the recession in late 2009 have an average default rate of approximately 11%, while those issued in the midst of the recovery in 2010 and early 2011 default at rates near 5%.

Borrowers' acceptance decisions also exhibit substantial variation across observables. Borrowers that receive larger loans have better outside options, as evidenced by a lower utility of acceptance. This result may seem counterintuitive given the existence of the credit elsewhere test – it should be easier to acquire a small amount of capital from a non-bank source – however, borrowers that request large loans may have easier access to personal or family funds, as well as equity from other sources, than those that seek smaller loans.

The primitives governing borrowers' acceptance choices also vary by the intended use of the loan (i.e., real estate vs. non-real estate) and whether the loan was issued in the SBA Recovery period. Borrowers seeking non-real estate loans with maturity of up to ten years have lower utility of acceptance than those seeking real estate loans but are less responsive to changes in loan prices. In the SBA Recovery period, both categories of borrowers become less responsive to price changes, which highlights the need to allow for changes in borrower composition across periods

Section 6 are not confounded by such compositional changes.

when estimating the model. Across all borrowers, the distribution of α implies an average elasticity of -2.1. Furthermore, price responsiveness and propensity to repay exhibit a sizable correlation with $\rho = 0.335$. Together, these borrower-side results imply that there is substantial heterogeneity, both observable and unobservable, in borrowers' acceptance and default decisions. This variation across borrowers informs the lenders' pricing decisions and precision of information.

5.2. Lender-Side Results

Lenders' decisions are governed by their marginal cost function, the associated pricing rule, and their choices of information quality. Figure 2 displays the distribution of marginal costs, including a simulated cost error, ω_{ij}. Estimates of the primitives underlying the cost function can be found in Appendix G. It is important to note that the cost estimates imply that banks act as if they lend one dollar at a cost of less than a dollar. There are a number of potential explanations for this finding. First, lenders may anticipate future profits from the relationship when issuing a 7(a) loan (Office of the Comptroller of the Currency, 2014). There are switching costs associated with changes in banking relationships (Kim *et al.*, 2003). If the nascent businesses that receive 7(a) loans survive their early years, they may rely on the same bank for deposit accounts and other loans in the future. This provides incentives for banks to lend at a discount at the outset, ensuring they capture the relationship and any ensuing profits. Second, lenders may face reputational costs for opting out of the 7(a) program. Thus, they choose to participate, despite price caps limiting the markups they are able to charge. Because I do not directly model these additional incentives, they are absorbed by the banks' model-implied lending costs. Importantly, there is no reason to believe these future-profit incentives or reputational costs vary across guarantee rates. The analysis throughout the remainder of the paper assumes the marginal costs of lending are policy-invariant.

The second aspect of the lender's decision problem is the choice of information precision. As mentioned in Section 4, I allow the signal distribution to vary by lender size, across periods (baseline vs. SBA Recovery), and across types of lenders (preferred vs. non-preferred). The heterogeneity in information precision captures: (1) any endogenous changes to signal precision in response to guarantee-rate variation

Parameter	Estimate (S.E.)	
	Components of β^R	Components of β^A
Constant	1.177	20.791
	(0.206)	(2.114)
Amt. Borrowed $\in$ (\$150,000, \$700,000]	0.036	-0.174
	(0.050)	(0.042)
Amt. Borrowed $\in$ (\$700,000, \$1,000,000]	-0.109	-0.256
	(0.076)	(0.060)
Amt. Borrowed $\in$ (\$1,000,000, \$2,000,000]	-0.000	-0.353
	(0.072)	(0.064)
Maturity $\leq$ 10 Years	-0.379	-3.482
	(0.047)	(0.363)
Event 2	0.409	-0.164
	(0.060)	(0.047)
Event 3	0.360	0.279
	(0.058)	(0.054)
Event 4	0.399	-0.243
	(0.055)	(0.049)
Components of $F_{\xi^R,\alpha}$		
μ_α (Maturity $\leq$ 10 Years, Baseline)	12.066	
	(1.333)	
μ_α (Maturity $\leq$ 10 Years, SBA Recovery)	11.053	
	(1.200)	
μ_α (Maturity $>$ 10 Years, Baseline)	16.015	
	(1.677)	
μ_α (Maturity $>$ 10 Years, SBA Recovery)	14.893	
	(1.527)	
σ_α	1.119	
	(0.310)	
ρ	0.335	
	(0.064)	

Table 4: Selected Estimates, Borrower-Side Parameters. This table presents estimates of selected borrower-side parameters. Standard errors, calculated as described in Appendix F, are displayed in parentheses. Full results can be found in Appendix G.

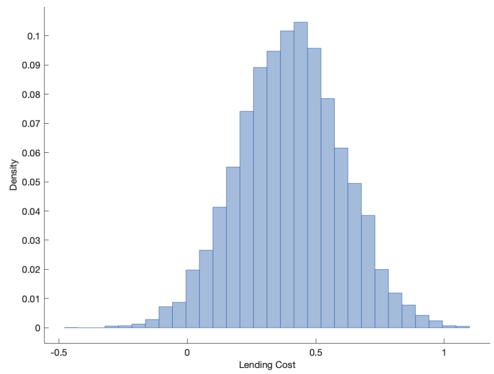


Figure 2: Estimated Lending Cost Distribution. The costs displayed in this figure include the shock, ω_{ij}. The distribution captures variation across banks in cost shifters, Z_{ij}, and the magnitude of the shock. It does not capture variance in the estimates of β^Z. These and the following plots were created using the gramm package (Morel, 2018).

and (2) differences in levels of information and policy responsiveness across lender sizes and types. The latter is crucial in this setting, as preferred lenders must meet SBA lending standards to be admitted to the program and are given substantially more autonomy in the lending process, providing them more scope to adjust their information acquisition practices in response to changes in incentives.

Table 5 presents estimates of the standard deviations of the lenders' signal distributions by lender size, period, and lender type. Lenders choose noisier signals, on average, in response to higher guarantee rates, suggesting the presence of an information effect. The magnitude of the aggregate effect is sizable: across all banks, the standard deviation of the signal distribution moves from 0.903 in the baseline to 1.276 in the SBA Recovery period, on average. This corresponds to a decrease in the signal-to-noise ratio $\left(\frac{1}{1+\sigma_\gamma^2}\right)$ from 0.551 to 0.380.

There is considerable heterogeneity across lender types in information-acquisition practices, consistent with the observable differences in the response to the policy changes between preferred and non-preferred lenders (see, e.g., Section 3). Results for the smaller banks – with assets $<$ \$100B – are consistent: preferred lenders obtain less precise signals of borrower quality, on average, than their counterparts. They also respond to changes in guarantees by collecting noisier information, while the response for non-preferred lenders is statistically indistinguishable from zero.

Parameter	Estimate (S.E.)		
	Assets < \$10B	Assets $\in$ [\$10B,\$100B)	Assets $\geq$ \$100B
S.D. of Signal Distribution: σ_γ			
Non-Preferred, Baseline	0.882	1.037	0.726
	(0.106)	(0.240)	(0.227)
Preferred, Baseline	0.951	0.692	1.005
	(0.130)	(0.198)	(0.131)
Non-Preferred, SBA Recovery	0.995	0.904	1.165
	(0.105)	(0.237)	(0.341)
Preferred, SBA Recovery	1.667	1.152	0.814
	(0.152)	(0.159)	(0.128)
Difference Across Periods (SBA Recovery - Baseline):			
Non-Preferred	0.113	-0.134	0.439
	(0.103)	(0.321)	(0.398)
Preferred	0.716	0.460	-0.192
	(0.142)	(0.202)	(0.138)

Table 5: Selected Estimates, Lender Information. This table presents estimates of the parameters governing lenders' information precision. Standard errors, calculated as described in Appendix F, are displayed in parentheses. Full results can be found in Appendix G.

This differential response captures the fact that, before being allowed to close a loan, preferred lenders require only a simple review by the SBA to ensure that a loan is eligible for a guarantee. On the other hand, non-preferred lenders must complete a standardized application packet to ensure that the due diligence process adheres to SBA requirements. While these banks may still have some room to alter their screening practices, the lack of complete autonomy constrains, and potentially even eliminates, their ability to shirk. The results for the largest banks – with assets $\geq$ \$100B – look different. The difference across periods for both preferred and non-preferred lenders is statistically indistinguishable from zero. This is consistent with large banks having standardized lending practices.

The estimates of signal precision map to unique costs of information ($\kappa_{\tilde{H}}$), which I back out using the first-order conditions of the ex-ante expected profit maximization problems specified in Equation 9. To operationalize the process of recovering these costs, I perturb the signal precision ($\frac{1}{\sigma_\gamma(H_{ij})^2}$) around its estimated value and compute a finite-difference estimate of the marginal revenue of information, which is known given the estimates of borrower and lender primitives.

	Assets $<$ \$10B	Assets $\in$ [\$10B,\$100B)	Assets $\geq$ \$100B
Non-Preferred, Baseline	0.0009	0.0012	0.0005
Preferred, Baseline	0.0010	0.0005	0.0011
Non-Preferred, SBA Recovery	0.0011	0.0009	0.0014
Preferred, SBA Recovery	0.0023	0.0014	0.0007

Table 6: Information Costs. This table presents estimates of the per-loan marginal cost of information, computed from the first-order condition associated with Equation 9.

Table 6 presents the estimates of the average cost of information acquisition per loan. For preferred lenders in the high-guarantee period, the average marginal cost of information corresponds to an outlay of 17 basis points for a normalized ten-year loan. The costs are lower for non-preferred lenders, consistent with the previous finding that these lenders collect information that is more precise. Heterogeneity in information-acquisition costs could be driven, for example, by differences in screening technology or borrower opacity. It is important to note that pre-existing relationships could influence the extent of opacity. While I restrict to the first loan observed in the sample, it is not necessarily the case that borrowers have no pre-existing relationship with the bank. Such "unobserved" relationships would presumably lead to estimates of information that is more precise and lower costs of acquisition. For the results presented in the remainder of the paper, I implicitly assume that the likelihood of being paired with a borrower with a pre-existing relationship does not change with the guarantee rate (i.e., information-acquisition costs are policy-invariant).

6. Guarantees, Information, and Policy Design

The descriptive results of Section 3 provide evidence of a lender-side response – in terms of loan characteristics and their relationship with borrower risk – when guarantees become more generous. However, these results capture the equilibrium impact of a guarantee-rate change, comprised of the guarantee pass-through, information effect, and any changes to borrower composition. To evaluate alternative policy arrangements, it is essential to first understand the economic forces underlying the observed response and their impact on borrowers across the distribution of risk. In this section, I answer three questions. First, what is the impact of an increase in guarantee generosity on prices, borrower surplus, and lender profits? Second, what role does the information effect play, and do all borrowers benefit from more generous guarantees? Third, is there an alternative policy design that leads to better average borrower outcomes, while holding expected government spending fixed?

6.1. Effects of Guarantees on Prices, Borrower Surplus, and Lender Profit

To examine the effect of guarantees on borrower and lender outcomes and to quantify the role of the information effect, I perform a decomposition exercise. I restrict attention to loans issued in the SBA Recovery period at a guarantee rate of 90%.[31] This homogenizes the sample in terms of observables and eliminates any changes to observable borrower composition in the high-guarantee period. For guarantee rates $\tilde{M} \in \{0.5, 0.6, 0.7, 0.8, 0.9, 1\}$, lenders solve their ex-ante profit maximization problem given their marginal cost of information acquisition, $\kappa_{\tilde{H}}$, the distribution of borrowers they face, and their costs of lending. Let $\sigma_{\gamma}^{*}(\tilde{M})$ denote the optimal standard deviation of the lender's signal noise distribution for a guarantee rate of $\tilde{M}$.

The decomposition exercise then consists of two main portions. First, I simulate (ξ_i^R,α_i) for each borrower from the estimated distribution. Then, I draw signals and compute prices and borrower surplus for each $\tilde{M} \in \{0.5, 0.6, 0.7, 0.8, 0.9, 1\}$ under two different scenarios: (1) standard deviation of signal noise fixed at $\sigma_{\gamma}^{*}(0.9)$, and (2) standard deviation of signal noise set at its optimal level, $\sigma_{\gamma}^{*}(\tilde{M})$. For the remainder of this section, I refer to the outcomes for $\tilde{M} = 0.9$ as the baseline. To

[31] I set the NPV of the ongoing guarantee fee (one component of the lending cost) to be constant at its baseline value ($\tilde{M}$ = 0.9). Fixing the ongoing fee throughout this exercise isolates the impact of the guarantee pass-through and information effect. If I were to allow the fee to vary with the guarantee rate, changes in lending cost would confound the magnitude of the guarantee pass-through. Also, for the counterfactuals, I remove any loan for which the marginal cost draw is negative. This occurs in a small number of cases (194) due to the assumption that ω_{ij} is drawn from a normal distribution.

quantify the guarantee pass-through, I examine the changes in outcomes across guarantees under Scenario 1 above. These changes hold the level of information fixed and thus isolate the direct effect of guarantees. The information effect is the difference between the outcome computed under Scenario 2 and that computed under Scenario 1 and captures the additional impact of bank moral hazard.

In each stage of the decomposition, I compute a measure of borrower surplus using the standard log-sum formula (see, e.g., Train (2009)), and scale by α_i so its units are equivalent to those for prices:

$$\text{Borrower Surplus}_{ij} = \frac{1}{\alpha_i} \log\left(1 + \exp(X_i^A \beta^A - \alpha_i p_{ij})\right). \tag{11}$$

Then, to scale these values to dollars over the normalized ten-year loan term, I multiply this value by the loan amount, B_{ij}. I also compute lender profits per loan, given the borrowers' default and acceptance decisions, again scaling this value by the loan amount, B_{ij}.

For all levels of guarantee generosity, $\tilde{M}$, lenders respond to guarantee-rate changes by adjusting the level of information they collect. The average level of information obtained, in equilibrium, is monotonically decreasing in $\tilde{M}$ for $\tilde{M} \in \{0.5, 0.6, 0.7, 0.8, 0.9, 1\}$. Table 7 displays the average signal-to-noise ratio across guarantee rates. Under a guarantee rate of 50%, the signal-to-noise ratio is, on average, 6.5% higher than under the baseline of 90%. An increase in the generosity of the guarantee decreases the marginal value of information, as the lenders do not respond as strongly to differences in borrowers' risk.

This change in information precision interacts with the guarantee pass-through to determine equilibrium outcomes. Table 7 additionally displays average prices, the standard deviation of prices, average borrower surplus, and lender profits across guarantee rates, both in levels and relative to the baseline rate of 90%. Prices decline slightly as guarantees rise but their dispersion falls by a more substantial amount, indicating an increase in pooled pricing and a potential distortion toward riskier borrowers. Turning to profit and borrower surplus, at any given guarantee rate, lenders receive a greater share of surplus, highlighting the importance of considering market power when analyzing lending policy interventions. Furthermore, profits are

Outcome	Guarantee Rate					
	50%	60%	70%	80%	90%	100%
Signal-to-Noise Ratio	0.433	0.422	0.415	0.410	0.407	0.405
	(+6.466%)	(+3.629%)	(+1.893%)	(+0.762%)	-	(-0.519%)
Price	1.147	1.147	1.147	1.147	1.147	1.146
	(+0.055%)	(+0.034%)	(+0.019%)	(+0.009%)	-	(-0.007%)
SD(Price)	0.063	0.062	0.062	0.061	0.061	0.061
	(+2.879%)	(+1.696%)	(+0.959%)	(+0.424%)	-	(-0.352%)
Borrower Surplus	1.169	1.170	1.171	1.171	1.172	1.172
	(-0.212%)	(-0.130%)	(-0.074%)	(-0.032%)	-	(+0.026%)
Lender Profit	3.405	3.431	3.460	3.487	3.515	3.544
	(-3.137%)	(-2.382%)	(-1.560%)	(-0.799%)	-	(+0.827%)

Table 7: Outcomes Across Guarantees. This table displays the average signal-to-noise ratio, average price, standard deviation of price, borrower surplus (over the normalized ten-year loan term), and lender profit across guarantee rates. The borrower surplus and profits are displayed in \$100,000s, while percent changes relative to the 90% baseline guarantee rate are shown below in parentheses.

more responsive to changes in the guarantee rate than is borrower surplus. However, as I describe in more detail later in this section, the modest borrower-surplus changes mask heterogeneity across the distribution of borrowers.

6.2. Information Effect and Distributional Consequences

To inform the design of alternative policies, it is useful to quantify the magnitude of the information effect and to consider the distributional impact of guarantee-rate changes. Importantly, if the information effect is sufficiently strong, then alternative policies that limit the moral hazard effect – and the associated distortions in allocation – likely lead to better outcomes for borrowers (i.e., higher average borrower surplus).

For the remainder of this section, I focus on borrower surplus as the outcome of interest. Figure 3 quantifies the magnitude of the guarantee pass-through and information effect. The green bars display the change in borrower surplus – relative to the baseline rate of 90% – under only a change to the guarantee, while the blue bars measure the additional change due to the information effect. This figure illustrates that the guarantee pass-through and information effect work in the same direction, as the information effect magnifies the impact of guarantee-rate changes on price offers and borrower surplus. However, both channels are small in magnitude, on average.

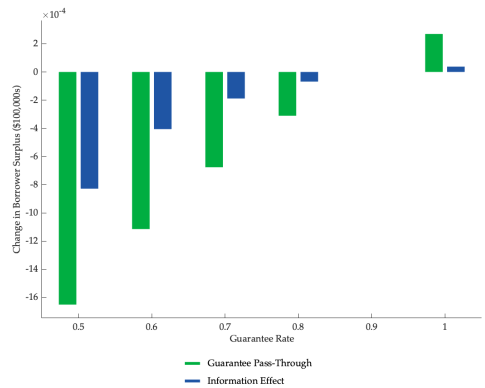


Figure 3: Guarantee Pass-Through and Information Effect. The guarantee pass-through measures the change in borrower surplus under a change to only the guarantee rate. The information effect measures the additional change when information endogenously adjusts.

As discussed, these modest average effects mask heterogeneity across the distribution of borrower risk. High-risk borrowers benefit disproportionately from generous guarantees, and this could come at the expense of their safer peers. Figure 4 displays the change in borrower surplus, relative to the baseline, separately for borrowers in each quintile of the distribution of the utility of repayment. High-risk borrowers, in the first quintile, benefit the most when guarantees become more generous. Relative to the baseline rate of 90%, average borrower surplus for the riskiest borrowers is approximately $1,500 lower under a rate of 50%. Scaling to all high-risk 7(a) loans issued between 2009 and 2011 – both inside and outside of the event windows of interest – this corresponds to a change in surplus of approximately $14 million. Notably, increasing the guarantee rate harms borrowers in the bottom two quintiles of the distribution (i.e., the safest borrowers), on average, although the magnitude of this harm is smaller than that of the gains to high-risk borrowers.

These results highlight stark heterogeneity in the incidence of loan guarantee programs. The risk protection, by itself, leads to gains for borrowers; bank moral hazard amplifies this effect for high-risk borrowers but offsets it for low-risk borrowers. While guarantee schemes are popular in small-business lending markets, they are not the only instrument available to policymakers. Because they create a moral hazard problem and need not benefit all borrowers, there is room for alternative policy designs that may temper the effects of bank moral hazard and offset a portion

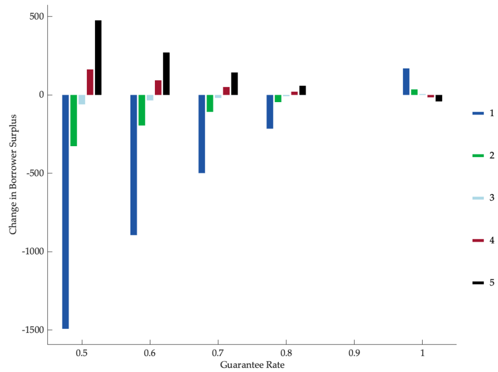


Figure 4: Borrower Surplus Across Guarantees and Risk. This figure displays changes in average borrower surplus under each guarantee rate relative to the baseline rate of 90%. The bar color indicates the quintile of the distribution of u_i^R.

of the losses absorbed by low-risk borrowers.

6.3. Hybrid Policy Design: Subsidy and Guarantee

The results of the decomposition show that the information effect plays a sizable role in influencing the outcomes of an increase in the guarantee generosity. This motivates examining ways to moderate the distributional impact of the program by providing incentives that act against the moral hazard problem. Given the observed difference in signal precision across lender types (preferred vs. non-preferred), one way to do this would be to increase oversight and remove the preferred lenders' autonomy. However, preferred lenders exist for a reason, and it may be prohibitively costly for the SBA to conduct an extensive review of each application.

Another alternative is to design lender incentives to expand credit but counteract the moral hazard problem. A cost subsidy increases expected profits for all borrower types. This places downward pressure on prices across the distribution of risk and could therefore alleviate some of the losses borne by low-risk borrowers. In this section, I show that combining such a subsidy with a less generous guarantee, which limits the informational response, leads to gains over the baseline policy with a guarantee of 90%.

I examine a policy in which lenders are provided a subsidy and a guarantee of 50% with the subsidy set such that expected government outlays are equal to those under the baseline guarantee (90%) and no subsidy. The subsidy, $S(\tilde{M})$, solves:

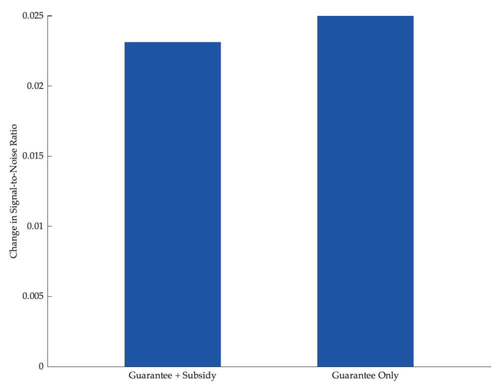
$$\sum_{ij} B_{ij} P^A(p_{ij}(0.9), \alpha_i, X_i^A) \left[0.9 \cdot P^D(\alpha_i, X_i^R) \cdot p_{ij}(0.9)\right] = \\ \sum_{ij} B_{ij} P^A(p_{ij}(\tilde{M}), \alpha_i, X_i^A) \left[\tilde{M} \cdot P^D(\alpha_i, X_i^R) \cdot p_{ij}(\tilde{M}) + S(\tilde{M})\right], \quad (12)$$

where $\tilde{M} = 0.5$, $p_{ij}(\tilde{M})$ is the price offered by lender j to borrower i under a guarantee of $\tilde{M}$, and marginal costs are: $\zeta_{ij} = \beta^Z Z_{ij} + \psi(0.9) + \omega_{ij} - S(\tilde{M})$.

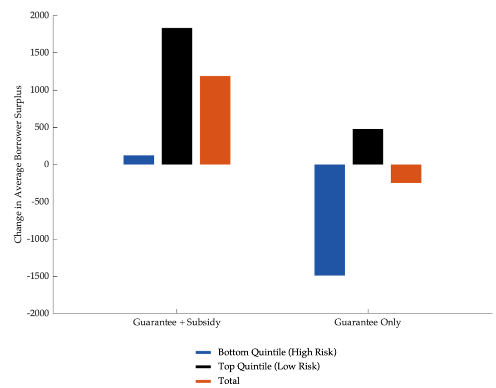
Under the hybrid policy, lenders collect information that is more precise than they do in the baseline. However, the magnitude of the change in the signal-to-noise ratio is lower than it would be absent the subsidy. The left-hand panel of Figure 5 displays the change in signal-to-noise ratio for the hybrid policy (guarantee + subsidy), as well as the change under only an adjustment of the guarantee (i.e., similar to the exercise considered in Section 6.1), when compared to the baseline 90% guarantee. Under a policy with a guarantee rate of 50% and a subsidy, lenders' average signal-to-noise ratio is almost 6% higher than under the status quo. While this change in signal precision is weaker under the hybrid policy than under only a guarantee-rate adjustment, in the remainder of this section, I show that the pass-through of the subsidy is sufficient to lead to gains for borrowers, on average.

The higher precision of information leads to gains for low-risk borrowers and losses for their higher-risk peers, dampening the distributional impact of the guarantee program. The right-hand panel of Figure 5 displays changes in borrower surplus relative to the baseline guarantee of 90% for (1) a hybrid policy with a guarantee of 50% and a subsidy defined as described above and (2) a guarantee-only policy with a rate of 50%. The comparison of borrower surplus under these schemes concisely captures the forces to consider when designing guarantee policies. I report extensions of these counterfactual results, considering alternative combinations of guarantees and subsidies, in Appendix I. The qualitative takeaways are identical.

The right-hand panel of Figure 5 displays the change in borrower surplus across all loans, as well as changes for borrowers in the top and bottom quintiles of the distribution of u_i^R. A hybrid policy with a guarantee rate of 50% and a subsidy set such that expected spending is fixed benefits borrowers, on average. In total, borrower surplus increases by approximately \$1,200 per loan relative to the status quo. Scaling to all loans issued between 2009 and 2011, this corresponds to a gain of \$56 million. However, not all borrowers benefit equally. High-risk borrowers experience only a small increase in surplus, and the aggregate gains accrue to lower-risk borrowers. Borrowers in the top quintile of the distribution of u_i^R experience gains in borrower surplus of over \$1,800 per loan, offsetting a portion of the heterogeneous impact of the status quo program. The resulting shift toward a less risky borrower composition decreases the aggregate default rate by 0.1 percentage point (1.1%).



(a) Signal-to-Noise



(b) Borrower Surplus

Figure 5: Changes to Signal-to-Noise and Borrower Surplus Under Hybrid Policy. This figure displays the change in the average signal-to-noise ratio and borrower surplus for (1) a hybrid policy with a guarantee rate of 50% and a subsidy set such that expected spending is the same as in the baseline and (2) a policy with a 50% guarantee rate and no subsidy. The estimates for borrower surplus are displayed separately for high-risk borrowers (bottom quintile of u_i^R), low-risk borrowers (top quintile of u_i^R), and all borrowers.

It is important to note that this hybrid policy result does not indicate an improvement in social welfare. There are a number of reasons why policymakers may place disproportionate weight on the surplus of high-risk borrowers (e.g., they are more innovative or tend to be individuals from demographic groups that traditionally found it difficult to obtain credit). But, the exercise demonstrates an important tradeoff in lending markets. Policymakers can induce lenders to extend funds at lower prices through two main channels: by providing ex-post insurance against default and by directly subsidizing lending costs. In the presence of costly information acquisition, these two methods can differ in their distributional impact. I show that a hybrid policy that includes both a subsidy and a guarantee outperforms the status quo policy in terms of borrower surplus. Moreover, these surplus gains are the result of a decline in the heterogeneity of the program's impact across the distribution of risk.

7. Conclusion

Policymakers frequently intervene in small-business lending markets in an attempt to expand financing to credit-constrained borrowers. Loan guarantee programs are widespread, and governments frequently rely on them during economic downturns. These interventions have an ambiguous effect on borrower surplus. The pass-through of guarantees could be heterogeneous across the distribution of risk, and their effect on loan prices may be amplified or offset by the effects of bank moral hazard.

In this paper, I develop and estimate a model that captures the impact of guarantees on lenders' information acquisition decisions. I first show that increasing the generosity of guarantees benefits borrowers and lenders by a modest amount, on average. However, not all borrowers are better off with more generous guarantees – high-risk borrowers benefit at the expense of their safer counterparts, driven by lenders' responses in their choice of information precision. The distributional consequences of guarantee programs, and their root in the bank moral hazard problem, suggest that room exists to design policy to expand credit while limiting the effects of moral hazard. I show that a hybrid policy with a guarantee of 50% and a subsidy set such that expected government spending does not change yields borrower-surplus gains of $1,200 per loan over the baseline baseline program (90% guarantee). This hybrid policy confers disproportionate gains to low-risk borrowers, which also improves the risk composition of the borrower pool.

These results demonstrate that bank moral hazard has an impact on the equilibrium response to policy changes in small-business lending markets. In the case of guarantee programs, it amplifies the heterogeneous impact of these interventions across the distribution of borrower risk. Furthermore, the counterfactual results suggest that alternative policies could temper the distributional impact by limiting the effects of moral hazard, and could lead to gains in borrower surplus.

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Appendices (For Online Publication)

A. Robustness of Descriptive Results

A.1. Changes to Loan Characteristics

In this section, I display a number of robustness checks for the estimates of changes to loan characteristics. Because the specifications shown in the main text rely on the selection of the relevant sample (i.e., which windows to examine), I first show that the results are robust to other window definitions. Table 8 displays results when restricting to loans issued within 14 days of a guarantee-rate change. The results from the main text are robust to this alternate definition.

	(1) Interest Rate (Pct.)	(2) Amt. Borrowed ($ Thousands)	(3) Loan Size $>$ 150,000	(4) Loan Term (Months)
Loans Issued Within 14 Days of Events				
SBA Recovery	-0.0753	59.61	0.0919	6.826
	(0.0264)	(19.10)	(0.0164)	(1.651)
Mean Outcome	5.87	585.29	0.83	168.22
Observations	5,028	5,028	5,028	5,028
Zip Code Dem. Controls	✓	✓	✓	✓
Business Type FE	✓	✓	✓	✓
NAICS (Two-Digit) FE	✓	✓	✓	✓
Real Estate FE	✓	✓	✓	✓
Event Date FE	✓	✓	✓	✓

Table 8: Robustness to Window Size (Loan Characteristics). This table presents results of Specification 1, restricting to loans issued within 14 days of guarantee-rate changes. All specifications include controls for zip code level demographics (median household income, total population, change in the housing price index since 2008), as well as fixed effects for business type, NAICS (two-digit), real estate, and event date. Standard errors are clustered by lender.

Next, I examine whether the results in the main text can be explained by variation in the composition of lenders. Table 9 displays results of the main regression specifications with lender fixed effects. These results provide the same qualitative conclusions as those in the main text, which suggests that the response to guarantee-rate increases does not act only through a change in lender participation.

	(1) Interest Rate (Pct.)	(2) Amt. Borrowed ($ Thousands)	(3) Loan Size > 150,000	(4) Loan Term (Months)
Loans Issued Within 42 Days of Events				
SBA Recovery	-0.0241	40.65	0.0532	2.303
	(0.0164)	(10.02)	(0.00874)	(1.007)
Mean Outcome	5.85	558.21	0.81	165.46
Observations	13,465	13,465	13,465	13,465
Zip Code Dem. Controls	✓	✓	✓	✓
Business Type FE	✓	✓	✓	✓
NAICS (Two-Digit) FE	✓	✓	✓	✓
Real Estate FE	✓	✓	✓	✓
Event Date FE	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓

Table 9: Robustness to Lender Fixed Effects (Loan Characteristics). This table presents results of an adjusted version of Specification 1, including loans issued within 42 days of guarantee-rate changes. All specifications include lender fixed effects. Additionally, they include controls for zip code level demographics (median household income, total population, change in the housing price index since 2008), as well as fixed effects for business type, NAICS (two-digit), real estate, and event date. Standard errors are clustered by lender.

In Table 10, I examine the results of the loan characteristic regressions, restricted to loans issued around the two events in which the guarantee expansions lapsed. The American Recovery and Reinvestment Act of 2009 and the Small Business Jobs Act of 2010 included guarantee expansions as only one piece of a larger legislative agenda. To ease concerns that results are influenced by confounding variation from other aspects of the legislation, I show that the conclusions of the descriptive analysis are robust to including only loans issued around the lapsation events. Because the expiration of the guarantee expansions occurred when funding ran out, it is unlikely that another, related policy change occurred contemporaneously.

I also examine the robustness of results to the inclusion of price outliers. Table 11 displays results for the main descriptive specifications including observations for which prices lie below the first percentile or above the 99th percentile. Qualitatively, the takeaways are identical.

Finally, I consider a specification that quantifies the incremental equilibrium policy response for high-risk borrowers. As discussed in the main text, I would

	(1) Interest Rate (Pct.)	(2) Amt. Borrowed ($ Thousands)	(3) Loan Size > 150,000	(4) Loan Term (Months)
Loans Issued Within 42 Days of Events				
SBA Recovery	-0.0424	82.86	0.0921	7.578
	(0.0232)	(14.74)	(0.0123)	(1.396)
Mean Outcome	5.87	572.99	0.82	165.92
Observations	7,267	7,267	7,267	7,267
Zip Code Dem. Controls	✓	✓	✓	✓
Business Type FE	✓	✓	✓	✓
NAICS (Two-Digit) FE	✓	✓	✓	✓
Real Estate FE	✓	✓	✓	✓
Event Date FE	✓	✓	✓	✓

Table 10: Robustness to Including Lapse Events Only (Loan Characteristics). This table presents results of Specification 1, restricting to loans issued within 42 days of lapses of guarantee-rate expansions. All specifications include controls for zip code level demographics (median household income, total population, change in the housing price index since 2008), as well as fixed effects for business type, NAICS (two-digit), real estate, and event date. Standard errors are clustered by lender.

ideally observe a set of riskless borrowers that could act as a control group. Given the purpose of the 7(a) program, these borrowers are unlikely to exist in this setting. Therefore, I instead compare the equilibrium difference in characteristics for borrowers of different risk levels.

To operationalize this analysis, I first estimate observable default risk using logistic regression of default on the set of observables defined in Section 3[32] for all loans issued between 2009 and 2011 outside of the at-issue event windows. Then, given observables, I predict the probability of default for each loan in the main analysis sample. I divide the sample into two risk groups: low-risk borrowers with default probability below the median and high-risk borrowers with default probability above the median. I then estimate the following specification:

$$Y_{ijt} = \delta \mathbb{I}(t = \text{SBA Recovery}) \times \mathbb{I}(i = \text{High-Risk}) + \alpha_{r(i)} + \gamma_t + \epsilon_{ijt}, \quad (13)$$

[32]For event date fixed effects, each observation is assigned to the closest guarantee-rate change (in time).

	(1) Interest Rate (Pct.)	(2) Amt. Borrowed ($ Thousands)	(3) Loan Size > 150,000	(4) Loan Term (Months)
Loans Issued Within 42 Days of Events				
SBA Recovery	-0.0582	57.03	0.0566	4.223
	(0.0172)	(10.64)	(0.00877)	(0.941)
Mean Outcome	5.85	557.55	0.80	164.02
Observations	14,278	14,278	14,278	14,278
Zip Code Dem. Controls	✓	✓	✓	✓
Business Type FE	✓	✓	✓	✓
NAICS (Two-Digit) FE	✓	✓	✓	✓
Real Estate FE	✓	✓	✓	✓
Event Date FE	✓	✓	✓	✓

Table 11: Robustness to Including Price Outliers (Loan Characteristics). This table presents results of Specification 1, including loans issued within 42 days of guarantee-rate changes. All specifications include observations corresponding to price outliers, which were removed in the analyses in the main text. Additionally, the specifications include controls for zip code level demographics (median household income, total population, change in the housing price index since 2008), as well as fixed effects for business type, NAICS (two-digit), real estate, and event date. Standard errors are clustered by lender.

where $\alpha_{r(i)}$ is a fixed effect for the risk group of borrower i, γ_t is a fixed effect for each week t, and δ is the coefficient of interest that measures the incremental change in characteristics in the high-guarantee period for higher-risk borrowers relative to lower-risk borrowers.

Table 12 displays results. The takeaways are similar to the main text for interest rates and loan terms. However, there is a negative point estimate, although not statistically significant, for the difference in the change in loan size for high- relative to low-risk borrowers. This suggests that the loan-size results shown in the main text could be driven – at least partially – by changes in borrower composition and that the interest rate and loan term are the most relevant margins along which lenders adjust to policy variation.

A.2. Pricing Regressions

This section explores the robustness of the pricing regressions. I first present results for the pricing regressions, instead estimated using the interest rate on the left-hand

	(1) Interest Rate (Pct.)	(2) Amt. Borrowed ($ Thousands)	(3) Loan Size > 150,000	(4) Loan Term (Months)
Loans Issued Within 42 Days of Events				
SBA Recovery × High-Risk	-0.0409	-27.14	0.0407	4.324
	(0.0222)	(19.39)	(0.0166)	(2.782)
Mean Outcome	5.86	557.78	0.81	164.35
Observations	13,994	13,994	13,994	13,994

Table 12: Changes to Loan Characteristics by Risk Group. This table presents results of Specification 13, including loans issued within 42 days of guarantee-rate changes. Standard errors are clustered by lender.

side and controlling for a flexible function of the guarantee rate, loan amount, and maturity. For this analysis, I replace the first-stage specification with:

$$r_{ijt} = f(M_{ijt}, B_{ijt}, T_{ijt}) + X_{it}\beta + \epsilon_{ijt},$$

where all variables as defined in the main text. There are two additions: r_{ijt} is the initial interest rate of the loan, and T_{ijt} is the maturity of the loan (in months). The function f is again a quadratic function and interactions of the guarantee rate, loan amount, and maturity.

The second stage becomes:

$$d_{ijt} = \gamma_1\epsilon_{ijt} + \gamma_2\mathbb{I}(t = SBA) + \gamma_3\epsilon_{ijt} \times \mathbb{I}(t = SBA) + g(M_{ijt}, B_{ijt}, T_{ijt}) + X_{it}\delta + e_{ijt},$$

where variables are defined analogously to those in the main text.

Table 13 displays results of the second stage. As in the main text, there is a positive correlation between ex-post default and the unobservable component of the interest rate. The correlation decreases during the high-guarantee period, which is consistent with lenders collecting noisier information about borrower quality when government guarantees are higher.

In Section 3, I show that the relationship between loan price offers and ex-post default is weaker in the SBA Recovery period than in the baseline. This suggests that risk is priced less precisely. However, I also observe that lenders bunch on the high-guarantee side of the threshold. This suggests that some of the change in the relationship between prices and default could be driven by time constraints (e.g., lenders rushing to ensure that a loan is approved at a high guarantee rate) rather than their response to the incentives of the guarantee program. To provide evidence that the response is driven by incentives rather than timing, I estimate the price regressions using only loans approved more than one week on either side of a policy change. Lenders are less likely to "shift" these loans and face time constraints during their due diligence process. The results are displayed in Table 14, which look similar to those shown in the main text.

	(1) Default	(2) Charge Off
ϵ	0.026	0.021
	[0.008,0.046]	[0.009,0.034]
$\mathbb{I}(t = SBA)$	-0.039	-0.031
	[-0.068,-0.009]	[-0.051,-0.010]
$\epsilon \times \mathbb{I}(t = SBA)$	-0.016	-0.014
	[-0.035,0.003]	[-0.028,-0.001]
Raw Correlation	0.034	0.039
SD(ϵ)	0.568	0.568
Observations	12,159	12,159

Table 13: Pricing Regression Robustness – Interest Rate. This table presents results for the second stage of the two-stage pricing regression, using the interest rate on the left-hand side of the first stage and controlling for a flexible function of the guarantee rate, loan amount, and maturity. The first column displays results for an indicator of default on the left-hand side, while the second column displays results for the share of the loan charged off. All specifications include quadratic terms and interactions of the guarantee rate, loan amount, and maturity and controls for zip code level demographics (median household income, total population, change in the housing price index since 2008), as well as fixed effects for business type, NAICS (two-digit), real estate, and event date. Block-bootstrapped (by lender) 95% confidence intervals are displayed in brackets; N=1,000.

	(1) Default	(2) Charge Off
ϵ	1.989	1.232
	[1.615,2.371]	[0.979,1.485]
$\mathbb{I}(t = SBA)$	-0.037	-0.032
	[-0.068,-0.007]	[-0.052,-0.012]
$\epsilon \times \mathbb{I}(t = SBA)$	-0.591	-0.415
	[-1.011,-0.164]	[-0.677,-0.132]
Raw Correlation	0.236	0.213
SD(ϵ)	0.038	0.038
Observations	10,308	10,308

Table 14: Pricing Regression Results - Loans Issued More than One Week From Policy Change. This table presents results for the second stage of the two-stage pricing regression, Specification 3, using only loans issued more than one week on either side of the policy change. The first column displays results for an indicator of default on the left-hand side, while the second column displays results for the share of the loan charged off. All specifications include quadratic terms and interactions of the guarantee rate and loan amount and controls for zip code level demographics (median household income, total population, change in the housing price index since 2008), as well as fixed effects for business type, NAICS (two-digit), real estate, and event date. Block-bootstrapped (by lender) 95% confidence intervals are displayed in brackets; N=1,000.

B. Balance of Macroeconomic Indicators

The empirical framework relies on an assumption of common shocks across SBA guarantee periods. This appendix presents analyses to examine the balance of macroeconomic activity in the high- and low-guarantee periods. I estimate the following specification:

$$Y_{it} = \alpha_0 + \alpha_1 \mathbb{I}(t = \text{SBA Recovery}) + \epsilon_{it},$$

and I display results with and without event fixed effects. Standard errors are clustered by week in all specifications to account for serial correlation. I restrict to dates within 42 days of guarantee-rate changes and, to be consistent with the main specifications, I remove data from one week following the second take-up of more generous guarantees.

The variables of interest fall into three broad categories. First, I examine the balance of variables that underly bank lending costs, namely the Federal Funds Rate[33] and the one-month LIBOR rate based on the U.S. dollar.[34] The latter variable also enters the SBA's Fixed Base Rate, which determines interest rate caps. Second, I consider variables that capture broader U.S. economic activity. Namely, I analyze balance of the market yield on U.S. Treasury Securities at 10-Year Constant Maturity[35] and the market yield of U.S. Treasury Securities at 3-Year Constant Maturity.[36] Third, I examine stock prices for the three largest U.S. banks at the time: Bank of America, JPMorgan Chase, and Citigroup.[37]

Results are displayed in Table 15. We do not observe large differences in cost

[33] Source: Effective Federal Funds Rate, Federal Reserve Bank of New York, available at https://www.newyorkfed.org/markets/reference-rates/effr.

[34] Source: ICE Benchmark Administration Limited (IBA), 1-Month London Interbank Offered Rate (LIBOR), based on U.S. Dollar [USD1MTD156N], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USD1MTD156N.

[35] Source: Board of Governors of the Federal Reserve System, Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity [DGS10], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS10.

[36] Source: Board of Governors of the Federal Reserve System, Market Yield on U.S. Treasury Securities at 3-Year Constant Maturity [DGS3], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS3.

[37] Source: Commodity Systems, Inc., retrieved from Yahoo Finance.

shifters and treasury yields, and most differences are not statistically significant. These results suggest that the adjustments to loan characteristics captured by the descriptive analysis are indicative of a response to the policy change rather than changes to lending costs. Bank stock prices are slightly higher in the SBA Recovery period, though the differences are marginally significant. These results are consistent with the policy change providing incentives for banking activity. In sum, the macroeconomic balance tests provide support for using framework that relies on temporal variation to analyze the effect of guarantees on equilibrium loan characteristics and outcomes.

	No Event FE	Event FE	Mean
Federal Funds Rate	-0.006	-0.005	0.185
	(0.006)	(0.006)	
One-Month LIBOR	-0.009	-0.012	0.336
	(0.027)	(0.007)	
Market Yield on U.S. Treasuries (10-Year Constant Maturity)	0.019	-0.001	3.048
	(0.104)	(0.052)	
Market Yield on U.S. Treasuries (3-Year Constant Maturity)	-0.020	-0.042	1.086
	(0.082)	(0.039)	
Bank of America Closing Stock Price	0.507	0.544	12.152
	(1.068)	(0.379)	
JPMorgan Chase Closing Stock Price	1.433	1.568	36.624
	(1.996)	(0.818)	
Citigroup Closing Stock Price	2.139	2.269	38.706
	(2.358)	(1.257)	

Table 15: Macroeconomic Indicator Balance. This table displays results of the macroeconomic balance specifications with (Column 1) and without (Column 2) event fixed effects. The time period of issue is the same as that for the main regression specifications, namely within 42 days of guarantee-rate changes. Standard errors are clustered by week. Sources for each of the variables are noted in the text of the Appendix.

C. Price and Ongoing Fee Calculation

I model the loan price as the present value of future cash inflows, discounted using the zero-coupon Treasury yield curve from the Federal Reserve, computed as described in Gürkaynak *et al.* (2007). In essence, the measure captures the price of a riskless asset that produces the same cash flows as a given loan and is similar in concept to the duration adjustment for corporate bonds discussed in van Binsbergen *et al.* (2023). My measure captures the stated interest rate, as well as the loan repayment term, and adjusts for heterogeneity in loan duration. To examine the robustness of the results to this price calculation, I also estimate the model assuming fixed, yearly-equivalent discount rate of 2% and a fixed, yearly-equivalent discount rate equal to the zero-coupon Treasury yield for the maturity equal to that of the loan. Results for these specifications can be found in Appendix H.

Denote r_{ij} the interest rate, T_{ij} the term (in months), and B_{ij} the amount borrowed. I assume that, each period, the borrower pays the monthly interest rate $\frac{r_{ij}}{12}$ on the remaining balance each period plus an equal share of the principal. In any given month, the remaining loan balance is

$$B_{ij} - (t-1)\frac{B_{ij}}{T_{ij}}.$$

The associated monthly payment at time t is given by

$$\frac{B_{ij}}{T_{ij}} + \frac{r_{ij}}{12}\left(B_{ij} - (t-1)\frac{B_{ij}}{T_{ij}}\right).$$

As described above, I discount each cash flow using the zero-coupon Treasury yield to the maturity t. That is, I compute the present value of the payments and then normalize by the size of the loan. This object takes the form:

$$R_{ij} = \frac{1}{B_{ij}} \sum_{t=1}^{T_{ij}} \frac{\frac{B_{ij}}{T_{ij}} + \frac{r_{ij}}{12}\left(B_{ij} - (t-1)\frac{B_{ij}}{T_{ij}}\right)}{(1+\delta_{ij,t})^t},$$

where $\delta_{ij,t}$ is the zero-coupon Treasury yield (monthly) at the time of loan approval for the lender-borrower pair ij to maturity t.

I then compute the annualized loan return as $y_{ij} = R_{ij}^{\frac{1}{T_{ij}/12}} - 1$. For the pricing regressions and structural analysis, I convert these yearly returns to a price for the modal loan maturity in the data, a ten-year loan:

$$p_{ij} = (1 + y_{ij})^{10}$$

I compute the duration-adjusted ongoing guarantee fee using a similar procedure. The ongoing guarantee fee, f, per dollar guaranteed is paid each year. I compute the present value of the ongoing fee as:

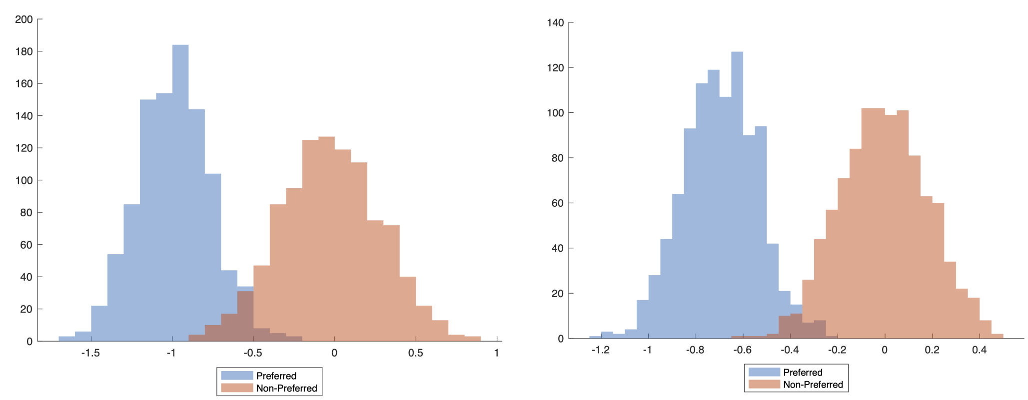
$$\psi(M_{ij}) = \frac{1}{B_{ij}} \sum_{\tilde{t}=1}^{Y_{ij}} \frac{M_{ij} f \left(B_{ij} - (\tilde{t} - 1) \frac{B_{ij}}{Y_{ij}} \right)}{(1 + \delta_{ij,\tilde{t}})^{\tilde{t}}},$$

where $\tilde{t}$ indexes years, and Y_{ij} is the maturity of the loan in years. As above, I convert it to the equivalent for a normalized ten-year loan.

D. Preferred Lenders

Preferred lenders are required to undergo screening by their SBA regional field office before being admitted to the program. Once approved, these lenders are given substantial independence in the lending process, and their loans are subject to less scrutiny than the loans of their counterparts. This streamlined application process suggests that preferred lenders are more able to adjust loan characteristics and respond to changes in policy, such as guarantee rates.

The analysis in the main text illustrates a differential response for preferred lenders – in terms of changes in loan characteristics – when guarantees are more generous. In this appendix, I first show a similar differential response along the dimension of risk pricing. For the pricing regressions, I estimate a two-stage framework similar to that in the main text separately for preferred and non-preferred lenders. Bootstrap distributions of interaction coefficients are displayed in Figure 6.



(a) Default

(b) Charge Off

Figure 6: Pricing Regression Heterogeneity – Preferred Lender Status. This figure presents the bootstrap distribution of the coefficient on the interaction of the indicator for the SBA Recovery period and the pricing residual. This coefficient is estimated from the second stage of the pricing regression and is recovered separately for preferred and non-preferred lenders. It includes loans issued within 42 days of guarantee-rate changes and includes the same controls as used in the main text.

The totality of the results indicate a clear differential response by preferred lenders. There are two natural next questions: (1) Do the lenders that participate in the program differ observably from those that do not? (2) Does the composition of preferred lenders change in the high-guarantee period? First, I address whether there are observable differences between the two types of lenders, beginning with their geographic location. Figure 7 displays the share of preferred lenders by state. These lenders are spread across geographies and appear not to cater to only a small number of markets.

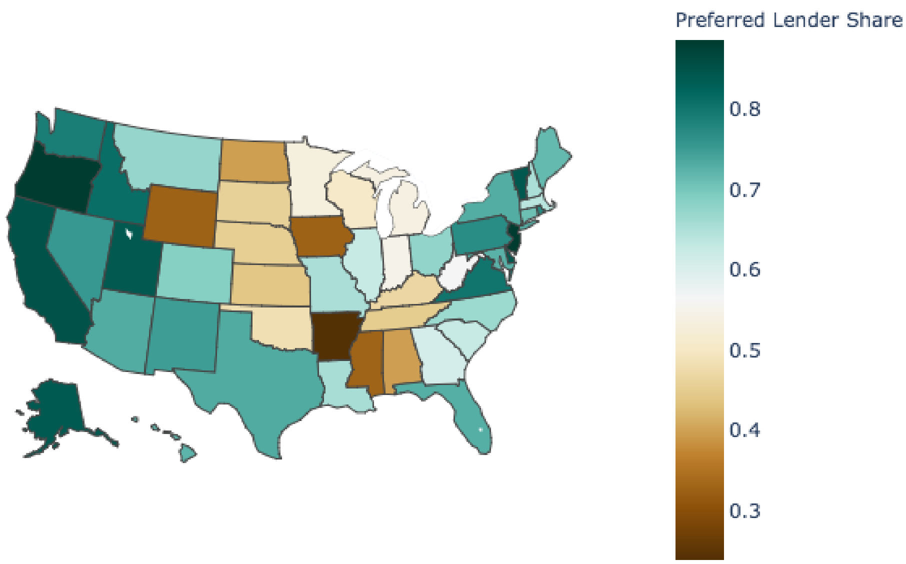


Figure 7: Preferred Lender Share by State. This figure displays a heat map of the share of preferred lenders by state. These shares are computed using all SBA 7(a) loans issued between 2009 and 2011.

While preferred lenders do not specialize in select geographic markets, they do tend to issue more loans than their counterparts. Banks in the top quartile of the distribution of the quarterly average of total loans are more likely to be preferred lenders than their smaller peers. In all, 35.1% of banks in the top quartile of total loan value are preferred lenders, while this share is lower (17.0, 14.4, and 7.5%, respectively) for banks in the third, second, and first quartiles. Because of this, I show that the qualitative takeaways of the descriptive results are the same when I restrict the sample to include only loans issued by banks in the top quartile of the distribution of total loans. Table 16 displays estimates for the specification with preferred-lender heterogeneity, restricted to loans issued by large banks. Furthermore, as mentioned in the main text, these lenders could differ along other, unobservable dimensions, so I allow information acquisition cost to flexibly vary across these categories of lenders in the structural model.

	(1) Interest Rate (Pct.)	(2) Amt. Borrowed ($ Thousands)	(3) Loan Size > 150,000	(4) Loan Term (Months)
Loans Issued Within 42 Days of Events				
SBA Recovery	0.0319	31.04	0.0264	0.0736
	(0.0385)	(24.99)	(0.0208)	(2.062)
Preferred Lender	-0.0125	-149.20	-0.107	0.645
	(0.0569)	(23.51)	(0.0265)	(3.391)
SBA Recovery × Preferred Lender	-0.0837	45.28	0.0576	4.234
	(0.0347)	(25.70)	(0.0263)	(2.657)
Mean Outcome	5.86	541.13	0.80	164.60
Observations	8,331	8,331	8,331	8,331
Zip Code Dem. Controls	✓	✓	✓	✓
Business Type FE	✓	✓	✓	✓
NAICS (Two-Digit) FE	✓	✓	✓	✓
Real Estate FE	✓	✓	✓	✓
Event Date FE	✓	✓	✓	✓

Table 16: Heterogeneity by Preferred Lender Status, Banks in Top Quartile of Total Loan Value (Loan Characteristics). This table presents results of the heterogeneity analysis using an adjusted version of Specification 1, including loans issued within 42 days of guarantee-rate changes but restricting to lenders in the top quartile of the distribution of quarterly average of total loans. All specifications include controls for zip code level demographics (median household income, total population, change in the housing price index since 2008), as well as fixed effects for business type, NAICS (two-digit), real estate, and event date. Standard errors are clustered by lender.

The next question is whether the composition of preferred lenders changes when guarantees are more generous. One may be concerned that increasing the generosity of guarantees changes lenders' incentives to be a part of the preferred lending program. If this were the case, then the differential response I document could be due to the existence of a different set of lenders in the high-guarantee period rather than a response to the policy change. In Table 17, I show that the majority of loans (96.6%) are issued by preferred lenders that participate both in the baseline and in the high-guarantee period. This is higher than the analogous share for non-preferred lenders (77.7%). This suggests that the high guarantees do not induce a new set of lenders to participate in the program and that the differential response is not driven by lender composition.

	Preferred		Non-Preferred	
	Number	Share	Number	Share
Baseline Only	10	0.001	231	0.056
SBA Recovery Only	321	0.032	687	0.167
Both Periods	9,548	0.966	3,197	0.777
Total	9,879	1.000	4,115	1.000

Table 17: Loans By Lender Participation and Lender Type. This table presents the number of loans issued by lenders that participate (1) only in the baseline period, (2) only in the SBA Recovery period, and (3) in both periods. The left-hand panel displays counts and shares for preferred lenders, while the right-hand panel displays counts and shares for non-preferred lenders.

E. Lender Competition

In this section, I provide evidence to support the assumption of lender market power in the structural model. The argument relies on one main institutional detail: the existence of the credit elsewhere test. For a borrower to receive funding through the SBA 7(a) program, they must not have outside funding options available. This detail implies that SBA lenders face limited, if any, competition from outside the program. For this reason, I focus on within-program competition in this section. Figure 8 shows the distribution of unique lenders by borrower and the distribution of loan applications by borrower. The vast majority of borrowers are associated with only a single lender and apply for only a single guarantee between 2009 and 2011. While these facts do not rule out the existence of soft offers (i.e., borrowers receiving loan offers without first being approved for a guarantee), they do support the notion of limited competition.

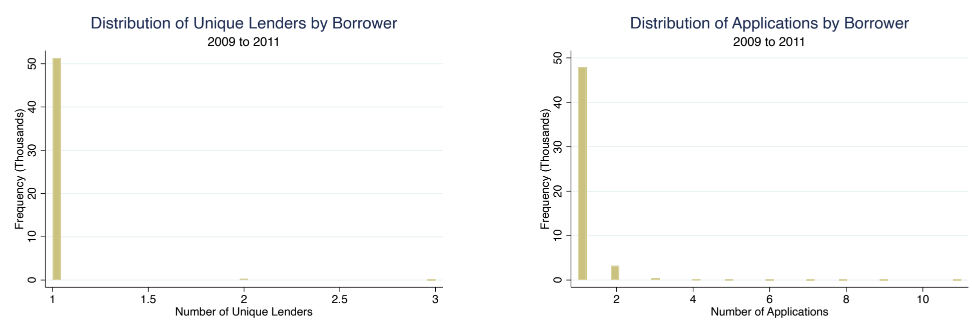


Figure 8: Borrower Applications and Lender Relationships. This figure displays the distribution of unique lenders by borrower (left-hand panel) and applications by borrower (right-hand panel) for all loans issued between 2009 and 2011.

F. Maximum Likelihood Procedure

As discussed in the main text, I observe acceptance, default, and prices and seek to recover the vector Θ of model primitives. Before discussing the likelihood, it is first useful to define two of its components, corresponding to the default/acceptance and pricing decisions. The probability of a borrower accepting and defaulting, given α and p_{ij}, is

$$Pr(d_{ij} = 1, a_{ij} = 1 | p_{ij}, \alpha; \Theta) = \Phi\left(\frac{-X_i^R\beta^R - \mu_{\xi^R|\alpha,s}}{\sigma_{\xi^R|\alpha,s}}\right)\frac{\exp(X_i^A\beta^A - \alpha p_{ij})}{1 + \exp(X_i^A\beta^A - \alpha p_{ij})}.$$

The probabilities for other combinations of default and acceptance take similar forms, so I do not write them explicitly here. The next component of interest is the density of the observed price offer to each borrower, which follows from the lender's first-order condition. Given the signal, I back out the implied marginal cost error, ω_{ij}, which satisfies:

$$\omega_{ij} = \frac{\int \frac{\partial P^A}{\partial p}(\alpha, p_{ij}, X_i^A)\left(1 - (1-M)P^D(\alpha, X_i^R)\right) p_{ij}\, f_{\alpha|s}(\alpha;\Theta)d\alpha}{\int \frac{\partial P^A}{\partial p}(\alpha, p_{ij}, X_i^A)\, f_{\alpha|s}(\alpha;\Theta)d\alpha}$$
$$+\frac{\int P^A(\alpha, p_{ij}, X_i^A)\left(1 - (1-M)P^D(\alpha, X_i^R)\right)\, f_{\alpha|s}(\alpha;\Theta)d\alpha}{\int \frac{\partial P^A}{\partial p}(\alpha, p_{ij}, X_i^A)\, f_{\alpha|s}(\alpha;\Theta)d\alpha} - \beta^z Z_{ij} - \psi(M_{ij}),$$

where

$$P^A(\alpha, p_{ij}, X_i^A) = \frac{\exp(X_i^A\beta^A - \alpha p_{ij})}{1 + \exp(X_i^A\beta^A - \alpha p_{ij})},$$

$$\frac{\partial P^A}{\partial p}(\alpha, p_{ij}, X_i^A) = -\alpha P^A(\alpha, p_{ij}, X_i^A)(1 - P^A(\alpha, p_{ij}, X_i^A)), \text{ and}$$

$$P^D(\alpha) = \Phi\left(\frac{-X_i^R\beta^R - \mu_{\xi^R|\alpha,s}}{\sigma_{\xi^R|\alpha,s}}\right)$$

Once ω_{ij} is recovered, define the density of the observed price offer, given a signal s, as follows:

$$g\left(p_{ij}|s;\Theta\right) = \frac{1}{\sigma_\omega}\phi\left(\frac{\omega_{ij}}{\sigma_\omega}\right)\frac{\partial\omega_{ij}}{\partial p_{ij}}.$$

The likelihood function then takes the following form:

$$\begin{aligned}\mathcal{L}(\Theta) &= \prod_{ij} \iiint Pr(d_{ij}, a_{ij}|p_{ij}, \xi^R, \alpha, s; \Theta) g(p_{ij}|\xi^R, \alpha, s; \Theta)\ f_{\xi^R,\alpha,s}(\xi^R, \alpha, s; \Theta) d\xi^R d\alpha ds \\ &= \prod_{ij} \iiint Pr(d_{ij}, a_{ij}|p_{ij}, \xi^R, \alpha; \Theta) f_{\xi^R,\alpha|s}(\xi^R, \alpha; \Theta) d\xi^R d\alpha\ g(p_{ij}|s; \Theta) f_s(s; \Theta) ds,\end{aligned}$$

where $f_{\xi^R,\alpha,s}$ is the joint density of ξ^R, α, and s given parameter vector Θ.

I obtain the maximum of the log-likelihood using the Interior/Direct Algorithm of Knitro and compute integrals using product-rule quadrature with 10 nodes in each dimension. I then obtain standard errors leveraging the fact that the maximum likelihood estimator is asymptotically normal, where the distribution is given by:[38]

$$\sqrt{N}(\hat{\Theta} - \Theta) \to N(0, I(\Theta)^{-1}),$$

where $I(\Theta) = -E\left[\frac{\partial^2 \log \mathcal{L}(\Theta)}{\partial\Theta\partial\Theta'}\right]$. I calculate the gradient of the log-likelihood analytically and estimate its Hessian using a finite-difference approximation. I report standard errors using the variance-covariance matrix computed using this Hessian.

[38] See, e.g., Greene (2012).

G. Full Results and Model Fit

G.1. Full Results

In Table 18, I present the full set of results for borrower- and lender-side primitives. The borrower-side estimates include the components of the utility of repayment, β^R, the components of the utility of acceptance, β^A, and the primitives governing the joint distribution of borrower repayment and price responsiveness, $\mu_\alpha(X_i^\alpha)$, σ_α, and ρ. The lender-side primitives include the S.D. of the cost shock, σ_ω, the components of the marginal cost function, β^Z, and the S.D. of the signal distribution for different lender types and periods, $\sigma_\gamma(H_{ij})$.

Parameter	Estimate (S.E.)	
	Components of β^R	Components of β^A
Constant	1.177	20.791
	(0.206)	(2.114)
Amt. Borrowed $\in$ (\$150,000, \$700,000]	0.036	-0.174
	(0.050)	(0.042)
Amt. Borrowed $\in$ (\$700,000, \$1,000,000]	-0.109	-0.256
	(0.076)	(0.060)
Amt. Borrowed $\in$ (\$1,000,000, \$2,000,000]	-0.000	-0.353
	(0.072)	(0.064)
Maturity $\leq$ 10 Years	-0.379	-3.482
	(0.047)	(0.363)
Event 2	0.409	-0.164
	(0.060)	(0.047)
Event 3	0.360	0.279
	(0.058)	(0.054)
Event 4	0.399	-0.243
	(0.055)	(0.049)
NAICS: 22	0.314	-0.396
	(0.380)	(0.095)
NAICS: 23	-0.116	-0.417
	(0.161)	(0.064)
NAICS: 31	-0.044	-0.422

	(0.196)	(0.070)
NAICS: 32	0.076	-0.420
	(0.189)	(0.067)
NAICS: 33	0.125	-0.464
	(0.170)	(0.068)
NAICS: 42	0.264	-0.502
	(0.171)	(0.072)
NAICS: 44	-0.013	-0.527
	(0.152)	(0.072)
NAICS: 45	-0.151	-0.450
	(0.170)	(0.068)
NAICS: 48	0.255	-0.373
	(0.207)	(0.064)
NAICS: 51	0.330	-0.372
	(0.266)	(0.074)
NAICS: 52	0.812	-0.527
	(0.314)	(0.081)
NAICS: 53	0.558	-0.506
	(0.250)	(0.075)
NAICS: 54	0.243	-0.511
	(0.164)	(0.072)
NAICS: 56	-0.079	-0.399
	(0.176)	(0.064)
NAICS: 61	0.589	-0.475
	(0.317)	(0.081)
NAICS: 62	0.320	-0.477
	(0.158)	(0.067)
NAICS: 71	-0.282	-0.419
	(0.181)	(0.068)
NAICS: 72	-0.130	-0.457
	(0.151)	(0.065)
NAICS: 81	0.064	-0.487
	(0.158)	(0.069)
Type: Individual	0.104	-0.053
	(0.072)	(0.017)
Type: Partnership	0.222	-0.005
	(0.135)	(0.027)
Normalized ΔHPI	-0.014	0.543
	(0.220)	(0.084)
Normalized Median HH Inc.	0.360	-0.186

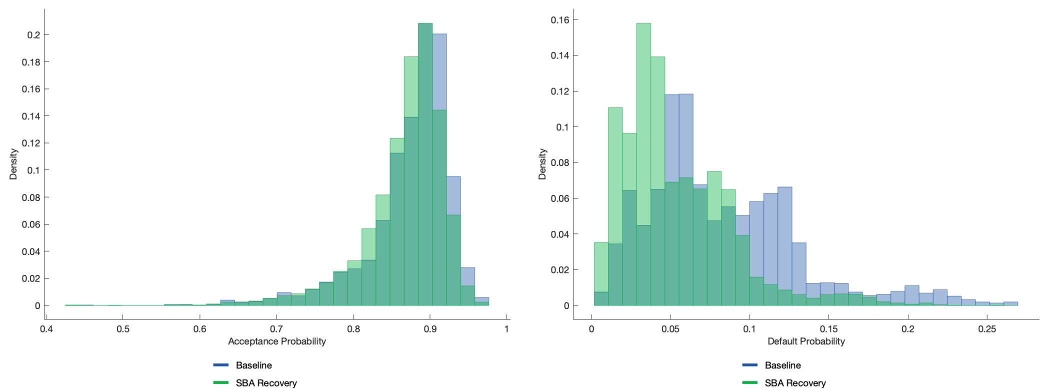
	(0.179)	(0.047)
Normalized Tot. Pop	0.010	-0.083
	(0.130)	(0.032)
SBA Recovery	0.176	-1.314
	(0.044)	(0.361)
Components of β^Z:		
Constant	-0.067	
	(0.083)	
Amt. Borrowed $\in$ (\$150,000, \$700,000]	-0.048	
	(0.017)	
Amt. Borrowed $\in$ (\$700,000, \$1,000,000]	-0.057	
	(0.024)	
Amt. Borrowed $\in$ (\$1,000,000, \$2,000,000]	-0.045	
	(0.021)	
Event 2	0.145	
	(0.029)	
Event 3	0.265	
	(0.037)	
Event 4	0.279	
	(0.035)	
Normalized Int. Bearing	0.139	
	(0.029)	
Normalized Non-Int. Bearing	-0.135	
	(0.025)	
Normalized Deposits	0.016	
	(0.030)	
One-Month LIBOR	0.907	
	(0.120)	
S.D. of Cost Shock, σ_ω:		
Constant	0.196	
	(0.012)	
Components of $F_{\xi^R,\alpha}$		
μ_α (Maturity $\leq$ 10 Years, Baseline)	12.066	
	(1.333)	

μ_α (Maturity $\leq$ 10 Years, SBA Recovery)	11.053
	(1.200)
μ_α (Maturity $>$ 10 Years, Baseline)	16.015
	(1.677)
μ_α (Maturity $>$ 10 Years, SBA Recovery)	14.893
	(1.527)
σ_α	1.119
	(0.310)
ρ	0.335
	(0.064)
S.D. of Signal Distribution: σ_γ	
Non-Preferred, Baseline, $<$ \$10B	0.882
	(0.106)
Preferred, Baseline, $<$ \$10B	0.951
	(0.130)
Non-Preferred, SBA Recovery, $<$ \$10B	0.995
	(0.105)
Preferred, SBA Recovery, $<$ \$10B	1.667
	(0.152)
Non-Preferred, Baseline, $\in$ [\$10B,\$100B)	1.037
	(0.240)
Preferred, Baseline, $\in$ [\$10B,\$100B)	0.692
	(0.198)
Non-Preferred, SBA Recovery, $\in$ [\$10B,\$100B)	0.904
	(0.237)
Preferred, SBA Recovery, $\in$ [\$10B,\$100B)	1.152
	(0.159)
Non-Preferred, Baseline, $\geq$ \$100B	0.726
	(0.227)
Preferred, Baseline, $\geq$ \$100B	1.005
	(0.131)
Non-Preferred, SBA Recovery, $\geq$ \$100B	1.165
	(0.341)
Preferred, SBA Recovery, $\geq$ \$100B	0.814
	(0.128)

Table 18: Full Results – Borrower- and Lender-Side Parameters

G.2. Acceptance and Default Probabilities

Figure 9 displays estimates of acceptance and default probabilities by period. Estimates for the baseline period are shown in blue, while the estimates for the SBA Recovery period are shown in green. These plots illustrate the observable variation both within and across periods in acceptance and default decisions. The main text examines, in more detail, the sources of this variation.



(a) Acceptance Probability (b) Default Probability

Figure 9: Estimates of Acceptance and Default Probabilities by Period. These figures display the predicted probability of default, conditional on X_i^R, and the predicted probability of acceptance, conditional on X_i^A. The distributions are induced by the sample distributions of X_i^R and X_i^A rather than by variance in the predicted probabilities.

G.3. Model Fit

In this section, I demonstrate the fit of the model. I rely on the sample of borrowers that were approved for guarantees within six weeks on either side of the guarantee policy changes. I simulate borrowers' unobservable propensity to repay and price responsiveness, as well as the lenders' signals, given the estimated precision of information. Lenders then optimize their price offers, and borrowers choose whether to accept and repay.

I pay particular attention to the extent to which the model captures variation in acceptance, default, and pricing decisions across policy regimes. Properly estimating how responsive decisions, and particularly the choice of price offers, are to guarantee-rate changes is essential both for disentangling the guarantee pass-through and information effect and for simulating counterfactual guarantee policies. Table 19 displays observed and simulated moments by policy regime. The model fits average prices, acceptance rates, and default rates well and captures changes across periods along each of these dimensions.

	Baseline		SBA Recovery	
Moment	Obs.	Sim.	Obs.	Sim.
$E[p_{ij}]$	1.160	1.159	1.145	1.145
$E[a_{ij}]$	0.903	0.877	0.865	0.870
$E[d_{ij}\|a_{ij}=1]$	0.083	0.084	0.059	0.055
$E[a_{ij}p_{ij}]$	1.049	1.015	0.992	0.994
$E[d_{ij}p_{ij}\|a_{ij}=1]$	0.100	0.101	0.070	0.065

Table 19: Model Fit. This table displays estimates of relevant moments using the observed and simulated data for both the Baseline and SBA Recovery periods. I denote the price offer as p_{ij}, an indicator of acceptance as a_{ij}, and an indicator of default as d_{ij}.

H. Robustness of Structural Results

In this section, I display a number of robustness checks for the results of the structural model. In particular, in the main text, I consider a model in which unobservable heterogeneity in demand takes the form of a random coefficient on price. Under this framework, adverse selection enters through the correlation of a borrower's unobservable utility of repayment and their price responsiveness. In Section H.1, I present a model with unobserved demand heterogeneity entering through a random coefficient on the constant term.

The results presented in the main text also rely on the price calculations described in Appendix C. In Section H.2, I present alternative price calculations, assuming first a constant discount factor of 2% and second a constant discount factor equal to the zero-coupon Treasury yield for the same maturity as the loan. I display results for these robustness specifications in Section H.3.

H.1. Random Coefficient on the Constant

When unobserved heterogeneity enters as a random coefficient on the constant, adverse selection enters through the correlation of the unobservable utility of repayment and utility of acceptance, across all prices. In the remainder of the section, I provide details on the structure of this model. Then, in Section H.3, I show that the results presented in the main text are qualitatively the same as those obtained using this alternate specification.

As in the main text, the utility of loan repayment is given by:

$$u_i^R = X_i^R \beta^R + \xi_i^R,$$

where X_i^R is the same vector of borrower covariates as used in the main text and ξ_i^R is an unobservable shifter of the utility of repayment. Borrowers default if $u_i^R < 0$.

The expression for the utility of acceptance differs from the one in the main text and is instead:

$$u_{ij}^A = X_i^A \beta^A - \alpha p_{ij} + \xi_i^A + \epsilon_{ij},$$

where X_i^A is the same vector of acceptance shifters as in the main text and ξ_i^A is an unobservable shifter of the utility of acceptance. This unobservable is jointly distributed with the unobservable shifter of repayment, ξ_i^R. Specifically, I parameterize this joint distribution as:

$$\begin{pmatrix} \xi_i^R \\ \xi_i^A \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma_{\xi^A} \\ \rho\sigma_{\xi^A} & \sigma^2_{\xi^A} \end{pmatrix} \right).$$

As in the main text, I make one assumption about the sign of ρ to ensure that prices are monotonic in signals. In this case, the non-advantageous selection assumption implies $\rho \leq 0$.

The lender's signal structure takes the same form as in the main text, and prices are set by solving:

$$\max_{p_{ij}} \int \int P^A(\xi^A, p_{ij}, X_i^A) \left[(1 - (1-M)P^D(\xi^A, X_i^R))p_{ij} - \zeta_{ij} \right] \; f_{\xi^A|s_{ij}}(\xi^A) d\xi^A,$$

where the quantities are defined analogously to those in the body.

H.2. Alternative Price Calculations

As detailed in Appendix C, the prices in the main text capture the present value of the loan's cash flows, discounted using the Treasury yield curve. To examine the robustness of this assumption, I also compute loan prices in two other ways. First, I assume a constant discount rate of 2%. Second, I assume a discount rate equal to the zero-coupon Treasury yield to the maturity of the loan. Under these alternative assumptions, R_{ij} becomes:

$$R_{ij} = \frac{1}{B_{ij}} \sum_{t=0}^{T_{ij}} \frac{\frac{B_{ij}}{T_{ij}} + \frac{r_{ij}}{12}\left(B_{ij} - (t-1)\frac{B_{ij}}{T_{ij}} \right)}{(1+\delta)^t},$$

where δ is the relevant monthly discount rate. I again annualize these returns and convert them to ten-year equivalents.

H.3. Results for Alternative Specifications

The results for the alternative specifications are qualitatively the same as those presented in the main text. In this section, I display updated versions of Tables 4 and 5 from the main text.

Coefficients of the utility of repayment and utility of acceptance generally, though not always, have the same sign and approximate magnitude as those in the main specification. The results for the lender-side parameters are also similar. The standard deviation of the signal noise for preferred lenders universally increases in the high-guarantee period for lenders with assets below $100 billion. The combination of these results suggests that the main takeaways of the paper are robust to defining an acceptance decision with unobserved heterogeneity on the constant term rather than the price coefficient and to other methods of computing loan prices.

	Estimate (S.E.)		
Parameter	Random Coefficient on Constant	Disc. Rate 2%	Disc. Rate: Treasury
Components of β^R:			
Constant	1.177	1.237	1.134
	(0.206)	(0.211)	(0.204)
Amt. Borrowed $\in$ ($150,000, $700,000]	0.035	0.051	0.028
	(0.050)	(0.049)	(0.050)
Amt. Borrowed $\in$ ($700,000, $1,000,000]	-0.113	-0.088	-0.129
	(0.076)	(0.074)	(0.073)
Amt. Borrowed $\in$ ($1,000,000, $2,000,000]	-0.000	0.055	-0.008
	(0.072)	(0.070)	(0.072)
Maturity $\leq$ 10 Years	-0.382	-0.446	-0.340
	(0.047)	(0.046)	(0.050)
Event 2	0.407	0.365	0.387
	(0.060)	(0.059)	(0.065)
Event 3	0.363	0.317	0.377
	(0.058)	(0.057)	(0.060)
Event 4	0.400	0.376	0.396
	(0.055)	(0.054)	(0.058)

Parameter	Estimate (S.E.) Random Coefficient on Constant	Disc. Rate 2%	Disc. Rate: Treasury
Components of β^A:			
Constant	19.981	29.834	19.326
	(1.741)	(3.120)	(1.127)
Amt. Borrowed $\in$ (\$150,000, \$700,000]	-0.142	-0.056	-0.069
	(0.032)	(0.041)	(0.035)
Amt. Borrowed $\in$ (\$700,000, \$1,000,000]	-0.212	-0.260	-0.161
	(0.046)	(0.064)	(0.049)
Amt. Borrowed $\in$ (\$1,000,000, \$2,000,000]	-0.298	-0.372	-0.254
	(0.047)	(0.066)	(0.048)
Maturity $\leq$ 10 Years	-4.046	-0.365	-5.465
	(0.412)	(0.397)	(0.490)
Event 2	-0.157	0.008	-0.138
	(0.039)	(0.054)	(0.044)
Event 3	0.242	-0.088	0.028
	(0.042)	(0.054)	(0.042)
Event 4	-0.213	-0.205	-0.379
	(0.038)	(0.054)	(0.044)
Price (Maturity $\leq$ 10 Years, Baseline)	-11.226	-	-
	(1.028)		
Price (Maturity $\leq$ 10 Years, SBA Recovery)	-10.303	-	-
	(0.916)		
Price (Maturity $>$ 10 Years, Baseline)	-15.541	-	-
	(1.407)		
Price (Maturity $>$ 10 Years, SBA Recovery)	-14.524	-	-
	(1.285)		

Parameter	Estimate (S.E.) Random Coefficient on Constant	Disc. Rate 2%	Disc. Rate: Treasury
Components of F_{ξ^R,ξ^A}			
σ_{ξ^A}	0.867	-	-
	(0.300)		
ρ	-0.404	-	-
	(0.112)		
Components of $F_{\xi^R,\alpha}$			
μ_α (Maturity $\leq$ 10 Years, Baseline)	-	22.163	9.209
		(2.377)	(0.600)
μ_α (Maturity $\leq$ 10 Years, SBA Recovery)	-	20.372	8.988
		(2.113)	(0.576)
μ_α (Maturity $>$ 10 Years, Baseline)	-	23.119	14.494
		(2.482)	(1.031)
μ_α (Maturity $>$ 10 Years, SBA Recovery)	-	21.255	14.279
		(2.215)	(1.010)
σ_α	-	0.924	1.733
		(0.254)	(0.152)
ρ	-	0.816	0.133
		(0.152)	(0.020)

Table 20: Robustness – Selected Borrower-Side Estimates

Parameter	Estimate (S.E.) Random Coefficient on Constant	Disc. Rate 2%	Disc. Rate: Treasury
S.D. of Signal Distribution: σ_γ			
Non-Preferred, Baseline, Assets $<$ \$10B	0.756	1.671	0.766
	(0.099)	(0.161)	(0.117)
Preferred, Baseline, Assets $<$ \$10B	0.758	2.209	0.477
	(0.122)	(0.202)	(0.189)
Non-Preferred, SBA Recovery, Assets $<$ \$10B	0.834	1.929	0.570
	(0.097)	(0.133)	(0.113)
Preferred, SBA Recovery, Assets $<$ \$10B	1.499	2.543	1.089
	(0.143)	(0.165)	(0.126)
Non-Preferred, Baseline, Assets $\in$ [\$10B,\$100B)	0.911	1.579	0.493
	(0.251)	(0.253)	(0.330)
Preferred, Baseline, Assets$\in$ [\$10B,\$100B)	0.445	1.348	0.379
	(0.153)	(0.160)	(0.139)
Non-Preferred, SBA Recovery, Assets $\in$ [\$10B,\$100B)	0.726	1.772	0.562
	(0.242)	(0.286)	(0.354)
Preferred, SBA Recovery, Assets $\in$ [\$10B,\$100B)	0.946	1.806	0.641
	(0.154)	(0.141)	(0.156)
Non-Preferred, Baseline, Assets $\geq$ \$100B	0.633	1.361	0.484
	(0.256)	(0.280)	(0.272)
Preferred, Baseline, Assets $\geq$ \$100B	0.868	1.704	0.662
	(0.126)	(0.165)	(0.161)
Non-Preferred, SBA Recovery, Assets $\geq$ \$100B	0.955	2.102	0.324
	(0.346)	(0.395)	(0.255)
Preferred, SBA Recovery, Assets $\geq$ \$100B	0.617	1.568	0.215
	(0.121)	(0.127)	(0.087)

Table 21: Robustness – Selected Lender-Side Estimates

I. Extensions: Hybrid Policy Counterfactuals

In the body of the paper, I present results that compare price offers and borrower surplus under (1) the baseline policy with a guarantee rate of 90% and no subsidy, (2) a hybrid policy with a guarantee rate of 50% and a subsidy set such that expected spending is the same as in policy (1), and (3) a policy with a guarantee rate of 50% and no subsidy. While comparing outcomes under these three policies illustrates the key forces at play when designing guarantee schemes in small-business lending markets, variation in rates and subsidies can be more flexible. In this section, I show how prices and borrower surplus vary under alternative policies.

Figure 10 displays contour plots with guarantee rates on the horizontal axis and subsidies on the vertical axis. Lighter colors signify higher borrower surplus. This contour plot illustrates two key points. First, borrower surplus is increasing in both the subsidy level and the guarantee rate. Second, gains accrue more quickly when subsidies increase than when guarantees are more generous, which is consistent with the main text's result that the hybrid policy yields higher aggregate borrower surplus.

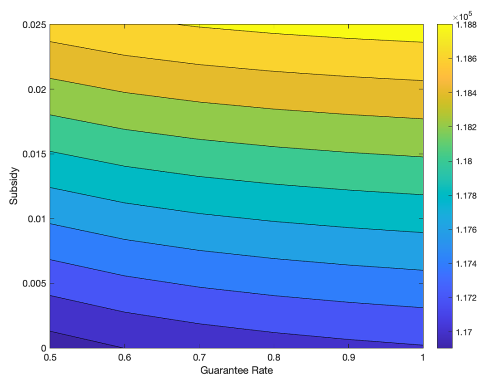


Figure 10: Borrower Surplus Across Guarantees and Subsidies. The contour plot displays average average borrower surplus, in $ over the normalized ten-year loan term, across guarantees and subsidies. Lighter colors indicate higher borrower surplus.