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Borrower-Lender Distance, Credit Scoring, and the Performance of Small Business Loans

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Abstract: We develop a theoretical model of decision-making under risk and uncertainty in which bank lenders have both imperfect information about loan applications and imperfect ability to make decisions based on that information. We test the loan-default implications of the model for a large random sample of small business loans made by U.S. banks between 1984 and 2001 under the SBA 7(a) loan program. As predicted by our model, both borrower-lender distance and credit-scoring contribute to greater loan defaults; the former finding suggests that distance interferes with information collection and monitoring, while the latter finding implies production efficiencies that encourage credit-scoring lenders to make riskier loans at the margin. However, we also find that credit-scoring dampens the harmful effects of distance, consistent with the conjecture that information generated by credit scoring models improves the ability of lenders to assess and price default risk.

JEL Codes: D81, G21, G28.

Key words: borrower-lender distance, credit scoring, small business loans.

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1. Introduction

Small business finance has traditionally been a local and close-knit affair. Small firms, whose informational opacity precludes them access to public capital markets, seek out local bank lenders whose geographic proximity allows them to observe and accumulate the "soft," non-quantitative information necessary to assess these firms' creditworthiness (Meyer 1998, Stein 2002, Scott 2004). This relationship-based approach remains the method used by many, if not most, community banks to underwrite their small business loans today.

But some exceptions to these tight location-based credit relationships began to emerge during the 1990s, when (a) the geographic distance between small business borrowers and their commercial bank lenders began to increase and (b) some banks began using credit scoring models and "hard," quantitative information to assess small business loan applications. Increasing geographic distances between small business borrowers and their bank lenders has been documented in a number of recent studies (e.g., Cyrnak and Hannan 2000; Degryse and Ongena 2002; Petersen and Rajan 2002; Wolken and Rohde 2002; Brevoort and Hannan 2004). In some cases the magnitudes have been substantial. For example, in 2001 the median borrower-lender distance for business loans originated with backing by the Small Business Administration (SBA) was approaching 20 miles, more than triple the distances observed in the mid-1980s (this study, see Table 1 below). The dissemination of small-business credit scoring technology has also been rapid. First implemented in the mid-1990s, by 1997 over half of large U.S. commercial banking companies were using credit scores to assess at least some of their small business loan applications (Mester 1997; Akhavein, Frame, and White 2005).

The apparent decline in the importance of borrower-lender proximity and in-person relationships for small business lending has potential implications for the supply and quality of small business credits as well as the strategies of banks that extend those loans. All else equal, greater geographic distances between informationally opaque firms and their bank lenders should increase the cost of lending and

reduce the supply of loans—e.g., bankers will make fewer in-person visits because of high travel expenses, resulting in less accurate information, poorer credit assessments, and higher rates of loan default. Arguably, the implementation of small business credit scoring models could either dampen or exacerbate those outcomes. If the predominant effect of credit scoring is to improve the quality of banks' information about borrower creditworthiness, or provide banks with better decision-making frameworks based on quantifiable rather than qualitative financial information, then credit scoring could mitigate the adverse information costs associated with borrower-lender distance. But if the predominant effect of credit scoring is to reduce banks' production costs by eliminating expensive on-site visits, reducing loan analysis time, or generating scale economies associated with automated lending processes (Mester 1997, Rossi 1998), then credit scoring could increase the profitability of the marginal loan application without any mitigation of distance-related information costs. Regardless, these developments (increased borrower-lender distance, increased use of credit scoring) have materially altered the optimal tradeoffs among information quality, customer service, loan production costs, and bank scale. These developments will likely have strategic ramifications going forward, e.g., whether banks do both relationship lending and transactional lending or engage exclusively in just one or the other (Boot and Thakor 2000; DeYoung, Hunter, and Udell 2004).

This study investigates the loan supply and loan performance effects associated with increased distance between bank lenders and their small business borrowers, and the possibility that new lending technologies and/or government loan subsidies either mitigate or exacerbate those effects. We construct a theoretical model of decision-making under risk and uncertainty based on earlier work by Heiner (1983, 1985, 1985a, 1986). This approach is consistent with the underlying design of the more recent lending models developed by Shaffer (1998) and Stein (2005). The key feature of all these models is the recognition that *imperfect information* leads to decision errors in which some good accounts are denied and bad accounts are approved—a result consistent with observed lending behavior. Following Heiner, however, we extend the decision model to include the possibility that lenders also have *imperfect decision skills*. As a result, lenders presented with the same information may behave differently depending on their

abilities to interpret and act on the available borrower and market information. By extending the model to incorporate both imperfect information and imperfect decision skills, we are able to analyze a broader set of questions—especially with respect to changing technology and borrower-lender distance—within a theoretical framework that is more consistent with observed lender behavior.

We derive a number of empirically testable hypotheses from the theory: (1) More generous government loan guarantees yield increased loan approval rates and increased loan defaults for all banks. (2) Less certain information, due to increased borrower-lender distance, yields reduced loan approval rates for all banks and increased loan defaults on average in a cross-section of heterogeneous lenders. (3) Improved decision-making ability due to the implementation of credit-scoring yields increased loan approval rates for all banks and decreased loan defaults on average in a cross-section of heterogeneous lenders. (4) Holding constant the impact of credit scoring on banks' decision-making abilities, improvements in bank cost or profit functions due to automated credit scoring processes (e.g., scale economies, fee generation, diversification effects) yield increased loan approval rates and increased loan defaults for all banks.

We test the loan-default predictions of our model using a random sample of 29,577 loans made by U.S. commercial banks between 1984 and 2001 under the Small Business Administration's flagship 7(a) loan program. In the U.S., policies designed to ensure that small businesses have access to credit date to the Reconstruction Finance Company in 1953, which later evolved into the SBA. SBA loans are critical to the flow of credit to financially marginal small businesses. For example, in 2001 the SBA reported a combined managed guaranteed loan portfolio of over $50 billion (mostly through the SBA 7(a) program), a substantial amount given that the total small business loan portfolio of U.S. commercial banks was roughly $120 billion.[1] Although these partial guarantees reduce lenders' exposure to credit risk—and as such are instrumental in the provision of credit to small business borrowers—these government subsidies do little to solve the underlying, and often severe, information problems associated

with these largely opaque firms. Since small businesses tend to create a disproportionate number of new jobs in market economies, these issues have special importance for economic policy.[2]

The data provide substantial support for the loan-default predictions of our theoretical model. More generous SBA subsidies are associated with higher loan default rates. All else equal, credit-scoring is associated with *higher* default rates, a result that is consistent with our theoretical prediction that reduced costs associated with automated small-business lending technology (i.e., increased profitability for the marginal loan applicant) will increase the profitability of the marginal loan applicant, and hence provide incentives for lenders to approve riskier loan applications. Greater borrower-lender distance is associated with higher default rates at non-credit-scoring banks, but not at credit-scoring banks, suggesting that scoring models may help mitigate the information problems associated with geographically distant borrowers. Consistent with this notion, we find suggestive evidence that credit-scoring banks are better able to price the risk of loan default into the interest rates on these especially opaque credits. Although we do not test the loan-supply predictions of our theory model here, we note that they are quite consistent with the findings of the extant empirical literature on credit scoring and the small business lending, e.g., Frame, Srinivasan, and Woosley 2001, Frame, Pahdi, and Woosley 2004, and Berger, Frame, and Miller 2005. Thus, our model provides an *ex post* theoretical foundation for these purely empirical studies.

To the best of our knowledge, this is the first study to test empirically the impact of either borrower-lender distance or credit-scoring on the probability of individual loan default. Our findings have implications for bank competition policy, for loan subsidy programs in general, and more specifically for the mission, management, and funding of the SBA program. Moreover, our theoretical model provides

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[1] As defined in the June 2001 Call Reports, small business loans include all commercial and industrial loans made in amounts less than $250,000.

formal underpinnings for both extant and future empirical studies of the effects of information uncertainty in both subsidized and non-subsidized bank lending—we note that the theoretical propositions (2), (3), and (4) outlined above are equally proscriptive regardless of loan subsidies or guarantees—and how these phenomena are affected by innovations in information technology.

2. Background and relevant literature

Because it is difficult for investors in public capital markets to assess the financial condition and creditworthiness of small businesses, these firms depend disproportionately on private debt finance (Bitler, Robb, and Wolken 2001; Petersen and Rajan 1994, Berger and Udell 1998).[3] Much of this funding is provided by nearby community bank lenders, located close enough to have personal knowledge of the firms' owners and managers (and often their suppliers and customers) and make frequent on-site visits. There is a growing body of academic work on small business lending and community banking; Berger and Udell (1998) and DeYoung, Hunter, and Udell (2004) provide broad reviews of the literature. In this section we focus more closely on the recent increases in small borrower-lender distance and small business credit scoring alluded to above; the potential substitution of automated credit scored lending for high-touch relationship lending to small businesses; and the likely effects of these developments on the quantity and quality of bank loans to small businesses.

2.1 Borrower-lender distance

A number of recent studies demonstrate that the geographic distances between banks and their small business borrowers increased during the past two decades. For example, Petersen and Rajan (2002) estimated that the distances between U.S. banks and their small business borrowers increased on average

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[2] According to the SBA, small businesses "provide 75 percent of the net new jobs added to the economy" (www.sba.gov). Some researchers argue that SBA estimates suffer from a variety of conceptual, methodological and measurement issues and as a result somewhat overstate the creation of jobs by small businesses (e.g., Davis, Haltiwanger and Shuh 1994,1996). However, at least one recent study finds a positive (albeit economically small) relationship between the level of SBA lending in a local market and future personal income growth in that market (Craig, Jackson, and Thomson 2005). New job creation and macroeconomic impact aside, SBA figures indicate that small businesses employ 52 percent of the private work force, contribute 51 percent of private sector output, and produce 55 percent of innovations (U.S. Small Business Administration 2000).

[3] According to Bitler, Robb, and Wolken's analysis of the 1998 Survey of Small Business Finances, 39 percent of small business respondents had a loan, a credit line, or a capital lease from a commercial bank. Finance companies, the second largest supplier, were used by only 13 percent of the respondents.

by about 3 to 4 percent per year during the two decades leading up to 1993.[4] Consistent with this trend, Cyrnak and Hannan (2000) found that the share of small business loans made by out-of-market banks in the U.S. approximately doubled between 1996 and 1998. Degryse and Ongena (2002) used travel time to measure borrower-lender distance for loans made by a large supplier of small business credit in Belgium, and found that this distance increased during the 1990s, albeit only at a rate of about 9 seconds per year.

Borrower-lender distance has been linked both theoretically and empirically to banking business strategies and banking industry structure. Using detailed spatial data from commercial loans made under the Community Reinvestment Act in 1997 through 2001, Brevoort and Hannan (2004) found that, within metropolitan areas, banks became less likely to lend as borrower-lender distance increased; moreover, this effect grew stronger over time and was strongest for smaller banks. Berger, Miller, Petersen, Rajan, and Stein (2005) found that large banks are more likely than small banks to make long-distance loans, and are less likely to foster long-lasting relationships with those borrowers. These findings are consistent with recent theories that increased competition in lending markets from large banking companies has caused small banks to focus more locally, where they arguably have the greatest informational advantages (e.g., Dell'Ariccia and Marquez 2004).[5]

Improvements in communications technology (fax machines, the Internet), greater information availability (credit bureaus), and increased capacity to analyze information (personal computers, financial software, credit scoring) have facilitated faster and more accurate information flows from borrowers to lenders. On the one hand, these innovations have reduced the frequency of in-person visits by improving loan officers' ability to perform off-site screening and monitoring of small business borrowers. On the other hand, these innovations have made credit analysis more portable: the nexus of laptop computers, spreadsheet programs, and internet connections has increased the productivity of loan officers' in-person

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[4] Petersen and Rajan (2002) did not observe an actual time series of data. Rather, they constructed a synthetic time series based on cross-sectional data in the 1993 NSSBF. They observed time indirectly based on the age of the bank-borrower relationship in 1993, and found that borrowers with longer banking relationships tended to be located closer to their banks.

visits to borrowers. By reducing the costs associated with borrower-lender distance, these developments have likely contributed to increases in these distances in recent years. Indeed, Hannan (2003) found that banks specializing in credit card lending (i.e., banks most experienced with credit scoring) accounted for the bulk of the increase in out-of-market small businesses lending in the U.S. between 1996 and 2001.[6]

Banking industry consolidation may also have contributed to increased borrower-lender distance. The number of U.S. banks has declined substantially over the past two decades, but the number of bank branch locations has increased. In 1985 there were about 14,500 banks operating more than 57,700 banking offices (about 4 offices per bank), but by 2000 there were about 8,300 banks operating over 72,400 banking offices (almost 9 offices per bank).[7] If the screening and monitoring of small business loans is performed largely by branch-based loan officers, then these structural changes may indicate that banks are moving closer to their small business customers in order to provide more convenient service.[8] If, on the other hand, the screening and monitoring of small business loans is performed largely by loan officers stationed at main bank offices, then the decline in the number of banks has increased the effective distance between borrowers and lenders.

Although to our knowledge no previous study has tested whether borrower-lender distance affects loan performance, some studies have examined whether and how geographic distance impacts the performance of banks and other firms. Using data from U.S. multi-bank holding companies during the 1990s, Berger and DeYoung (2001, 2005) concluded that geographic dispersion impedes the ability of senior headquarters managers to control the actions of local loan officers; they also found that this result dissipated over time, suggesting that technological progress allowed banks to partially mitigate distance-related control problems. Using division-level data from U.S. corporations between 1991 and 2003,

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[5] Ergungor (2005) concludes that increased competition has also reduced the risk-adjusted profitability of relationship lending at community banks in recent years.

[6] For example, credit scoring enabled San Francisco-based Wells Fargo to make loans in virtually all 50 states prior to 1996, even though the bank had no branches outside California at the time.

[7] Based on data from the Federal Deposit Insurance Corporation website, www.fdic.gov.

Landier, Nair, and Wulf (2005) found that employees in divisions located geographically further from the corporate headquarters were more likely to be laid off; they also found that this relationship was weaker in "hard information intensive" industries, an indication that ease-of-information-transfer influences geographically distant business decisions. Using data on corporate loans made by a foreign bank in Argentina in 1998, Liberti (2005) found that soft information was more important for loans approved or denied at the local branch, while hard information was more important for loans approved or denied by loan officers located further away. These findings have obvious parallels for the costs associated with borrower-lender distance and the efficacy of credit-scoring lending technologies.[9]

2.2 Small business credit scoring

Credit scoring models use statistical modeling techniques to transform quantifiable information—sometimes referred to as "hard" information—about a borrower (e.g., her income, debt load, financial assets, employment history, and credit history) or a small business (business credit reports, company financial ratios, sales figures, corporate structure, and industry identity) into a numerical "credit score" that ranks individual borrowers based on their likelihood of defaulting on a loan. Banks first used credit scores to screen applicants for consumer loans (credit cards, auto loans) and quickly became standard tools in mortgage lending.[10] The key innovation that spurred banks to apply credit-scoring models to small business lending was the discovery that a small business owner's *personal* credit information was a strong predictor of her *business* creditworthiness (Berger, Frame, and Miller 2005). Because households are less economically diverse than the small businesses they own and operate—which, for example, can range from traditional corner groceries to innovative software developers—this realization in effect reduced the degree of heterogeneity across small business loans and made it possible to securitize and sell

[8] There is some evidence to the contrary: banks typically locate their new branches close to the *existing* branches of their rivals, which leaves the distance between bank branches and existing small businesses on the whole relatively unchanged (Chang, Chaudhuri, and Jayarante 1997). Moreover, it is unlikely that the geographic distribution of small business borrowers has changed much over time, since small business activity is closely linked to the geographic distribution of cities and the economic activity found there.

[9] Other studies have found that large geographic distance between the home and host countries may impede the expansion of cross-border banking companies (e.g., Buch 2003; Berger, Buch, DeLong, and DeYoung 2004).

small business loans in the secondary market. Indeed, Dell'Ariccia and Marquez (forthcoming) argue that a reduction in the heterogeneity of borrower information across lenders (perhaps through widespread adoption of credit scoring) has implications for lender competition, loan quality, and loan supply. Mester (1997) provides a basic primer on credit scoring models for both consumer and small business lending. Frame and White (2004) review the relatively small academic literature on technological innovation in banking, of which small business credit scoring studies comprise a substantial portion. Roszbach (2004) reveals some systematic financial inefficiencies in the implementation of credit scoring models, using data on over 13,000 loan applications processed by a large Swedish bank in the mid-1990s.

Used in isolation, credit scoring may not improve the amount or accuracy of banks' information about borrowers and/or banks' abilities to make correct lending decisions—however, credit scoring approaches deliver a well-defined information set at less expense to the bank, and permit banks to make faster decisions on loan applications. Thus, the potential benefit of credit scoring depends on the manner in which banks use it. Consider two different ways that banks can use small business credit scoring models. First, credit scoring might be used as a first-stage filter to inexpensively identify loan applications that should clearly be rejected or approved, followed by a more thorough second-stage analysis of the "grey area" loan applications based on a broader set of (qualitative and quantitative) information. If done correctly, this approach can reduce a bank's overall loan screening expenses without compromising loan quality. Second, credit scoring might be used to automatically approve or reject all loan applications. This approach reduces loan screening expenses through even greater reductions in expensive human inputs; moreover, if loan volumes are large enough, automated credit scoring can fundamentally alter the economics of the lending process by capturing scale-based reductions in unit costs, diversifying away idiosyncratic risk, generating fee income from loan origination and loan servicing, and recycling scarce bank capital by securitizing the loans and selling them to other financial institutions. On the potential downside, because credit scores are imperfect predictors of loan default based on a relatively small set of

[10] In addition to aiding in the approval and denial of loan applications, credit-scoring models can be used to price new loans, monitor existing loans, identify candidates for cross-selling opportunities, and target prospective loan

quantifiable information about a borrower, a greater number of unqualified loan applications are likely to be approved, all else equal. These loan screening mistakes, or type II errors, are likely to be more frequent for heterogeneous pools of loan applications like small business loans, and less frequent for more homogeneous pools of loan applications like conforming home mortgages.

The only systematic database describing whether, when, and how bank lenders use small business credit scoring is based on a 1998 Federal Reserve Bank of Atlanta survey of the lead banks at 190 of the largest 200 commercial bank holding companies in the U.S. (see Frame, Srinivasan, and Woosley 2001). Surveying large banks made sense: even prior to the dissemination of small business credit scoring technology, large banks were already more likely than small banks to use quantitative, hard-information approaches to business lending (Cole, Goldberg, and White 2000). These data have been used in a number of recent studies (including this one) of small business credit scoring by U.S. banks, and have generated a number of useful findings and interesting conclusions.

Frame, Srinivasan, and Woosely (2001) found a substantial increase in small business lending at the large banks that adopted credit scoring techniques, and concluded that credit scoring lowered information costs and by doing so reduced the value of traditional small bank-small borrower lending relationships. Frame, Pahdi, and Woosley (2004) found that small business credit scoring contributed equally to increasing the supply of small business loans in both high income and low-to-moderate income areas. Akhavein, Frame, and White (2005) found that banks with large numbers of branch locations are more likely to adopt small business credit scoring techniques, suggesting that senior managers in these organizations use the technology as a control mechanism over branch bank managers and loan officers. Berger, Frame, and Miller (2005) found that banks that use small business credit scoring experience higher nonperforming loan ratios, especially when these banks use credit scores to automatically accept or reject loan applications.

These extant empirical studies suggest a direct link between the adoption of credit scoring and lending volume and, possibly, credit scoring and loan performance. It is within the context of these

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customers. For a discussion, see Mays (2004, Chapter 1).

empirical studies that we outline a theoretical model of lending decisions under risk and uncertainty: both to provide a theoretical basis for these extant empirical findings, and as a support for our own empirical analysis of geographic distance, credit scoring, and the performance of SBA loans.

3. Lending decisions under uncertainty: A conceptual framework

Underwriting and monitoring loans requires lenders to have extensive information about their borrowers, their business environment, and general economic conditions. But neither the information observed by the lender, nor the lender's decision-making skills, are perfect, and these imperfections can result in sub-optimal lending decisions and loan outcomes that worsen, rather than improve, bank performance. As discussed above, information can become less perfect with borrower-lender distance—as the business and economic environment becomes more remote from the lender's local lending area, and the choice of a lending technology (e.g., relationship lending versus automated credit scoring) may either exacerbate or mitigate information imperfections.

Conventional analysis of decision-making under risk and uncertainty applies a strict framework in which agents know all possible events, know the outcomes of those events, use all available information to assign probabilities to those events, and then based on that information choose actions that maximize expected performance (e.g., profit or utility). In this conventional framework, uncertainty is narrowly defined: it arises only when decision makers have less-than-perfect information. Behavioral theories of economic decision-making admit a richer definition of uncertainty: it can occur when perfectly informed agents lack the ability to make perfect decisions.[11] In this fashion, we construct a general model of decision-making under uncertainty in which decisions are influenced both by the quality of the information available to the decision maker and the quality of the decision maker's interaction with that information. This framework, which borrows heavily from Heiner (1983, 1985, 1985a, 1986), is easily

applicable to bank lender decision-making, and quite naturally yields testable hypotheses on how changes in lending technology, borrower-lender distance, and government loan guarantees impact the supply of loans and the probability of loan default.[12]

3.1. Two components of decision-making under uncertainty

We define uncertainty with respect to both imperfect information and imperfect decision skills. As a result of the uncertainty, not only are decision makers exposed to errors due to random events (i.e., risk) but also errors due to incorrect interpretation of information. In this section we outline a simple model of decision-making under uncertainty in which decisions are conditional on the lender's ability to interpret the decision environment. This model leads to lender behavior that is based on rules that are rational, though not necessarily optimal.[13]

Let S represent all relevant states of nature, embracing all possible combinations of local and national economic growth, interest rates, price movements, job market conditions, changes in asset values, and other external factors that affect general loan repayment performance. Let X represent all information available to the decision maker about each state of nature S. In the context of our discussion, X includes borrower-specific and loan-specific information, such as the applicant's financial profile, credit history, debt burden, collateral, cash flows, terms of the loan, etc. Finally, let A represent the set of actions available to the decision maker.[14] We will characterize A narrowly as the loan approval/denial decision, which the lender makes conditional on his imperfect information X and his imperfect decision skills. Thus, the lender may make inappropriate decisions, such as selecting action $\alpha \in A$ (loan approval)

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[11] As described by McFadden (1999), "…decision makers have trouble handling information and forming perceptions consistently, use decision-making heuristics that can fail to maximize preferences, and are too sensitive to context and process to satisfy rationality postulates formulated in terms of outcomes." Because these aspects of the decision-making process are consistent with our on-site observations of bank lending behavior during the bank examination process, we develop a theoretical model that explicitly incorporates imperfect decision-making skills. In the context of our model, uncertainty is closely related to the type of uncertainty outlined by Knight (1933).

[12] See also Beshouri and Glennon (1996) for an application of this analysis to bank lending decisions.

[13] This feature of the model—i.e., the emergence of rule-governed decision-making behavior—is very much consistent with the decision-making process used by banks in practice, as reflected by the detailed sets of lending rules present in most banks' underwriting policy guidelines.

when conditions suggest that selecting action $\beta \in A-\alpha$ would increase performance (type II error), or selecting $\beta \in A-\alpha$ (loan denial) when conditions suggest that selecting $\alpha \in A$ would increase performance (type I error).[15]

We represent the lender's *imperfect information* by the probabilities that the information in his possession either correctly or incorrectly identifies the true state of nature. Let $S^*_\alpha \subset S$ represent the subset of possible states of nature in which choosing action α is optimal, and let $X^*_\alpha \subset X$ represent the subset of information that signals to the lender that α is the best choice. Then let $r^X_\alpha = p(X^*_\alpha|S^*_\alpha)$ be the conditional probability that the information received (X^*_α) correctly signals that the optimal states of nature for selecting α exist and $w^X_\alpha = p(X^*_\alpha|S-S^*_\alpha)$ the conditional probability that this same information is received when non-optimal states of nature for selecting α exist; and let $\rho^X_\alpha = r^X_\alpha/w^X_\alpha$ measure the relative *reliability of the information* (Heiner, 1986). As the information becomes more reliable, $r^X_\alpha \to 1$, $w^X_\alpha \to 0$, and $\rho^X_\alpha \to \infty$.

We represent the lender's *imperfect decision skills* by a decision function B(x) which maps information $x \in X$ into actions A.[16] The decision function incorporates the limitations placed on decision skills that lead to decision errors beyond those generally associated with risk (i.e., imperfect information). More formally, let $r^B_\alpha = p(B(x)=\alpha|X^*_\alpha)<1$ be the conditional probability that action α is selected when optimal messages are received; let $w^B_\alpha = p(B(x)=\alpha|X-X^*_\alpha)>0$ be the conditional probability that action α is selected when non-optimal messages are received; and let $\rho^B_\alpha = r^B_\alpha/w^B_\alpha$ measure the relative *reliability of a lender's behavior* in responding to information. As lenders become more reliable at responding correctly to information received, $r^B_\alpha \to 1$, $w^B_\alpha \to 0$, and $\rho^B_\alpha \to \infty$.

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[14] For ease of exposition, we define A in terms of a single decision-making dimension: approve/deny. However, our analysis would hold over a multi-dimensional representation of A that included the broader set of underwriting decision variables used by banks in practice, such as: loan amount/credit line, loan price, loan collateral, loan fees, term of loan, etc.

[15] As stated above, this representation of the approve/deny decision process is consistent with the modeling framework used by Stein (2005) and Shaffer (1998) in which decision errors (especially the approval of bad borrowers) are incorporated into the model.

[16] Note that we separate the decision function B(x) from the performance function (e.g., profit maximization). This contrasts with conventional choice theory, in which the decision function is the performance function (e.g., lenders

We can jointly express the uncertainties due to imperfect information and imperfect decision skills in a single reliability ratio. Assume that the choice of α is correct ($s \in S^*_\alpha$). Then a lender can select α under two scenarios: if the analyst receives information that α is optimal ($x \in X^*_\alpha$) and correctly interprets this information ***or*** if he receives information that β is optimal ($x \in X-X^*_\alpha$) and incorrectly interprets this information. More formally, the joint conditional probability that α is the right choice is

$$\begin{aligned} r^{XB}_\alpha &= p(B(x)=\alpha|S^*_\alpha) \\ &= p(X^*_\alpha|S^*_\alpha)\, p(B(x)=\alpha|X^*_\alpha) + p(X-X^*_\alpha|S^*_\alpha)\, p(B(x)=\alpha|X-X^*_\alpha) \\ &= r^X_\alpha r^B_\alpha + (1-r^X_\alpha)\, w^B_\alpha. \end{aligned} \tag{1}$$

Similarly, the joint conditional probability that α is the wrong choice is

$$w^{XB}_\alpha = w^X_\alpha r^B_\alpha + (1-w^X_\alpha)\, w^B_\alpha. \tag{2}$$

The ratio of the joint conditional probabilities that α is the right relative to the wrong choice (i.e., equations 1 and 2) is the *joint reliability ratio* (Heiner, 1986):

$$\rho^{XB}_\alpha = \frac{r^{XB}_\alpha}{w^{XB}_\alpha} = \frac{r^X_\alpha r^B_\alpha + (1 - r^X_\alpha)\, w^B_\alpha}{w^X_\alpha r^B_\alpha + (1 - w^X_\alpha)\, w^B_\alpha} = \frac{r^X_\alpha (\rho^B_\alpha - 1) + 1}{w^X_\alpha (\rho^B_\alpha - 1) + 1}. \tag{3}$$

This ratio illustrates that uncertainty due to imperfect information (r^X_α and w^X_α) and uncertainty due to imperfect decision-making skills (ρ^B_α) are interactive in determining ρ^{XB}_α. As information becomes more perfect (i.e., $r^X_\alpha \to 1$, $w^X_\alpha \to 0$), $\rho^{XB}_\alpha \to \rho^B_\alpha$; as decision-making skills become more perfect (i.e., $r^B_\alpha \to 1$, $w^B_\alpha \to 0$), $\rho^{XB}_\alpha \to r^X_\alpha / w^X_\alpha = \rho^X_\alpha$; and as both information and decision-making skills become perfect, $\rho^{XB}_\alpha \to \infty$.[17]

The assumption that lenders do not always know how their actions affect performance is critical to our argument: instead of acting optimally (i.e., selecting the action that maximizes expected profits),

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choose actions that maximize profits). It can be shown that the decision and performance functions are equivalent in the special case when decision skills are perfect (see Heiner 1985).

lenders in our model restrict their behavior until they are reasonably confident they will gain from selecting a particular action. This is consistent with observed lender behavior: in practice, underwriting guidelines that impose restrictions on the loan officers to respond to information that is difficult to interpret. These guidelines generally include threshold values for specific underwriting ratios, pricing sheets, and other well developed "rules-of-thumb" that reduce the discretion of loan officers.[18] Relying on decision rules, of course, will inevitably lead to decision errors. The conditional probability that α is the right choice can be expressed in terms of type I errors (incorrectly rejecting a loan application), and the conditional probability that α is the wrong choice can be expressed in terms of type II errors (incorrectly accepting a loan application). Defining the probabilities of type I and type II errors as $t_I = p(B(x)\neq\alpha|S^*_\alpha)$ and $t_{II} = p(B(x)=\alpha|S-S^*_\alpha)$, respectively, then it follows that $r^{XB}_\alpha = 1-t_I$ and $w^{XB}_\alpha = t_{II}$.

3.2. A joint reliability condition

We now derive a decision rule as outlined by Heiner (1985a). Let $g^e_\alpha = p^s_\alpha r^{XB}_\alpha g_\alpha$ be the expected gain from correctly selecting α, where $p^s_\alpha = p(S^*_\alpha)$ is the unconditional probability that α is the correct choice (i.e., $s\in S^*_\alpha$) and $g_\alpha = \pi(\alpha;S^*_\alpha)$ is the performance gain from correctly selecting α. Let $l^e_\alpha = (1-p^s_\alpha) w^{XB}_\alpha l_\alpha$ be the expected loss from incorrectly selecting α, where $l_\alpha = \pi(\alpha;S-S^*_\alpha)$ is the performance loss from incorrectly selecting α. We make the reasonable assumption that p^s_α, g_α, and l_α are known to the lender.[19] The lender will benefit from selecting α if the expected gain exceeds the expected loss, that is, if

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[17] It is possible to write a more general form of our model using a one-step reliability ratio (i.e., r_α/w_α) in which the probabilities of correctly and incorrectly selecting α are functions of a multi-dimensional uncertainty variable that encompasses both sources of uncertainty: imperfect information i and imperfect perception p (i.e., u=u(i,p)). However, we believe our two-step framework that explicitly distinguishes between these two sources of uncertainty allows us to better demonstrate the potentially offsetting effects of increased borrower-lender distance and the implementation of credit scoring techniques. Moreover, our extended model better reflects the multi-dimensional aspects of the uncertainty lenders face in practice.

[18] For example, banks may establish discrete "cut-off" values that restrict loan officers from taking applications or approving loans unless the borrower has collateral in excess of some fixed percentage of loan value, the borrower's operating earnings exceed interest expenses by some fixed multiple, or the borrower resides within the bank's local lending area. In the latter case, restricting lending to geographic areas most familiar to the analyst may increase the reliability of information and/or reduce the likelihood of analyst decision errors, and thus increase the likelihood the bank will benefit (i.e., increase profits) from the analyst decisions. Stein (2005) provides an analysis of how such cut-off values might be set in various lending environments.

[19] More specifically, we assume that these values are known in the sense that the lender can reasonably estimate them based on its experience making loans in its primary lending area (i.e., its geographic footprint).

$p^s_\alpha r^{XB}_\alpha g_\alpha > (1-p^s_\alpha) w^{XB}_\alpha l_\alpha$. Rearranging terms yields the condition that must be satisfied for the lender to benefit from selecting a specific action α under uncertainty (Heiner, 1986):

$$\rho_\alpha^{XB} = \frac{r_\alpha^{XB}}{w_\alpha^{XB}} > \frac{l_\alpha}{g_\alpha}\frac{(1-p_\alpha^s)}{p_\alpha^s} = T_\alpha . \tag{4}$$

The inequality has a straightforward interpretation: the lender will approve a loan application (i.e., select α) only when the joint reliability of the lender's information and ability to use that information (ρ^{XB}_α) exceeds some minimum expected performance bound (T_α) necessary to improve expected lender performance. It is intuitive that this minimum bound is determined by the expected relative return, l_α/g_α, and the inverse of the odds that the conditions for correctly selecting α exists, $(1-p^s_\alpha)/p^s_\alpha$. It is clear from equation (4) that the lender is more likely to approve loan applications with high values of r^{XB}_α, p^s_α and g_α and low values of w^{XB}_α and l_α. Of course, not all loans that *ex ante* satisfy (4) will improve *ex post* performance, but expected and actual performance should converge with repeated selection of α.

Our characterization of equation (4) presumes a representative bank with fixed values of g_α and l_α, a fixed expectation of p^s_α based on the lender's experience, and (hence) a single minimum performance bound T_α. We do not require, however, that p^s_α, g_α, and expected p^s_α remain fixed across lenders—in fact, we expect that these values are different across lenders. For example, lenders that are economically or strategically efficient (e.g., due to low production overhead, additional sales revenue from marketing ancillary financial services to borrowers, or adroit hedging of credit risk), will have "better" expected profit functions π(α;S) that generate higher expected performance gains g^e_α and/or lower expected performance losses l_α for all values of α and S. Similarly, a lender's perceptions of current and future economic conditions, its experience making loans in the local market, the acumen of the typical small businessperson in that market, or the types of loans the bank makes (e.g., construction loans, operating loans, mortgage loans) will influence the bank's expectations of the unconditional probability p^s_α that making a loan is the correct choice. For these reasons, we reasonably assume that lenders within a cross section of loan data (such as we use below in our empirical tests) operate with different estimated

minimum performance bounds T_α. This condition is crucial for the interpretation of our theoretical results and the application of these results in our empirical tests.

3.3. Graphical presentation

The unit-probability box in Figure 1 reflects the inherent trade off between type I and type II errors as the lender increases the frequency of selecting α. Moving from bottom-to-top in the box causes $r^{XB}_\alpha \rightarrow 1$, increasing the conditional probability that α is correctly chosen (fewer type I errors). Moving from left-to-right causes $w^{XB}_\alpha \rightarrow 1$, increasing the conditional probability that α is incorrectly chosen (more type II errors). In the upper-left corner of the box (where $r^{XB}_\alpha=1$, $w^{XB}_\alpha=0$, and the joint reliability ratio $\rho^{XB}_\alpha=\infty$), the lender has both perfect information and perfect decision skills and as a result makes no type I or type II errors (i.e., $t_I = t_{II} =0$).

More realistically, lenders have both imperfect information and imperfect decision skills (i.e., $\rho^{XB}_\alpha<\infty$); under these circumstances both type I and type II errors are determined by the frequency with which the lender selects α. We represent the tradeoff between type I and type II errors in Figure 1 by the *reliability ratio curve* (RRC) passing through points X, Y, and Z.[20] The RRC represents the locus of all attainable joint reliability ratios $r^{XB}_\alpha/w^{XB}_\alpha$ for a given level of uncertainty associated with imperfect information and decision-making skills.

The frequency of selecting α increases along the RRC from the bottom-left to the upper-right corner of the unit-probability box. The decision to never select α is represented by a point in the lower-left corner of the box, where both the probability r^{XB}_α of correctly selecting α and the probability w^{XB}_α of incorrectly selecting α are zero; in this extreme case the probability of making a type I error by incorrectly rejecting a good loan application is one ($t_I = 1-r^{XB}_\alpha = 1$) while the probability of making a type II error by incorrectly accepting a bad loan application is zero ($t_{II} = w^{XB}_\alpha = 0$). In contrast, the decision to

always select α is represented by a point in the upper-right corner of the unit-probability box, where the probability r^{XB}_{α} of correctly selecting α is one (e.g., t_I=0) and the probability w^{XB}_{α} of incorrectly selecting α is also one (e.g., t_{II}=1).[21] Thus, moving along the RRC requires a lender to make a tradeoff between type I and type II errors.

The concave shape of the RRC is economically intuitive. A lender located at (0,0) is not "in the market" in the sense that she never selects α, and she will enter the market only if it is expected to improve her performance. Holding g_{α}, l_{α}, and p^{s}_{α} constant, entry requires r^{XB}_{α} (the probability of correctly approving a good loan) to be large relative to w^{XB}_{α} (the probability of incorrectly approving a bad loan). The shape of the RRC in Figure 1 is consistent with these entry incentives, as the reliability ratio $\rho^{XB}_{\alpha} = r^{XB}_{\alpha}/w^{XB}_{\alpha}$ (the slope of the RRC) is high in the neighborhood (0,0). Moreover, loan applications in this "entry neighborhood" will be those with the most complete and most easily interpretable information, because lenders that select α only infrequently will select their borrowers judiciously. Thus, a lender who enters the market—say, locating at point X where the frequency of selecting α is relatively low—will make very few type II errors but will commit a large number of type I errors, and as a result will have a high joint reliability ratio $\rho^{XB}_{\alpha} = r^{XB}_{\alpha}/w^{XB}_{\alpha} = (1-t_I)/(t_{II})$. Selecting α more frequently—moving from point X to points Y or Z—requires the lender to consider applications with increasingly less complete or less easily interpretable information; this causes w^{XB}_{α} to increase more rapidly than any given increase in r^{XB}_{α} (i.e., the RRC is concave), resulting in a declining joint reliability ratio $\rho^{XB}_{\alpha,}$, a decreasing probability of type I errors, and an increasing probability of type II errors.

The reliability condition, equation (4), is represented in Figure 1 by the intersection of the RRC and T_{α} curves at point Y. The *minimum expected performance bound* T_{α} is linear, indicating a constant

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[20] The reliability ratio curve is also more commonly referred to as the Receiver Operating Characteristics (ROC) curve used in the signal-detection literature (Green and Swets 1974) and in the credit scoring and risk measurement literature (e.g., Engelmann, et al. 2003; Stein 2003, 2005; Blöchlinger and Leippold 2005). The concave slope of the curve is consistent with most empirical studies of behavior in the signal-detection experiments and the assumption that a likelihood-ratio criteria underlies the decision rule (e.g., Green and Swets 1974; Heiner 1986).

[21] In this case the reliability ratio equals one (i.e., ρ^{XB}_{α}=1), which represents the lower bound on the value of the reliability ratio; this result reflects the concave slope of the curve in Figure 1. See Green and Swets (1974) for a discussion of this constraint.

expected loan default rate everywhere along its length.[22] It can be interpreted as the joint reliability ratio above which selecting α is expected to improve performance, and below which choosing α is expected to worsen performance. The optimal frequency of selecting α is represented by the length of the RRC curve to the left of its intersection with T_α.

Note that entry by lenders is not inevitable. When T_α lies everywhere above the RRC curve—as illustrated by the unlabeled dashed line in Figure 1—the optimal frequency of selecting α is zero, with the lender locating at the lower-left corner of the box. This important corollary implies that uncertainty (as opposed to risk) may prevent lenders from extending credit even if expected profits are greater than zero. In this case, it would take either a reduction in uncertainty (i.e., RRC becomes more concave) or a more favorable combination of gains, losses, and/or expected p^s_α (i.e., T_α becomes less steep) for the lender to enter the market.

3.4. Comparative Statics

Figures 2, 3, and 4 illustrate how the equilibrium frequency of selecting α, and the impact this has on the expected loan default rates, are affected by the following exogenous shocks: improved loan performance losses associated with more generous government loan guarantees (or equivalently, improved loan performance gains associated with credit scoring); increased information imperfection associated with greater borrower-lender distance; and improved lender decision-making skills associated with the implementation of credit-scoring techniques. In each case, we present comparative static results for (a) a single representative lender (or alternatively, a group of identical banks) as well as for (b) a heterogeneous cross-section of lenders.

In Figure 2 we demonstrate the effects of a reduction in expected performance losses l_α (perhaps due to increased government loan guarantees), or equivalently an increase in expected performance gains g_α (perhaps due to credit scoring-related efficiencies in producing loans), on the selection of α. We start in

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[22] This can be seen by rewriting the slope as a ratio of type I and type II errors, i.e., $T_\alpha = (1-t_I)/t_{II}$, which follows from the definitions $t_I = 1-r^{XB}_\alpha$ and $t_{II} = w^{XB}_\alpha$ and the condition that the slope $T_\alpha = r^{XB}_\alpha(Y)/w^{XB}_\alpha(Y)$ is fixed.

equilibrium at point A for a single Lender A. Holding both information imperfection and decision-making skills constant (i.e., a fixed RRC), the ratio of expected loan returns l_α/g_α falls, causing a downward rotation of the minimum performance bound from T to T′. Because a larger number of loan applications now exceed the minimum performance bound, the lender selects α more frequently, moving along its RRC from A to A′. Because type II errors increase relatively faster than type I errors decline along the RRC, the lender's expected loan default rate will increase.[23]

The above analysis is applicable for either a single lender or a homogeneous group of lenders with identical RRCs. However, we empirically test the implications of this model using a cross-section of loans made by heterogeneous lenders, so we need to introduce inter-bank differences to our analysis and explore whether and how these differences alter our comparative static predictions. Consider Lender B that faces relatively more imperfect information and/or has relatively worse decision-making skills; this lender faces the dashed RRC in Figure 2. Due to this generally higher level of uncertainty, Lender B chooses α less frequently (takes less risk) than Lender A in equilibrium.[24] Regardless, the downward rotation from T to T′ has a similar effect on Lender B: the lender moves from B to B′, selecting α more frequently because more loan applications now exceed the minimum performance bound, and by doing so accepts a higher loan default rate. Hence, loan default rates increase with the loan performance ratio l_α/g_α, both for an individual bank and for a heterogeneous cross-section of banks.

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[23] The comparative statics in Figure 2 are consistent with the conventional theoretical wisdom regarding the effects of a government loan guarantee program. The increase in loan supply (higher α, reduced type I errors) in this scenario is consistent with the policy objective of expanded credit access, and the increase in the expected default rate (reduced slope of T_α') is consistent with the necessity of extending loan guarantees to encourage lenders to make loans to risky borrowers rationed out of the regular credit markets. We also note the corollary to this result: a decrease in government loan guarantees will increase the losses borne by the lender in the event of default (higher l_α) and reduce the expected loan default rate. This corollary corresponds to a policy lever the SBA has used in recent years to reduce its credit exposure (see Table 1 below).

[24] Since point A lies further along its RCC than does Point B, it corresponds to a larger value of α.

In Figure 3 we demonstrate the effect of increased information imperfection (perhaps due to an increase in borrower-lender distance) on the selection of α.[25] Again, we start in equilibrium at point A for a single Lender A. Holding both expected performance losses/gains constant (i.e., a fixed performance bound T_A) and decision-making skills constant, greater information uncertainty pushes all attainable joint reliability ratios further from the upper-left corner, making the RRC less concave. Because a smaller percentage of loan applications now exceed the minimum expected performance bound T_A , the lender selects α less frequently, moving from point A to point A′. The expected loan default rate does not change, as both the new and old equilibria just satisfy the lender's minimum performance standard T_A .

In a cross-section of lenders some banks will have higher or lower minimum performance bounds, caused by inter-bank differences in lending strategies, production techniques, risk-management practices, or local market conditions. Consider an inefficient lender B that operates with relatively high loan performance losses l_α and/or relatively low loan performance gains g_α; this lender faces the dashed minimum performance bound T_B in Figure 3. Facing worse loan returns, Lender B chooses α less frequently (takes less risk) than Lender A in equilibrium.[26] Regardless, the reduced concavity of the RRC has a similar effect on Lender B: the lender moves from B to B′, selecting α less frequently because fewer loan applications now exceed its minimum performance bound, but leaving its expected loan default rate unchanged. The crucial analytical point here is one of relative magnitudes: increased information imperfection causes a relatively substantial reduction in the loan approval rate α for the low-risk Lender B, but only a small decrease in α for the high-risk Lender A (i.e., BB′>AA′). Although the expected default rates for both lenders are unchanged in equilibrium, the overall composition of approved applications shifts toward high-risk loans, and as a result the expected average loan default rate increases. In this case, lender heterogeneity affects the cross-sectional empirical prediction.

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[25] We recognize that geographic distance is just one component, albeit an important one, of the informational distance between a borrower and a lender (Ghemawat 2001). For example, informational distances are likely to be greater in a monopoly market where a single bank lends to all borrowers, as opposed to a competitive market where multiple banks specialize in loans to certain industries.

In Figure 4 we demonstrate the effect of improved decision-making ability (perhaps due to the implementation of credit-scoring techniques) on the selection of α. Starting in equilibrium at point A and holding both expected performance losses/gains and information imperfection constant, improved decision-making skills pushes all attainable joint reliability ratios closer to the upper-left corner, resulting in a more concave RRC. Because a larger percentage of loan applications now exceed the minimum expected performance bound T_A, the lender selects α more frequently, moving from point A to point A′. Once again, the expected loan default rate for the individual Lender A does not change.

Now consider the Figure 4 analysis for the case of heterogeneous lenders. Again, let Lender B be a relatively inefficient lender that—facing worse loan returns and the dashed minimum performance bound T_B—chooses α less frequently (takes less risk) than Lender A in equilibrium. The increased concavity of the RRC moves the lender from B to B′, selecting α more frequently because more loan applications now exceed its minimum performance bound, but leaving its expected loan default rate unchanged. As before, this is a relatively substantial increase in the loan approval rate α for the low-risk Lender B compared to the small increase in α for the high-risk Lender A (i.e., BB′>AA′). This shifts the overall composition of approved applications toward low-risk loans, and as result the expected average loan default rate declines.[27]

Before proceeding to our empirical tests, we point out that our theoretical model provides a conceptual framework that is absent from, and also consistent with the results of, the extant empirical literature on credit scoring and small business lending. Frame, Srinivasan, and Woosely (2001) and Frame, Pahdi, and Woosley (2004) both found that small business lending increased at banks that adopted credit scoring techniques, consistent with the quantity-increasing information effects in Figure 4. Frame, Srinivasan, and Woosely (2001) concluded that credit scoring approaches reduced the cost of acquiring

[26] Since point A lies further along the same RCC than does Point B, it corresponds to a larger value of α.

[27] Shaffer (1998) provides a different theoretical explanation for this negative relationship: if all banks shift from relationship lending to credit scored lending—so that all banks are now using the same standards—then applicants rejected by one bank become more likely to be rejected by other banks as well, reducing the number of poor credit risks that get loans (and eventually default) via re-application.

information, consistent with the analysis in Figure 2. And Berger, Frame, and Miller (2005) found higher nonperforming loan ratios at banks that credit-scored small business loans, consistent with an analysis in which the potential default-increasing cost effects associated with credit scoring in Figure 2 offset the potential default-reducing information effects associated with credit scoring in Figure 4.

4. Empirical implementation

We test the loan default implications of our theoretical model using a discrete-time hazard model and a large random sample of loans guaranteed under the Small Business Administration's 7(a) program and originated by U.S. commercial banks between 1984 and 2001. We do not test the theoretical loan supply implications of our model—i.e., the frequency with which lenders choose α—because our random sample of loans does not include the entire quantity of small business loans supplied by these lenders.

4.1. Small business loan data

The SBA 7(a) loan program provides loan guarantees for small business firms that are otherwise unable to access credit through conventional means; as indicated earlier, a substantial portion of dollar value of credit to small U.S. businesses flows through this program. Our data set is a random sample of 29,577 SBA 7(a) loans originated by 5,535 qualified SBA program lenders between January 1984 and April 2001. We observe each loan quarterly, beginning with the quarter in which it was originated and continuing on through the quarter in which the loan either matured, paid-off early, or defaulted. There are 491,512 loan-quarters in our data. Table 1 provides some annual descriptive statistics for the loans in our data sample.

The SBA provides loan guarantees to eligible businesses through qualified financial institutions (mainly but not exclusively commercial banks) that select the firms to receive loans, initiate SBA involvement, underwrite the loans within SBA program guidelines, and monitor and report back to the SBA the progress of these loans. Under the 7(a) program, the SBA shares all loan losses *pro rata* with the lending institution (i.e., the SBA does not take a first-loss position), based on the remaining outstanding balances of both principal and interest at the time of default and the contractual guarantee percentage stipulated by the SBA at the time of the loan. Because lenders share in the losses, they have (perhaps

reduced) incentives to screen for creditworthiness, monitor on an ongoing basis, or set appropriate loan interest rates and contract terms.[28] The lender typically holds and services the loan until maturity; however, there is also a secondary market for the guaranteed portion of these loans, and this market facilitates the securitization of portfolios of SBA loans.[29] Loans in arrears more than sixty days may be put back to the SBA in exchange for a payment equal to the guaranteed portion of the remaining outstanding principal plus delinquent interest.

We cannot identify whether or not the individual loans in our data were originated using a credit scoring tool. Instead, we distinguish between credit-scoring and non-credit-scoring lenders based on the findings of a survey of the 200 largest U.S. bank holding companies taken in 1998. (See Frame, Srinivasan, and Woosely 2001 for a description of this survey.) While this survey provides the best extant source on the dissemination of small-business credit-scoring techniques at U.S. banking companies, these data have some obvious limitations. First, we do not know whether these lenders credit scored all, or just a portion, of their small business loan applications. Second, we cannot identify lenders that adopted credit-scoring technology after 1997. Third, we cannot identify credit-scoring lenders affiliated with banking companies too small to be included in the survey. While these limitations are not desirable, they are not especially problematic. The first limitation simply constrains the form with which we state our credit-scoring hypothesis: We test whether *banks that use credit scoring models* have different default patterns, not whether *credit-scored loans* have different default patterns. We address the second limitation by estimating our regression models for a sub-sample of pre-1998 data. The third limitation is unlikely to be meaningful insofar as small business credit scoring was almost exclusively a large bank activity prior to 1998.

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[28] The credit risk associated with long-term SBA loans, as well as the intertemporal default patterns of those loans, has been shown to be quantitatively similar to those of speculative grade debt. See Glennon and Nigro (2005, Table 1).

[29] While is it permissible to securitize the unguaranteed portion of an SBA loan, most lenders retain this portion of the loan for its upside risk and to better maintain the borrower-lender relationship. Only 59 securitization transactions between 1994 and 2000 used either unguaranteed portions of SBA 7(a) loans or conventional small business loans as collateral (Board of Governors 2000).

The data in Table 1 show that the number of scoring banks (by our definition) increases between 1993 and 1997 as this technology became more widely implemented, after which the number of scoring banks declines due to industry consolidation.[30] Although only a handful of the 5,535 banks in our sample used credit scoring, these banks were generating approximately one out of every three loans during the final years of our sample. Default rates for SBA loans exhibit a mild cyclical pattern during our sample period, but the overall trend is downward: from a high of around 27% for loans originated in 1984, to a low of around 5% for loans originated in 2001. Declining default rates may be associated with improved macroeconomic conditions during these years, an improved climate for small businesses, or improvements in the SBA loan program itself.[31] (Note that the default percentages in Table 1 reflect the ex post probability of default over the full life of the loan. Statistics for the quarterly default rates, which better correspond to the hazard-rate concept in our empirical model, are displayed in Table 2.)

The data suggest several changes in the SBA program over time. For example, the SBA guarantee percentage declined substantially during the late-1990s, from around 86% for loans originated in 1995 to less than 70% for loans originated at the end of our sample period. By reducing the value of the lender's put option, a lower guarantee should increase lenders' incentives to carefully screen and monitor loans. Consistent with this, the interest rate premium ratio (the loan interest rate divided by the prime rate) increased from 1.47 in 1995 to 2.13 in 2001, suggesting that lenders reacted to increased loss exposure (lower SBA guarantees) by charging higher interest rates.[32] The percentage of loans sold off by the originating lenders also increased substantially at the end of the sample period, evidence of a more liquid secondary market for the guaranteed portion of SBA loans.

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[30] Because we do not have data to identify lenders that adopted credit scoring for the first time after 1997, the final column of Table 1 understates the number of credit-scoring lenders in 1998 through 2001.

[31] The large declines in defaults and prepayments at the very end of the sample period are due mostly to right-censoring in the data (i.e., recently originated loans that have not yet matured, and therefor are less likely to have either defaulted or pre-paid). Note, however, that the average default rate had fallen to near 8% for loans originated in 1993, which by end of our sample period had seasoned well beyond their quarters of peak default risk.

[32] It is unlikely that the monotonic increase in the interest rate premium ratio 1995-2001 was completely caused by a decrease in the prime rate charged by U.S. banks. The average annual prime rates during 1995 through 2000 were, respectively, 8.83%, 8.27%, 8.44%, 8.35%, 8.00%, and 9.23%. The prime rate did decline to an annual average of 6.91% for all of 2001, but our data sample ends in April of that year.

The average distances between SBA lenders and their small business customers increased markedly toward the end of our sample period. Between 1983 and 1993, the median borrower-lender distance fluctuated in a tight band between 5.65 miles and 7.37 miles, but began accelerating soon after that, reaching 10 miles by 1997 and 20 miles by 2001. Borrower-lender distance increased for *both* credit-scoring and non-credit-scoring banks, an indication that changes in industry conditions other than credit scoring (e.g., spatial structure of lenders relative to borrowers, new computer technology, remote internet access) allowed or required lenders to reach further to make small business loans. But the most dramatic increase in borrower-lender distance is for the credit-scoring lenders: half of the loans originated by these banks in 2001 were to borrowers located 142 miles or more from the lending office.

Loans made by credit-scoring lenders carried lower SBA guarantee rates on average: for example, only 63 percent for loans originated by scoring lenders in 2001, compared to 73 percent for non-scoring lenders. This suggests that the SBA may have considered credit-scored loans to be riskier than average (although we have no direct evidence to support this conjecture). Non-credit-scoring banks were substantially more likely to sell-off the guaranteed portions of these loans: for example, 50 percent of the loans originated by non-scoring lenders in 2001 were sold-off, compared to only 37 percent for scoring lenders. This likely reflects the difference in the liquidity needs of the mostly small non-scoring banks (median assets of $231 million) and the mostly large scoring banks (median assets of $23 billion) that have much greater access to financial market funding (U.S. Government Accounting Office 1999).

4.2. A discrete-time hazard modeling approach

The discrete-time hazard framework is an empirical analog to the semi-parametric Cox proportional hazard model (Allison 1990; Shumway 2001; Brown and Goetzmann 1995; Deng 1995). Consistent with all empirical approaches based on hazard functions, we measure the likelihood that loan i ($i = 1,2,\ldots,N$) originated at time $t = 0$ will default during some time period $t > 0$ ($t= 1,2,\ldots T$), given that it has not defaulted up until that time. More specifically, the discrete-time hazard approach requires us to report our data in an 'event history' format: a series of binary variables $D_i(1),\ldots D_i(T)$, where $D_i(t)=1$ if

loan i defaults during time period t, and $D_i(t)=0$ otherwise.[33] These N separate event histories for each loan i are 'stacked' one on top of the other, resulting in a column of zeros and ones having $\sum_{i=1}^{N} T_i$ rows. This event-history data design permits a hazard model to be estimated using qualitative dependent variable (e.g., logit or probit) techniques. We define D^*_{it} as a latent index value that represents the unobserved propensity of loan i to default during time period t, conditional on covariates X and W:

$$D^*_{it} = \mathbf{X_i}\boldsymbol{\beta} + \mathbf{W_{it}}\boldsymbol{\gamma} + \varepsilon_{it} \tag{5}$$

$$= \mathbf{Z}\boldsymbol{\phi} + \varepsilon_{it}$$

where **X** is a vector of time-invariant covariates, **W** is a vector of time-varying covariates, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the corresponding vectors of parameters to be estimated, and ε is an error term assumed to be distributed as standard logistic. We write (5) more compactly using $\mathbf{Z} = [\mathbf{X},\mathbf{W}]$ and $\boldsymbol{\phi} = \begin{bmatrix} \beta \\ \gamma \end{bmatrix}$ to represent the full set of time-invariant and time-varying covariates and parameters, respectively. We further define:

$$D_{it} = 0 \text{ if } D^*_{it} \leq 0$$

$$D_{it} = 1 \text{ if } D^*_{it} > 0$$

so that the probability that $D_{it} = 1$ (that is, the probability that loan i defaults during period t conditional on having survived until period t, or the hazard rate) is given by:

$$\text{prob}(D^*_{it} > 0) = \text{prob}(\mathbf{Z}\boldsymbol{\phi} + \varepsilon > 0)$$

$$\text{prob}(D^*_{it} > 0) = \text{prob}(\varepsilon > -\mathbf{Z}\boldsymbol{\phi})$$

$$\text{prob}(D_{it} = 1) = \Lambda(\mathbf{Z}\boldsymbol{\phi}) \tag{6}$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function. We estimate equation (6) using standard binomial logit techniques. Based on the construction of the data, we refer to this empirical approach as a

[33] Measuring time in quarters, the event history $D_i(1),...D_i(t),...D_i(T)$ for a 3-year loan will be five zeros followed by a one (0,0,0,0,0,1) if that loan defaults in the sixth quarter after it was originated, but will be a string of twelve zeros if that loan does not default. Loans that are prepaid prior to their contractual maturity, or right-censored loans (still performing but not yet mature at the end of our sample period), are also represented by strings of zeros.

'stacked-logit' model. The stacked-logit is a very flexible approach compared to most other multivariate hazard function models: in addition to allowing for time-varying covariates on the right-hand-side of the logit model, this approach does not require us to impose any parametric restrictions (e.g., a Weibull distribution) on the loan default distribution (the hazard function).

4.3. Regression specification and hypothesis tests

We specify the stacked-logit model as follows:

$$\begin{aligned}\Pr[\, D_{it}=1|\mathbf{Z}\,] \;=\; \Lambda[\; & SBA\%_i,\ lnDISTANCE_i,\ SCORER_{ij},\ lnDISTANCE_i{*}SCORER_{ij},\\ & MATURITY_i,\ FIRMSIZE_i,\ NEWFIRM_i,\ HHI_i,\ URBAN_i,\ CLP_{ij},\ PLP_{ij},\\ & BANKSIZE_{ij},\ RESERVES_{ij},\ CHARGEOFFS_{ij},\ JOBGROWTH_{it},\\ & INCOMEGROWTH_i,\ POLICY9401_i,\ POLICYPOST89_i,\ LOANAGE_{it}\,;\ \boldsymbol{\phi}\,] \qquad (7)\end{aligned}$$

where i indexes the loan and j indexes the lender. The binary dependent variable D_{it} equals one if loan i defaulted in quarter t, and equals zero in all other quarters during the life of the loan. With the exception of the time-varying covariates (JOBGROWTH, INCOMEGROWTH and LOANAGE, defined below), all other variables are measured in the quarter in which the loan was originated. Table 2 shows definitions, summary statistics, and data sources for each of the variables specified in (7). Our main statistical tests are provided by the coefficient estimates on the variables SBA%, lnDISTANCE, SCORER, and lnDISTANCE*SCORER. The remainder of the variables used to specify the model (discussed in detail below) were selected largely based on the specification used in Glennon and Nigro (2005b).

SBA% equals the percentage of the outstanding loan balance guaranteed by the SBA. SBA% is our (inverse) proxy for expected performance losses l_α, or more exactly, the reduction in loss given default due to the government guarantee. We expect a positive estimated coefficient on SBA%, consistent with movement from point A to point A′ (or point B to point B′) in Figure 2.

DISTANCE equals the mile distance "as the crow flies" between the Zip Code centroid of the small business borrower and the Zip Code centroid of the lending office, which may or may not be the bank's head office. Recognizing that the cost-per-mile of travel is decreasing in distance (i.e., time and

cost economies of scale in distance), we specify this variable in natural logs.[34] Thus, the natural log of borrower-lender distance lnDISTANCE is our proxy for information imperfection, or more exactly, the potential deterioration in the quality of lender information about borrower creditworthiness due to the increased costs of gathering information associated with distance.[35] We expect a positive estimated coefficient on lnDISTANCE, consistent with the net cross-sectional increase in loan default rates illustrated in Figure 3.

SCORER is a binary variable equal to one if the lender is affiliated with a banking organization that used credit-scoring to screen at least some of its small business loan applications.[36] SCORER is our proxy for the lender's decision-making ability, or more exactly, the potential improvement in lenders' assessments of borrower creditworthiness made possible by credit-scoring models. If this is the predominant effect of credit scoring, then we expect a negative estimated coefficient on SCORER, consistent with the net cross-sectional decrease in loan default rates illustrated in Figure 4. However, our theoretical model allows for two possible offsetting outcomes. First, credit-scoring approaches rely on a limited set of quantifiable variables, and as such they may be informationally inferior to traditional lending regimes and result in increased information imperfection, with offsetting (default-increasing) effects as illustrated in Figure 3. Second, the scale economies, revenue synergies, and risk diversification effects associated with credit-scoring approaches may improve expected loan performance gains and losses, with offsetting (default-increasing) effects as illustrated in Figure 2.

As an empirical question, the estimated marginal effect of SCORER on loan default will reflect the *net* decision-making, information imperfection, and financial performance effects associated with

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[34] We also estimate (7) using discrete measures of borrower-lender distance. See Table 3 below.

[35] The degree of information available in the market about a borrowing firm is difficult to observe and measure. Studies in the finance literature typically use the size of a borrowing firm to proxy for information availability. (For a recent critique of this practice, see Holod and Peek 2005, who use publicly-traded versus privately-held status to proxy for information availability.) In this study, we do not use firm size as a proxy for information because the borrowing firms in our sample are very small (mean number of employees = 12) and none are publicly traded; even the largest of the firms in our sample are informationally opaque to lenders other than those with whom they already have lending relationships.

[36] We also estimate (7) using an alternative version of SCORER equal to one only if lenders used a fully automated credit scoring approach that prohibited loan officers from overruling their models' accept/reject decisions.

small-business credit scoring.[37] While it is not possible to empirically identify these separate credit-scoring effects, the interaction term lnDISTANCE*SCORER may disentangle them to some extent. We expect a negative estimated coefficient on lnDISTANCE*SCORER if (as implied by comparing the symmetric opposite effects in Figures 3 and 4) improved decision-making from credit-scoring techniques either partially or fully mitigates the informational imperfection associated with borrower-lender distance.

We delay our discussion of the remaining right-hand-side control variables until the next section. Note that equation (7) *does not* include a loan pricing term, such as an interest-rate spread, on the right-hand-side. We would like to test whether and under what circumstances SBA loans are risk-priced—for example, do credit-scoring techniques generate information that allows lenders to more accurately risk-price these especially opaque credits? But performing such a test within our framework raises endogeneity issues: under normal circumstances, loan spreads will be endogenous to the probability of loan default, because banks charge higher interest rates for riskier loans. We deal with this issue in the following straightforward fashion: we first estimate equation (7) as specified above without a loan pricing variable, and then we re-estimate it after adding a loan pricing variable (results displayed in the Appendix to this paper). Our loan pricing variable SPREAD equals the loan interest rate divided by prime interest rate at the time of the loan.[38]

5. Results

Table 3 displays complete estimation results for our discrete-time hazard model (7) using the full data sample and alternative specifications of the key test variables SCORER and DISTANCE. Tables 4a through 4d display partial estimation results for various sub-samples of the data (by time period, loan

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[37] The theoretical ambiguity between the information-enhancing and cost-reducing effects of lending information technology is also present in Hauswald and Marquez (2003), although their model focuses primarily on the impact of these effects on competitive loan pricing.

[38] We were also concerned about the potential for collinearity stemming from pricing tradeoffs between SPREAD and SBA%, but this concern turned out to be unfounded. Banks typically take maximum advantage of the SBA guarantee available to them; for example, 90 percent of the loans in our random sample carry guarantees within 15 basis points of the maximum guarantee percentage for their loan type and lending status. The correlation between SPREAD and SBA% is only 0.01 in our data, and statistical tests based on the estimated regression variance-covariance matrix rejected the hypothesis of collinearity between these two variables. Thus, there would appear to be little meaningful substitution in practice between loan rates and loan guarantees.

size, lender size, and borrower-lender distance). Estimated logit coefficients appear in the top of these tables along with Chi-square tests of statistical significance. The marginal effects reported at the bottom of each table allow us to interpret the economic significance of changes in the values of the main test variables.[39]

5.1. Results from full-sample regressions

The full sample yields strong statistical evidence consistent with the predictions of our theoretical model. We find positive and statistically significant coefficients on SBA% in all of the regression specifications displayed in Table 3, in line with the prediction that higher loan guarantees will yield higher loan default rates. The economic effect is non-trivial. Based on the estimates in column [1], a ten percentage point increase in SBA% at the means of the data (from 80% to 90%, or approximately one standard deviation) is associated with about a 4.8 percent increase in the probability of loan default in a given quarter.[40] Coupled with the sub-sample results reported in later tables, these findings are consistent with the straightforward financial notion that insurance (e.g., in the form of loan guarantees) provides incentives for risk-taking; while in our theoretical model this increased risk-taking is accompanied by increased amounts of loans, we cannot test for loan supply effects given the constraints of our data.

We also find positive and statistically significant coefficients on lnDISTANCE in both columns [1] and [2], consistent with the theoretical prediction that greater information uncertainty (e.g., due to increased borrower-lender distance) will yield higher loan default rates. Based on the estimates in column [1], a doubling of borrower-lender distance at the means of the data (from 66 miles to 132 miles, well less than one standard deviation) is associated with a 2.4 percent increase in the probability of loan default in a given quarter.[41] Of course, as discussed above, the costs associated with borrower-lender distance are not

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[39] The marginal effects are constructed as follows: We calculated the derivatives with respect to the three main test variables (lnDISTANCE, SCORER, and SBA%) based on the estimated logit coefficients; evaluated these derivatives separately for each loan-quarter observation in our data; and took the unweighted averages of these evaluated derivatives across all observations. Greene (1997) shows that this procedure is preferred to the standard method of derivatives evaluated at the sample means, and that the two approaches are equivalent in large samples.

[40] The calculation is (0.00430*.10)/0.00897 = 0.04796, where .00897 is the mean quarterly loan default rate from Table 2.

[41] The calculation is (0.00031*ln2)/0.00897 = 0.02395.

constant. (Recall that we specify DISTANCE in natural logs because travel expenses increase at a decreasing rate with distance.) We test the loan default-distance relationship more flexibly in column [3], where borrower-lender distance is specified in discrete rather than continuous terms. DIST2550 equals one when borrower-lender distance is between 25 and 50 miles, and DIST50UP equals one when borrower-lender distance is greater than 50 miles.[42] Relative to "local" loans made to borrowers less than 25 miles from the bank, loans between 25 and 50 miles from the bank were about 11 percent more likely to default, and loans more than 50 miles from the bank were about 22 percent more likely to default.[43] Thus, we find that borrower-lender distance is positively associated with loan default probability (holding underwriting technique constant) both at the means, and away from the means, of the data.

The results for SCORER are consistent with the following scenario from our theoretical model: on average, the effects of credit scoring-related improvements in decision-making ability (which reduce loan default rates, see Figure 4) are more than offset by the effects of credit scoring-related improvements in bank profit functions (which increase loan default rates, see Figure 2) and/or credit-scoring related reductions in information quantity and/or quality (which increase loan default rates, see Figure 3). That is, we find positive and statistically significant coefficients on SCORER in all of the regression specifications reported in Table 3. This net economic effect is substantial. Based on the estimates in column [1], and holding borrower-lender distance constant, the quarterly probability of loan default was about 22.7 percent higher for loans made by banks that used credit scoring to underwrite at least some of their small business.[44] We find similar results in column [2] where we redefine SCORER to equal one only for lenders that used a fully automated, non-discretionary approach to small-business credit scoring in which loan officers were not allowed to overrule their models' accept/reject decisions. Holding

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[42] While 25 miles and 50 miles are *ad hoc* choices, note that both thresholds exceed the median borrower-lender distance in every year of our analysis (see Table 1). The loans in our sample were distributed as follows: 74% in the less-than-25-miles category, 10% in the 25-to-50-miles category, and 16% in the greater-than-50-miles category. This distribution is consistent with Wolken and Rohde (2002) who reported that 70 percent of all small business loans in 1998 were accessed from financial institutions within 30 miles of the business.

[43] The calculations are 0.00097/0.00897 = 0.10814 and 0.00198/0.00897 = 0.2207, respectively.

[44] The calculation is (0.00204*1)/0.00897 = 0.2272.

borrower-lender distance constant, the quarterly probability of loan default was about 16.8 percent higher for loans made by banks that used an automated credit scoring approach.

While it is not possible to completely disentangle the various effects of credit scoring on loan default rates, our regressions yield some suggestive evidence. The coefficient on the interaction term lnDISTANCE*SCORER is negative and statistically significant, consistent with our theory model's prediction that the improved decision-making ability associated with credit scoring techniques should partially or fully mitigate the informational uncertainty associated with borrower-lender distance. Based on the estimates in column [1], the marginal effect of lnDISTANCE conditional on SCORER=0 equals 0.00036, which for a doubling of borrower-lender distance translates into a 2.8 percent increase in the quarterly probability of loan default. When SCORER=1, however, the marginal effect equals –0.00011, which translates into a relatively small 0.8 percent reduction in the loan default rate for a doubling of distance. These results suggest that the deleterious impact of increased borrower-lender distance on loan default rates was, on average, largely neutralized at banks that used credit scoring techniques.

Distance may impact the transmission of information differently for local loans and longer-distance loans, and this differential may in turn determine the choice of a lending technology. For example, banks may choose a relationship lending approach for borrowers close enough to visit inexpensively, but choose a transactional credit-scored lending approach for far-away borrowers too costly to visit in-person. Indeed, the data displayed in Table 1 above imply a causal connection between the introduction of small business credit-scoring and average borrower-lender distance. Moreover, the regression results in column [3] suggest that allocating underwriting approaches in this fashion is optimal. For "local" loans made to borrowers less than 25 miles from the bank, credit scoring <u>increased</u> the quarterly probability of loan default by about 23 percent—but for loans made to borrowers more than 50 miles from the bank, credit scoring <u>decreased</u> the likelihood of loan default by about 5.4 percent.

5.2. Control variables

For the most part, the rest of the coefficients reported in Table 3 have sensible signs and are statistically significant. Small business loans with shorter maturities (i.e., 3-year and 7-year maturities:

MATURITY3 and MATURITY7) were more likely to default than loans with longer maturities (i.e., 15-years). This may have to do with the nature of the amount and type of collateral at stake (long-term loans tend to be larger, and are secured by land and buildings) or the fact that long-term loans are more likely to be securitized and hence the lender has reputational capital at stake.[45] Borrowers that are less than 3-years old at loan origination (NEWFIRM) were more likely to default on their loans than more mature small businesses. Holding these age effects constant, larger borrowers (FIRMSIZE) were also more likely to default.

Competitive rivalry among banks is associated with higher loan defaults. Although the coefficient on HHI is never statistically significant, the coefficient on the interaction term HHI*URBAN is statistically negative, indicating that increased concentration (reduced competitive rivalry) was associated with lower default rates in urban markets. This finding is consistent with Petersen and Rajan (1994, 1995), who argue that lenders in concentrated markets are more likely to cultivate relationships with their small business clients (e.g., engage in careful monitoring that reduces loan default rates). We emphasize that the welfare implications of this result are ambiguous, because concentrated markets are likely to generate a smaller supply of loans.

Experienced SBA lenders with good lending records (i.e., certified lenders and preferred lenders: CLP and PLP) were less likely to make loans that defaulted. Large lenders (BANKSIZE) also had lower loan default rates, perhaps because these lenders could afford to attract and retain high-quality staff that specialize in underwriting and monitoring loans, or perhaps because small banks face more limited growth opportunities and face pressure to grow their loan portfolios by reaching further into the risk pool. All else equal, banks that wrote-off large amounts of bad loans in the recent past (CHARGEOFFS) were more likely to originate small business loans that eventually defaulted (perhaps indicating an appetite for

[45] The average 15-year loan in our sample was $253,000, compared to $131,000 for 7-year loans and $57,000 for 3-year loans. About 26 percent of the 15-year loans in our sample were sold by the original lender, compared to about 18 percent of 7-year loans and less than 2 percent of 3-year loans.

credit risk), and banks with high levels of loan loss reserves (RESERVES) were less likely to originate small business loans that eventually defaulted (perhaps indicating a low tolerance for insolvency risk).

Robust economic activity at the time of loan origination (INCOMEGROWTH) and during the life of the loan (JOBGROWTH) were both associated with reductions in loan defaults. As expected, default rates were higher for loans originated under the relatively liberal SBA credit policies between 1994 and 2001 (POLICY9401), and default rates were lower for loans originated after the passage of the Federal Credit Reporting Act of 1989 which required the SBA to improve its risk-management practices (POLICYPOST89), ceteris paribus. The piecewise hazard function (the LOANAGE terms) has the familiar concave shape, with quarterly default rates peaking on average eight or nine quarters after loan origination.

We re-estimated each of the regressions in Table 3 after adding SPREAD to the right-hand-side. The results, displayed in Appendix Table A3, indicate that loans carrying a higher contractual risk premia were more likely to default: the coefficient on SPREAD is always positive and significant. This may reflect a causal relationship that runs from expected default probability to loan interest rates—that is, lenders are able to risk-price at least some portion of these informationally opaque loans. Alternatively, SPREAD may merely be a proxy for some other unobserved (by us) variable that is related to the risk of the loan. Regardless, we note that the signs, magnitudes, and statistical significance of the other coefficients are unchanged from Table 3, so any estimation biases caused by endogeneity are minimal.

5.3. Results from sub-sample regressions

We re-estimated equation (7) for sub-samples of loans based on the years in which the loans were originated (Table 4a), the size of the loan (Table 4b), the size of the lender (Table 4c), and borrower-lender distance (Table 4d). Our main results are relatively robust to these additional tests; results that deviations from the full-sample results in Table 3 are economically sensible and in some cases are instructive for public policy.

Table 4a displays selected results from three sub-sample regressions: the portion of the sample during or before the Atlanta Fed credit-scoring survey (pre-1999), the first half of the sample period

(1984-1992), and the second half of the sample period (1993-2001). The coefficient on SBA% remains positive throughout, but is statistically insignificant in regressions [4] and [5]. This is more likely due to the general lack of variation in SBA% during the early part of our sample period (see Table 1) than any differential response of lending banks to loan subsidies. The coefficient on lnDISTANCE remains positive and statistically significant throughout, but the magnitude of this effect declines substantially over time. This suggests that advances in information, financial, and/or communications technologies over time better equipped banks to deal with the uncertainties of lending at long geographic distances. Perhaps because of these improvements, the marginal impact of SCORER declined somewhat over time, although the coefficient on this variable remained positive and significant throughout.

Table 4b contains selected results from sub-sample regressions for loans in amounts less than $100,000, for loans in amounts less than $250,000, and for loans in amounts greater than $100,000. The coefficient on SBA% remains positive and significant for the small loan sub-samples, but equals zero for the large loan (>$100,000) sub-sample. This result implies that the SBA subsidy encourages banks to approve loan applications from the smallest businesses—which involve the most information uncertainty—but does not influence banks' accept/reject decisions for loans from larger businesses which (assumedly) have better access to credit in any event. The coefficients on lnDISTANCE and SCORER are positive and significant throughout, and both tend to get larger as the loans in the sub-sample become larger. These results may indicate, respectively, that larger borrowers search longer and further for loans (resulting in a positive link between loan size, distance, and loan default) and that the informational inadequacies of credit scored lending (relative to relationship lending) are amplified at larger, more complex borrowers. The coefficient on the interaction term SCORER*lnDISTANCE is negative as before, although it becomes statistically non-significant for the sub-sample of very small loans (≤$100,000).

Table 4c contains selected results from sub-sample regressions for loans originated by small banks (less than $1 billion in growth-adjusted 2001 dollars) and by large banks (all other banks).[46] The results for the small bank sub-sample are robust to the full-sample results with the exception of the coefficient on SBA%, which was statistically non-significant. Evidently, the underwriting practices of small, relationship-based lenders tend to be unaffected by loan guarantees, in contrast to larger banks who are more likely to treat small business loans as financial transactions and/or are willing to relax their underwriting standards in the presence of this credit insurance. The results for the large bank sub-sample are robust to the full-sample results with the exception of the coefficient on SCORER*lnDISTANCE, which remains negative but becomes statistically non-significant.

Table 4d contains selected results from sub-sample regressions for loans made to borrowers at various geographic distances from the lending office: 0-to-10 miles, 10-to-25 miles, 25-to-50 miles, and greater than 50 miles. Given this method of sub-sampling (which truncates the upper end of DISTANCE in the first three sub-samples), it is not surprising that the coefficient on lnDISTANCE is statistically positive only for the greater-than-50-miles regression. The coefficient on SCORER is positive and significant only in the 0-to-10 mile regressions. This result is consistent with those reported earlier in Table 3, column [3]: loans to borrowers closest to the lender are exactly the loans for which transactional credit-scored lending should perform the worst relative to relationship lending, as close geographic proximity should maximize the informational advantages of personal borrower-lender relationships. Similarly, the coefficient on SBA% is positive and significant only in the 0-to-10 mile group, suggesting that SBA loan guarantees enticed banks to make loans to opaque borrowers located close-by where monitoring is relatively easy, but not at longer distances where monitoring is more costly.

We also re-estimated the regressions in Tables 4a through 4d after putting SPREAD on the right-hand-side. The results are displayed in Appendix Tables A4a through A4d. The signs, magnitudes, and

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[46] The size threshold was $1 billion for banks in 2001. For previous years, an index (2001=100) was used to reduce the size threshold by an amount equal to the nominal annual growth rate of the median U.S. commercial bank.

statistical significance of the coefficients on our main test variables SBA%, lnDISTANCE, SCORER, and lnDISTANCE*SCORER are robust to this change, suggesting that any statistical bias due to the endogeneity of SPREAD is immaterial. The estimated coefficients on SPREAD in these regressions are collectively consistent with the conjecture that credit-scoring underwriting techniques generate an information set that allows lenders to more accurately price loan default risk. The coefficient on SPREAD is positive and significant only in sub-samples with relatively high percentages of credit-scored loans: in the latter part of the sample after credit-scoring had been introduced (A4a), for small-sized loans which are more likely to be credit-scored (A4b), for large banks which are more likely to be using credit-scoring techniques (A4c), and for long-distance loans which are more likely to be credit-scored (A4d).

6. Conclusions and implications for policy

Over the past two decades the geographic distance between small business borrowers and their commercial bank lenders has increased dramatically, largely due to improvements in information, communications, and financial technologies that allow quicker and more efficient analysis of information about small borrower creditworthiness. In this study, we develop a theoretical model of lender decision-making under risk and uncertainty that yields testable implications about the impact of borrower-lender distance, credit-scoring technologies, and government loan subsidies on the performance of small business loans. We test these implications using a random sample of 29,577 small business loans made by U.S. commercial banks between 1984 and 2001 under the SBA 7(a) loan program. Because in recent years a substantial portion of the small business loans in the U.S. were originated through this program, our findings have substantial relevance for the overall creation and performance of small business credit. We believe this is the first study to test the impact of borrower-lender distance, credit-scoring models, and the tradeoff between these two phenomena on the probability of loan default.

We find substantial support in the data for the predictions of our theoretical model. The probability of loan default increased with borrower-lender distance, both at the means of the data as well as for small business borrowers located further away. According to our estimates, this deleterious impact of distance declined over time, implying that changes in banking industry structure (e.g., a consolidated

and thus more efficient industry) and/or information and communications technologies (e.g., portable computers, spreadsheet analysis, the Internet) during our sample period improved banks' abilities to lend to small businesses.

Importantly, we find that the default-increasing effects of borrower-lender distance were substantially mitigated at banks that used credit-scoring models to screen at least some of their small business loan applications. After controlling for these distance-related effects, however, we find that lenders that used credit-scoring models experienced *higher* default rates. This finding suggests that banks are willing to accommodate the costs of higher expected default rates in exchange for ancillary benefits associated with high-volume credit-scored and securitized lending strategies (e.g., scale economies, fee generation, diversification, recycling of equity capital). Alternatively, this finding could also indicate that credit-scoring underwriting processes simply collect less information, and thus lead to more loan approval errors. We feel that the former explanation is more likely than the latter explanation, given that the strongest statistical associations between loan interest rates and ex post loan defaults occur in sub-samples with high concentrations of credit-scored lending. In either case, these findings complement those of Berger, Frame, and Miller (2005), who found that credit-scoring banks not only tend to make higher volumes of small business loans, but these loans tend to be riskier. Our results are robust to whether credit-scoring banks used a fully automated approach or allowed loan officers the discretion to overrule these models.

We find that government loan guarantees and competition in local lending markets are both associated with higher probabilities of loan default. These findings illustrate the inherent tradeoff between public policies aimed at increasing the quantity of small business credit (e.g., providing government subsidies, encouraging market competition) and the resulting information problems that may encourage banks to allocate funds to uncreditworthy borrowers. On average, our results indicate that SBA guarantees have little effect on loan default probabilities at small banks, but are associated with substantially higher default probabilities for small loans—hence, these government loan subsidies tend to influence the behavior of large transactions-based lenders that treat small business loans like consumer lines of credit,

but tend not to influence the underwriting practices of small relationship-based lenders. The link in the data between market competition and high default rates is consistent with Petersen and Rajan (1994, 1995), who argue that lenders in concentrated (noncompetitive) markets are more likely to cultivate relationships with their small business clients, e.g., careful monitoring that reduces loan default rates, but in doing so may limit overall loan supply by denying loans to other good applicants.

Our results also highlight some interesting questions for SBA policy. Starting in 2005, general tax revenues (which have helped fund the program since its creation in the early 1950s) will no longer be available to subsidize losses on defaulted 7(a) loans, and the program will become self-funded.[47] Under the new budgeting, lender fees in 2005 increase to 0.54% from 0.25% of the total loan amount, and borrower fees double from to 0.25% of the loan amount. To remain a financially viable program under these tighter fiscal constraints, it is imperative that the SBA have the tools and expertise needed to measure and manage risk at least as well as the lenders that use the program. Our results suggest that credit-scoring has improved the ability of (predominantly large) banks to measure small business credit risk; thus, if the loan subsidies provided by the SBA are not adequately risk-priced, it will be a straightforward proposition for these banks to shift credit risk to the SBA. The SBA faces a difficult problem: while its financial viability may depend on linking its fee structure to credit scores, doing so will reduce the availability of loan and loan guarantees to truly opaque small businesses for which credit scoring is less efficient—the exact market failure that SBA was created to address.

While we believe that our empirical findings for SBA loans provide important lessons for the creation and performance of small business credit in general, we acknowledge that these findings will not generalize seamlessly to non-government-guaranteed small business lending. However, we stress that our empirical findings, and also the predictions of our theoretical model, have implications that stretch well beyond the SBA program. For instance, the majority of the theoretical propositions derived and

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[47] See John Roesti, "Effort to Revive Subsidy for 7(a) Fails," American Banker, February 11, 2005, and Rob Blackwell and Hannah Bergman, "U.S. Budget: What's In And What's Out For Industry," American Banker, February 08, 2005. The subsidy to the SBA 7(a) program amounted to approximately $80 million in fiscal 2004.

empirically tested here are proscriptive for any type of credit-scoreable lending (e.g., credit cards, auto loans, home mortgages, or non-subsidized small business loans). Moreover, these propositions provide a formal theoretical basis that is largely missing from the extant empirical literature on credit scoring and small business lending; and indeed, these theoretical propositions are quite consistent with the findings of those empirical studies. Finally, while our theory has implications for both loan default and loan supply, but we only test the former in this study; using loan-level data to test the loan-supply implications of our model is a potentially fruitful area for future research.

References

Akhavein, J.D., W.S. Frame, and L.J. White. 2005. "The Diffusion of Financial Innovations: An Examination of the Adoption of Small Business Credit Scoring by Large Banking Organizations." *Journal of Business* 78: 577-596.

Allison, Paul (1995). Survival Analysis Using the SAS System: A Practical Guide, Cary, North Carolina: SAS Institute.

Brown, S. and W. Goetzmann (1995). "Performance Persistence," Journal of Finance, 50 (2), June, 679-98.

Berger, A.N., C. Buch, G. DeLong, and R. DeYoung. 2004. "The Comparative Advantages of Nations at Exporting Financial Institutions Management via M&As." *Journal of International Money and Finance* 23(3): 333-366.

Berger A.N. and R. DeYoung. 2001. "The Effects of Geographic Expansion on Bank Efficiency." *Journal of Financial Services Research* 19: 163-184.

Berger A.N. and R. DeYoung. 2005. "Technological Progress and the Geographic Expansion of the Banking Industry." *Journal of Money, Credit, and Banking* (forthcoming).

Berger A.N., W.S. Frame, and N. Miller. 2005. "Credit Scoring and the Availability, Price, and Risk of Small Business Credit." *Journal of Money, Credit, and Banking* 37: 191-222.

Berger A.N., N.H. Miller, M.A. Petersen, R.G. Rajan, and J.C. Stein. 2005. "Does function follow organizational form: Evidence from the lending practices of large and small banks." *Journal of Financial Economics* 76: 237-269.

Berger A.N. and G.F. Udell. 1998. "The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle." *Journal of Banking and Finance* 22: 613-673.

Beshouri, C. and D. Glennon. 1996. "CRA as Market Development or Tax: An Analysis of Lending Decisions and Economic Development." *Proceedings of a Conference on Bank Structures and Competition,* Federal Reserve Bank of Chicago, 556-585.

Bitler, M.P., A.M. Robb, and J.D. Wolken. 2001. "Financial services used by small businesses: Evidence from the 1998 survey of small business finances." *Federal Reserve Bulletin* 87: 183-205.

Blöchlinger, A. and M. Leippold. 2005. "Economic Benefit of Powerful Credit Scoring," unpublished manuscript.

Boot, A.W.A., and A.V. Thakor. 2000. "Can relationship banking survive competition?" *Journal of Finance* 55, 679-713.

Board of Governors of the Federal Reserve System. 2000. *Report to Congress on Markets for Small-Business and Commercial-Mortgage-Related Securities.* Washington, D.C.

Brevoort, K.P., and T.H. Hannan. 2004. "Commercial Lending and Distance: Evidence from Community Reinvestment Act Data." Federal Reserve System Board of Governors, FEDS working paper 2004-24.

Buch, C.M. 2003. "Information or Regulation: What is Driving the International Activities of Commercial Banks?" *Journal of Money, Credit, and Banking* 35(6): 851-870.

Chang, A., S. Chaudhuri, and J. Jayarante. 1997. "Rational herding and the spatial clustering of bank branches: an empirical analysis." Unpublished manuscript.

Cole, R.A., L.G. Goldberg, and L.J. White. 2004. "Cookie-Cutter versus Character: The Micro Structure of Small-Business Lending by Large and Small Banks." *Journal of Financial and Quantitative Analysis* 39.

Craig, B., W.E. Jackson III, and J.B. Thomson. 2005. "SBA-Loan Guarantees and Local Economic Growth," unpublished manuscript.

Cyrnak A. and T. Hannan. 2000. "Non-Local Lending to Small Business." Working paper, Board of Governors of the Federal Reserve System.

Davis, S., J. Haltiwanger, and S. Schuh. 1994. "Small Business and Job Creation: Dissecting the Myth and Reassessing the Facts," *Labor Markets, Employment, and Job Creation*, edited by L. Solomon and A. Leoinson, Boulder, CO: Westview Press, 13-32.

Davis, S., J. Haltiwanger, and S. Schuh. 1996. *Job Creation and Destruction*, Cambridge, MA, MIT Press.

Degryse, H., and S. Ongena. 2002. "Distance, Lending Relationships, and Competition." Working paper, University of Tilburg.

Dell'Ariccia, G. and R. Marquez. 2004. "Information and Bank Credit Allocation," *Journal of Financial Economics* Vol. 72, No. 1, pp. 185-214.

Dell'Ariccia, G. and R. Marquez. "Lending Booms and Lending Standards," *Journal of Finance*, forthcoming.

DeYoung, R., W.C. Hunter, and G.F. Udell. 2004. "The Past, Present, and Probable Future for Community Banks." *Journal of Financial Services Research* 25(2/3): 85-133.

Engelmann, B., E. Hayden, and D. Tashe. 2003. "Measuring the Discriminative Power of Rating Systems." Deutsche Bundesbank, Discussion Paper Series 2: Banking and Financial Supervision, No. 01/2003.

Ergungor, O.E. 2005. "The profitability of bank-borrower relationships." *Journal of Financial Intermediation* 14: 485-512.

Frame, W.S., and L.J. White. 2004. "Empirical Studies of Financial Innovations: Lots of Talk, Little Action?" *Journal of Economic Literature* 42: 116-144.

Frame, S. M., M. Padhi and L. Woosley (2004) Credit Scoring and the Availability of Small Business Credit in Low- and Moderate-Income Areas." Financial Review. February 2004 (39). Pages 35-54.

Frame, S., A. Srinivasan and L. Woosley "The Effect of Credit Scoring on Small Business Lending." Journal of Money, Credit, and Banking. August 2001 (33). Pages 813-25.

Ghemawat, P. 2001. "Distance Still Matters: The Hard Reality of Global Expansion." *Harvard Business Review*, September: 137-147.

Glennon, D. and P. Nigro. 2005a. "Measuring the Default Risk of Small Business Loans: A Survival Analysis Approach," *Journal of Money, Credit, and Banking* 37: 923-948.

Glennon, D. and P. Nigro. 2005b. "An Analysis of SBA Loan Defaults by Maturity Structure," *Journal of Financial Services Research* 28: 77-111.

Green, D.M. and J.A. Swets. 1974. *Signal Detection Theory and Psychophysics*. John Wiley and Sons, Inc. New York, NY.

Greene, W.H. 1997. *Econometric Analysis*, 3rd edition. Upper Saddle River: Prentice Hall.

Hannan, T.H. 2003. "Changes in Non-Local Lending to Small Business." *Journal of Financial Services Research* 24: 31-46.

Hauswald, R. and R. Marquez. 2003. "Information Technology and Financial Services Competition." *Review of Financial Studies* 16: 921-948.

Heiner, R.A. 1983. "The Origin of Predictable Behavior." *American Economic Review* 73: 560-93.

Heiner, R.A. 1985. "Origin of Predictable Behavior: Further Modeling and Applications." *American Economic Review* 75: 391-96.

Heiner, R.A. 1985a. "Uncertainty, Signal Detection Experiments, and Modeling Behavior," in R. Langlois, ed. The New Institutional Economics, New York: Cambridge University Press.

Heiner, R.A. 1986. "The Economics of Information when Decisions are Imperfect," in Alan J. and Heather W. MacFadyen, ed. Economic Psychology: Intersections in Theory and Application, Elsevier Science Publications BV (North-Holland), 291-350.

Holod, D. and J. Peek. 2005. "Asymmetric Information and Liquidity Constraints: A More Complete Test." Federal Reserve Bank of Chicago: *Proceedings from a Conference on Bank Structure and Competition*.

Knight, R.H. 1933. *Risk, Uncertainty, and Profit.* Boston: Houghton-Mifflin.

Landier, A, V.B. Nair, and J. Wulf. 2005. "Geographic Dispersion and Corporate Decision-Making," unpublished manuscript.

Liberti, J.M. 2005. "How Does Organizational Form Matter? Communication, Distance, and Soft Information," unpublished manuscript.

Mays, E. 2004. *Credit Scoring for Risk Managers*. Mason, Ohio: Thomson, South Western.

McFadden, D. 1999. "Rationality for Economists?" *Journal of Risk and Uncertainty* 19: 73-105.

Mester, L.J. 1997. "What's the Point of Credit Scoring?" Federal Reserve Bank of Philadelphia, *Business Review* September/October: 3-16.

Meyer, Lawrence. 1998. "The Present and Future Roles of Banks in Small Business Finance." *Journal of Banking and Finance* 22: 1109-1116.

Mitchell, J. "Automated Scoring Cuts Wait for Loan Decisions," *Dallas Morning News*, July 15, 1996, p. 1D.

Petersen, M.A. and R.G. Rajan. 1994. "The Benefits of Lending Relationships: Evidence from Small Business Data." *Journal of Finance* 49: 3–37.

Petersen, M.A. and R.G. Rajan. 1995. "The Effect of Credit Market Competition on Lending Relationships." *Quarterly Journal of Economics* 110: 407–43.

Petersen, M.A. and R.G. Rajan. 2002. "The Information Revolution and Small Business Lending: Does Distance Still Matter?" *Journal of Finance* 57: 2553-2570.

Rose, P.S., W.L. Scott. 1984. "Heterogeneity in Performance Within the Bank Holding Company Sector: Evidence and Implications." *Journal of Economics and Business* 36: 1-14.

Rossi, C.V. 1998. "Mortgage Banking Cost Structure: Resolving an Enigma." *Journal of Economics and Business* 50(2): 219-234.

Roszbach, K. 2004. "Bank Lending Policy, Credit Scoring, and the Survival of Loans," *Review of Economics and Statistics* 86: 946-958.

Scott, J.A. 2004. "Small Business and the Value of Community Financial Institutions." *Journal of Financial Services Research* 25: 207-230.

Shaffer, S. 1998. "The Winner's Curse in Banking." *Journal of Financial Intermediation* 7: 359-392.

Shumway, Tyler (2001). "Forecasting Bankruptcy More Accurately: A Simple Hazard Approach," Journal of Business, January, 101-124.

Stein, J.C. 2002. "Information Production and Capital Allocation: Decentralized vs. Hierarchical Firms." *Journal of Finance* 57: 1891-1921.

Stein, R.M. "Power, Profitability, and Prices: Why Powerful Models Increase Profits and How to Define a Lending Cutoff If You Must." Technical Report #021223, Moody's KMV, NY (2003).

Stein, R.M. "The Relationship Between Default Prediction and Lending Profits: Integrating ROC Analysis and Loan Pricing." *Journal of Banking and Finance* 29(5): 1213-1236.

U.S. Government Accounting Office (GAO). 1999 (May). "Small Business Administration Size of the SBA 7(a) Secondary Markets is Driven by Benefits Provided."

U.S. Small Business Administration (SBA). 2000 (June). "Small Business Lending in the United States."

Wolken, J.D., and Rohde, D. 2002. "Changes in the Location of Small Businesses' Financial Service Suppliers between 1993 and 1998," Federal Reserve Board internal memorandum.

Table 1

Characteristics of a random sample of 29,577 SBA 7(a) loans to small businesses between 1984 and 2001. Mean data by year.
* indicates years for which we lack complete information for identifying banks that credit score small business loans.

Year	# of loans		defaulted		prepaid		sold		interest rate premium ratio		SBA guarantee percentage		median borrower-lender distance (miles)		# of scoring banks
1984	722		26.59%		55.54%		16.48%		1.48		86.75%		5.894055		0
1985	539		24.30%		53.62%		13.73%		1.44		87.33%		6.256428		0
1986	820		19.39%		55.12%		12.20%		1.34		85.26%		5.653255		0
1987	818		16.87%		52.93%		20.17%		1.32		84.51%		6.100676		0
1988	748		18.85%		50.27%		19.25%		1.41		84.10%		5.925328		0
1989	877		18.02%		66.02%		28.62%		1.57		84.47%		6.543702		0
1990	958		20.98%		63.26%		32.78%		1.57		84.81%		6.266364		0
1991	994		15.49%		61.77%		31.69%		1.46		84.67%		7.371263		0
1992	1198		11.52%		64.27%		22.89%		1.11		84.52%		6.720779		0
1993	1517		8.24%		62.10%		22.02%		1.03		84.57%		7.127364		3
1994	2353		14.70%		56.40%		16.70%		1.15		83.88%		8.17149		8
1995	4053		18.16%		53.29%		14.10%		1.47		86.29%		8.307432		46
1996	2406		18.70%		49.54%		16.46%		1.56		79.11%		9.01835		62
1997	2926		17.29%		43.40%		22.05%		1.64		77.60%		10.80256		196
1998	2702		13.32%		33.68%		24.74%		1.83		75.53%		13.82023		155*
1999	2576		8.27%		28.96%		30.33%		1.88		70.34%		18.02538		101*
2000	2545		8.49%		17.80%		54.91%		2.21		70.13%		16.61338		95*
2001	825		4.85%		9.33%		45.35%		2.13		69.42%		21.48488		48*
	Scoring banks	**Other banks**	**Scoring banks**	**Other banks**	**Scoring banks**	**Other banks**	**Scoring banks**	**Other banks**	**Scoring banks**	**Other banks**	**Scoring banks**	**Other banks**	**Scoring banks**	**Other banks**	
1995	198	3855	18.69%	18.13%	53.03%	53.31%	2.53%	14.69%	1.41	1.47	85.46%	86.33%	11.96463	8.187252	46
1996	240	2166	21.25%	18.42%	48.33%	49.68%	1.25%	18.14%	1.48	1.57	79.51%	79.07%	15.87786	8.623599	62
1997	870	2056	15.63%	18.00%	45.63%	42.46%	9.31%	27.45%	1.58	1.67	76.48%	78.07%	18.7987	9.342866	196
1998	949	1753	15.17%	12.32%	36.88%	31.95%	10.01%	32.59%	1.78	1.86	71.77%	77.57%	57.64412	9.167257	155*
1999	1134	1442	8.11%	8.39%	33.42%	25.45%	13.29%	42.96%	1.81	1.94	63.35%	75.83%	40.48208	10.50884	101*
2000	1031	1514	9.02%	8.12%	20.76%	15.79%	35.86%	63.92%	2.20	2.22	63.57%	74.59%	103.3715	9.922439	95*
2001	325	500	4.62%	5.00%	9.54%	9.20%	37.41%	49.63%	2.17	2.10	63.28%	73.41%	142.3353	11.61691	48*

Table 2

Summary statistics for variables used in estimation of equation (7). Random sample of 29,577 small business loans made in the SBA 7(a) loan program between 1984 and 2001 for which we have full information.

Variable Name	Definition	Data Source	**Full sample** (1984-2001) 491,512 loan-quarters 5212 lenders		**Full Sample** (1984-2001) 29,577 loans Unstacked	
			Mean	**Std Dev**	**Mean**	**Std Dev**
Default (time-varying)	Dependent Variable. = 1 if loan i defaulted at time t.	SBA	0.00896	0.09423	0.14889	0.35599
SBA%	= percentage of outstanding loan balance guaranteed by the SBA.	SBA	0.81426	0.09086	0.80002	0.10229
DISTANCE	= straight-line distance in miles between borrower and lending office of the lending institution.	SBA, Call Report	49.9667	237.619	65.7478	293.1521
lnDISTANCE	= natural log of DISTANCE.	SBA, Call Report	2.05697	1.90133	2.2134	1.94163
SCORER	= 1 if lender used credit scoring models to evaluate at least some of its small business loans at t=0.	Akhavein, Frame, and White (2001)	0.11405	0.31787	0.16130	0.36782
SPREAD	= loan interest rate divided by prime rate at the time of the loan.	SBA, Haver	1.31260	0.34576	1.57933	0.50579
MATURITY3	= 1 for 3-year loans.	SBA	0.07940	0.27037	0.13602	0.34281
MATURITY7	= 1 for 7-year loans.	SBA	0.62362	0.48448	0.64658	0.47804
NEWFIRM	= 1 if borrower is 3-years old or less.	SBA	0.30683	0.46118	0.32427	0.46811
FIRMSIZE	= number of full-time employees at borrowing firm.	SBA	12.4566	100.6588	12.3148	100.8332
HHI	= deposit-based Herfindahl index in local market of the borrower.	FDIC Summary of Deposits	0.19890	0.12171	0.19051	0.11603
URBAN	= 1 if borrower is located in a Metropolitan Statistical Area.	Call Report	0.79435	0.40417	0.82003	0.38417
CLP	= 1 if lender was a "certified" SBA lender.	SBA	0.19051	0.39270	0.16259	0.36900
PLP	= 1 if lender was a "preferred" SBA lender.	SBA	0.11599	0.32022	0.12790	0.33399
BANKSIZE	= lender assets (billions of 2001 $).	Call Report	12.8454	2.36233	13.1648	2.51285
CHARGEOFFS	= ratio of lender's loan charge-offs to assets.	Call Report	1.65677	0.91779	1.64625	0.88016
RESERVES	= ratio of lender's loan loss reserves to assets (x100).	Call Report	0.00393	0.00739	0.00369	0.00708
POLICY9401 (time-varying)	= 1 if loan was originated under liberal SBA credit policies in 1994-2001.		0.59504	0.49088	0.68925	0.46281
POLICYPOST89 (time-varying)	= 1 if loan was originated after the 1989 Federal Credit Reporting Act which required SBA to improve its risk management practices.		0.77987	0.41433	0.83832	0.36816
JOBGROWTH (time-varying)	= percent employment growth in borrower's industry and home state in quarter t.	BEA/Haver	0.00526	0.02850	0.00337	0.02422
INCOMEGROWTH	= percent income growth in borrower's industry and home state in loan origination quarter.	BEA/Haver	0.01488	0.01166	0.014939	0.011385
LOANAGE(x,y) (time-varying)	= 1 for loans between x and y quarters old in quarter t. This variable is used to specify a piecewise hazard function, and enters regression multiple times, once each for the following values of (x,y): (4,5), (6,7), (8,9), (10,12), (13,15), (16,20), and (21+).	SBA				

Table 3

Results from discrete-time hazard model (stacked-logit) estimation of equation (7). Dependent variable is loan default. Random sample of 29,577 SBA 7(a) loans between 1984 and 2001 for which we have full information, of which 4,044 defaulted during sample period. N = 491,512 loan-quarter observations. All variable definitions are displayed in Table 2.

	[1]		[2] SCORER=AUTOAPP		[3] Discrete DISTANCE	
Variable	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**
Intercept	-6.7042	<.0001	-6.7343	<.0001	-6.6657	<.0001
SBA%	0.4859	0.0154	0.4302	0.0283	0.4985	0.0127
lnDISTANCE	0.0416	<.0001	0.0398	<.0001		
DIST2550					0.1282	0.0200
DIST50UP					0.2627	<.0001
SCORER	0.3407	0.0003	0.2877	0.0303	0.2873	<.0001
SCORER*lnDISTANCE	-0.0513	0.0263	-0.0548	0.0870		
SCORER*DIST2550					-0.1423	0.3673
SCORER*DIST50UP					-0.3060	0.0034
MATURITY3	0.6244	<.0001	0.6213	<.0001	0.6278	<.0001
MATURITY7	0.6120	<.0001	0.6114	<.0001	0.6144	<.0001
FIRMSIZE	0.0003	0.0005	0.0003	0.0006	0.0003	0.0005
NEWFIRM	0.1994	<.0001	0.2022	<.0001	0.1991	<.0001
HHI	0.0395	0.8580	0.0453	0.8376	0.0057	0.9793
HHI*URBAN	-0.8422	0.0043	-0.8293	0.0048	-0.8700	0.0032
URBAN	0.1594	0.0513	0.1579	0.0534	0.1815	0.0263
CLP	-0.2016	<.0001	-0.2071	<.0001	-0.2014	<.0001
PLP	-0.3276	<.0001	-0.3276	<.0001	-0.3343	<.0001
BANKSIZE	-0.0198	0.0269	-0.0128	0.1267	-0.0212	0.0178
RESERVES	-0.0599	0.0022	-0.0621	0.0015	-0.0603	0.0020
CHARGEOFFS	6.4443	0.0005	6.6271	0.0003	6.4746	0.0005
INCOMEGROWTH	-1.0227	0.0759	-1.0350	0.0725	-1.0248	0.0762
JOBGROWTH	-4.1241	0.0012	-4.0353	0.0016	-4.1593	0.0012
POLICY9401	0.3230	<.0001	0.3337	<.0001	0.3211	<.0001
POLICYPOST89	-0.3805	<.0001	-0.3828	<.0001	-0.3764	<.0001
LOANAGE(4,5)	1.4915	<.0001	1.4914	<.0001	1.4915	<.0001
LOANAGE(6,7)	1.7156	<.0001	1.7154	<.0001	1.7156	<.0001
LOANAGE(8,9)	1.8180	<.0001	1.8177	<.0001	1.818	<.0001
LOANAGE(10,12)	1.7663	<.0001	1.7658	<.0001	1.7663	<.0001
LOANAGE(13,15)	1.7206	<.0001	1.7194	<.0001	1.7207	<.0001
LOANAGE(16,20)	1.6439	<.0001	1.6413	<.0001	1.6433	<.0001
LOANAGE(21+)	1.4128	<.0001	1.4083	<.0001	1.4126	<.0001
Marginal effects:						
SBA%	0.00430		0.00381		0.00441	
lnDISTANCE	0.00031		0.00032			
DIST2550					0.00097	
DIST50UP					0.00198	
SCORER	0.00204		0.00150		0.00202	
lnDISTANCE(SCORER=0)	0.00036		0.00035			
lnDISTANCE(SCORER=1)	-0.00011		-0.00016			
DIST2550 (SCORER=0)					0.00110	
DIST2550 (SCORER=1)					-0.00016	
DIST50UP (SCORER=0)					0.00226	
DIST50UP (SCORER=1)					-0.00049	

Table 4a

Selected sub-sample results for discrete-time hazard model (stacked-logit) estimation of equation (7).
Data sub-samples based on year in which loan was originated. Dependent variable is loan default.

	[4] Survey years only 1984 -1998		[5] First half 1984 -1992		[6] Second half 1993 -2001		[7] Second half 1993-2001	
Variable	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**
SBA%	0.3081	0.2044	0.1579	0.7011	0.3786	0.0905	0.4927	0.0338
lnDISTANCE	0.0408	<.0001	0.0583	0.0002	0.0240	0.0260	0.0303	0.0138
SCORER	0.3773	0.0005					0.3002	0.0022
SCORER*lnDISTANCE	-0.0480	0.0917					-0.0383	0.1147
N	435,305		166,933		324,579		324,579	
D=1	3,935		1,412		2,992		2,992	
D=0	431,370		165,521		321,587		321,587	
Marginal effects:								
SBA%	0.00275		0.00132		0.00345		0.00449	
lnDISTANCE	0.00032		0.00049		0.00022		0.00021	
lnDISTANCE(SCORER=0)	0.00036						0.00027	
lnDISTANCE(SCORER=1)	-0.00008						-0.00009	
SCORER	0.00250						0.00191	

Table 4b

Selected sub-sample results for discrete-time hazard model (stacked-logit) estimation of equation (7). *Data sub-samples based on size of loan.* Dependent variable is loan default.

	[8] Loan ≤ $100,000		[9] Loans ≤ $250,000		[10] Loan > $100,000	
Variable	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**
SBA%	0.7033	0.0060	0.6641	0.0027	-0.0646	0.8577
lnDISTANCE	0.0349	0.0054	0.0391	0.0002	0.0509	0.0009
SCORER	0.2241	0.0515	0.3306	0.0010	0.5878	0.0004
SCORER*lnDISTANCE	-0.0225	0.4267	-0.0440	0.0730	-0.1052	0.0103
N	271,307		409,390		220,205	
D=1	2,746		3,775		1,658	
D=0	268,561		405,615		218,547	
Marginal effects:						
SBA%	0.00703		0.00605		-0.00048	
lnDISTANCE	0.00032		0.00030		0.00030	
lnDISTANCE(SCORER=0)	0.00034		0.00035		0.00037	
lnDISTANCE(SCORER=1)	0.00014		-0.00006		-0.00057	
SCORER	0.00176		0.00216		0.00266	

Table 4c

Selected sub-sample results for discrete-time hazard model (stacked-logit) estimation of equation (7). *Data sub-samples based on size of originating bank.* Dependent variable is loan default.

	[11] Bank assets ≤ $1 billion in growth-adjusted 2001 dollars		[12] Bank assets > $1 billion in growth-adjusted 2001 dollars	
Variable	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**
SBA%	0.2390	0.4924	0.5764	0.0202
lnDISTANCE	0.0530	<.0001	0.0257	0.0792
SCORER	0.8734	0.0020	0.2535	0.0146
SCORER*lnDISTANCE	-0.3447	0.0040	-0.0281	0.2792
N	224,492		267,019	
D=1	2,049		2,355	
D=0	222,444		264,664	
Marginal effects:				
SBA%	0.00216		0.00502	
lnDISTANCE	0.00045		0.00017	
lnDISTANCE(SCORER=0)	0.00048		0.00022	
lnDISTANCE(SCORER=1)	-0.00408		-0.00002	
SCORER	0.00244		0.00160	

Table 4d

Selected sub-sample results for discrete-time hazard model (stacked-logit) estimation of equation (7).
Data sub-samples based on borrower-lender distance. Dependent variable is loan default.

Variable	[13] DISTANCE between 0 and 10 miles		[14] DISTANCE between 10 and 25 miles		[15] DISTANCE between 25 and 50 miles		[16] DISTANCE greater than 50 miles	
	Coefficient	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**	**Coefficient**	**p>Chi Sq.**
SBA%	0.6167	0.0441	0.2424	0.5774	0.0148	0.9818	0.3990	0.3387
lnDISTANCE	0.0103	0.5314	0.0407	0.7593	0.3024	0.2458	0.0966	0.0907
SCORER	0.4067	0.0007	0.9067	0.4199	4.0637	0.1020	-0.2280	0.6168
SCORER*lnDISTANCE	-0.0556	0.4249	-0.3134	0.4432	-1.0969	0.1221	0.0640	0.4515
N	269,057		110,674		46,507		65,274	
D=1	2,346		977		436		645	
D=0	266,711		109,697		46,071		64,629	
% SCORER=1	7.85%		12.36%		16.29%		48.71%	
Marginal effects:								
SBA%	0.00532		0.00211		0.00014		0.00389	
lnDISTANCE	0.00005		0.00010		0.00149		0.00118	
lnDISTANCE(SCORER=0)	0.00009		0.00035		0.00273		0.00090	
lnDISTANCE(SCORER=1)	-0.00055		-0.00250		-0.00900		0.00165	
SCORER	0.00311		0.00047		0.00201		0.00101	

Figure 1
Unit probability box and lender equilibrium.

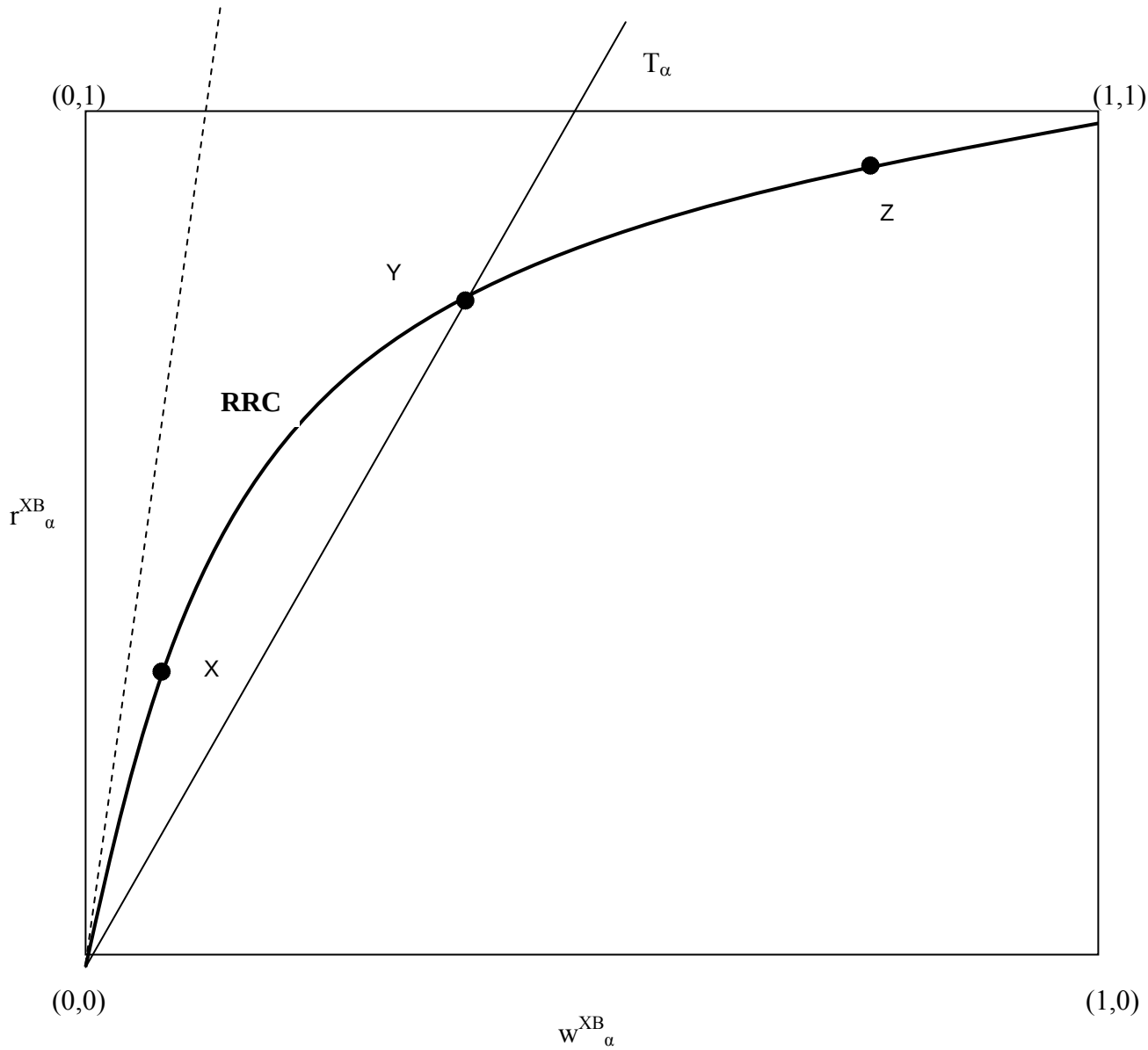


Figure 2
Reduced loan performance losses (or increased loan performance gains).

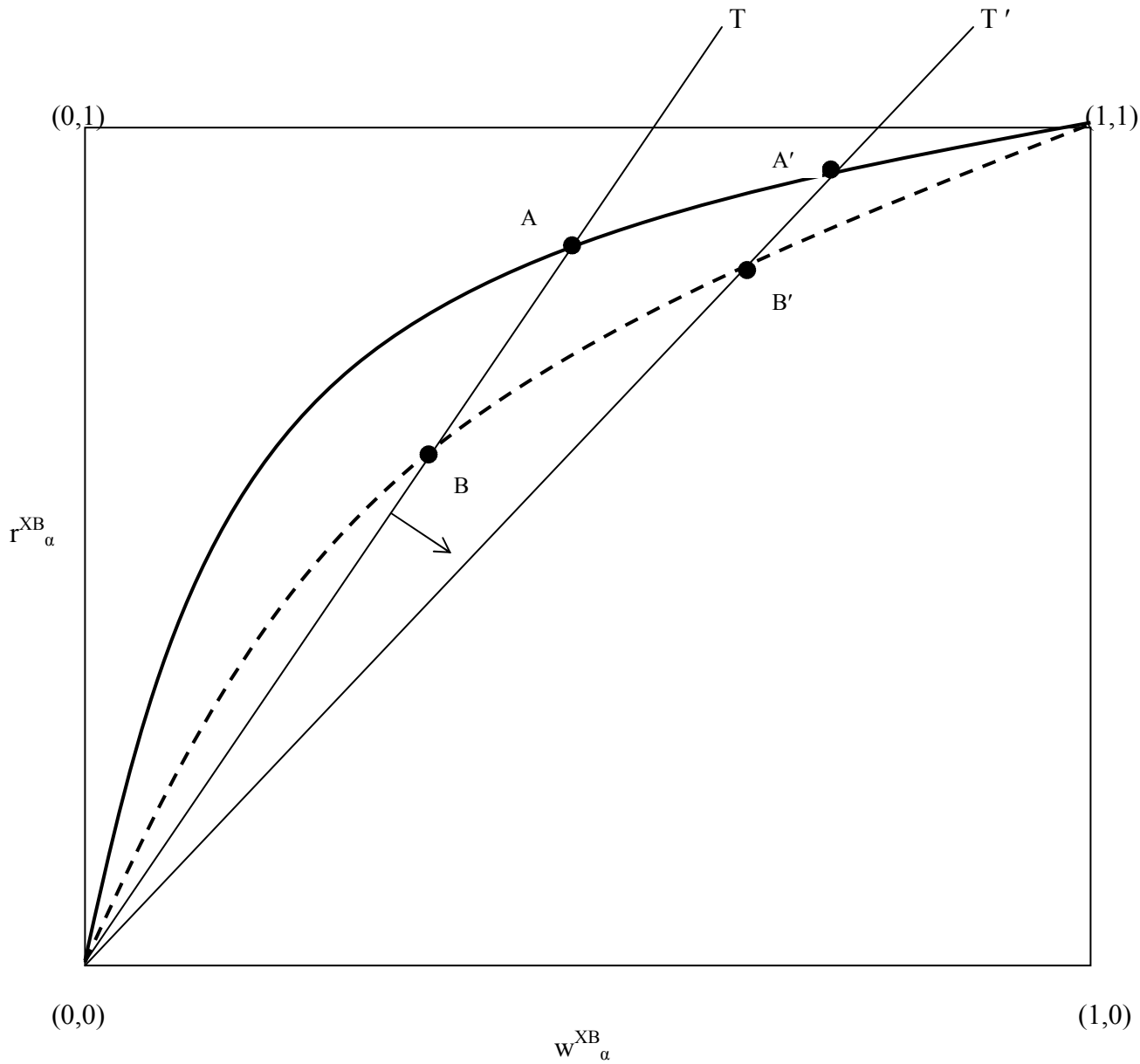


Figure 3
Increased information uncertainty.

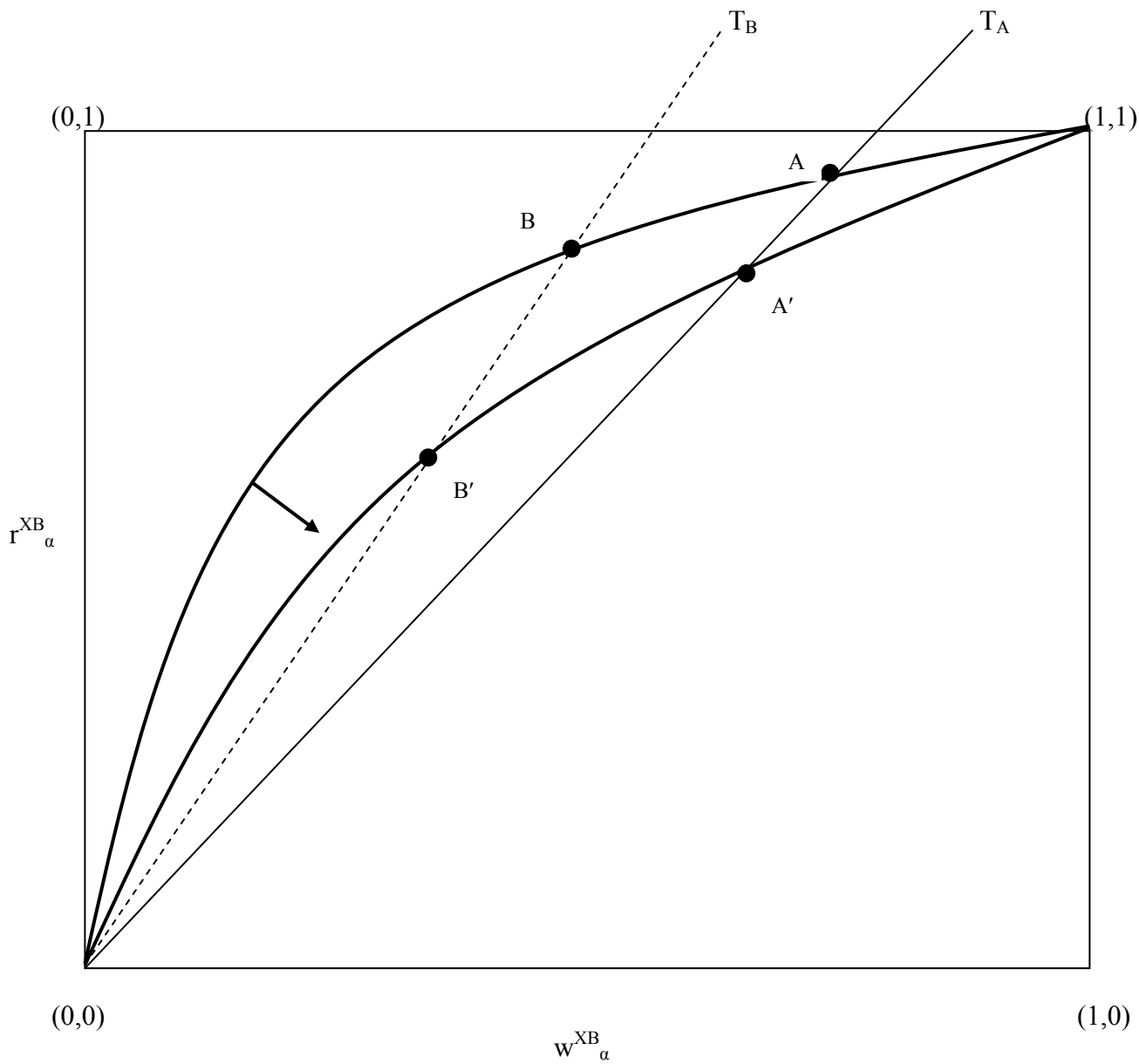
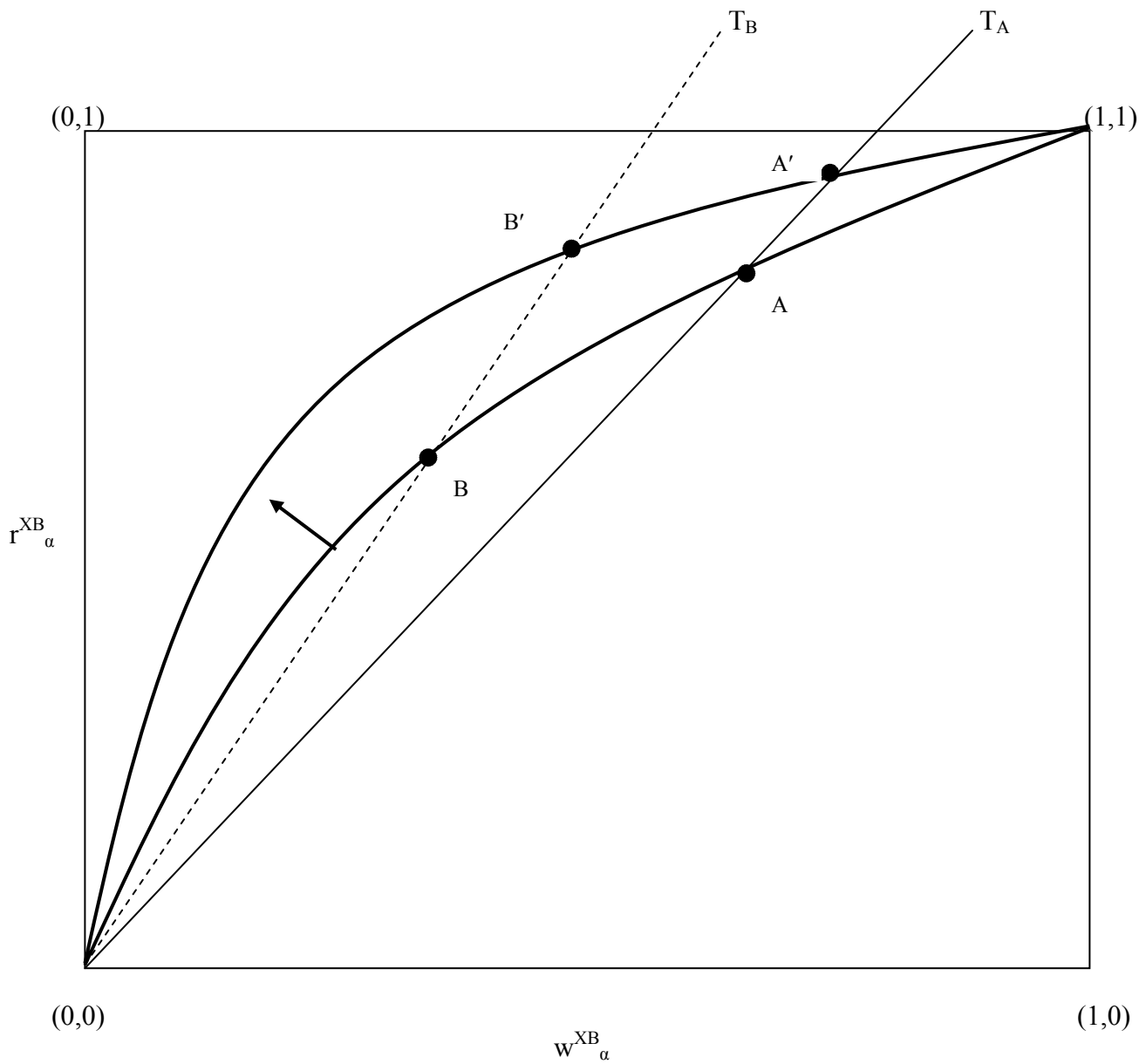


Figure 4
Improved decision-making ability.



Appendix Table A3

Corresponds to Table 3, but includes SPREAD on right-hand-side of regressions.

Variable	[1] Coefficient	[1] p>Chi Sq.	[2] SCORER=AUTOAPP Coefficient	[2] p>Chi Sq.	[3] Discrete DISTANCE Coefficient	[3] p>Chi Sq.
Intercept	-6.9081	<.0001	-6.9446	<.0001	-6.8712	<.0001
SBA%	0.5633	0.0055	0.5198	0.0091	0.5773	0.0044
lnDISTANCE	0.0413	<.0001	0.0390	<.0001		
DIST2550					0.1276	0.0206
DIST50UP					0.2622	<.0001
SCORER	0.3409	0.0003	0.2942	0.0265	0.2820	0.0001
SCORER*lnDISTANCE	-0.0544	0.0184	-0.0572	0.0730		
SCORER*DIST2550					-0.1415	0.3698
SCORER*50UP					-0.3187	0.0023
SPREAD	0.1153	0.0067	0.1188	0.0051	0.1162	0.0063
MATURITY3	0.6195	<.0001	0.6164	<.0001	0.6229	<.0001
MATURITY7	0.6046	<.0001	0.6037	<.0001	0.6071	<.0001
FIRMSIZE	0.0003	0.0005	0.0003	0.0005	0.0003	0.0005
NEWFIRM	0.1959	<.0001	0.1984	<.0001	0.1954	<.0001
HHI	0.0336	0.8790	0.0389	0.8603	-0.0001	0.9995
HHI*URBAN	-0.8361	0.0046	-0.8218	0.0053	-0.8630	0.0035
URBAN	0.1563	0.0561	0.1549	0.0581	0.1781	0.0293
CLP	-0.1959	<.0001	-0.2006	<.0001	-0.1957	<.0001
PLP	-0.3297	<.0001	-0.3293	<.0001	-0.3365	<.0001
BANKSIZE	-0.0196	0.0288	-0.0133	0.1140	-0.0210	0.0187
RESERVES	-0.0562	0.0041	-0.0580	0.0030	-0.0566	0.0038
CHARGEOFFS	6.3999	0.0006	6.5703	0.0004	6.4309	0.0005
INCOMEGROWTH	-0.9512	0.0989	-0.9609	0.0956	-0.9524	0.0995
JOBGROWTH	-4.2375	0.0009	-4.1615	0.0011	-4.2735	0.0009
POLICY9401	0.3185	<.0001	0.3289	<.0001	0.3166	<.0001
POLICYPOST89	-0.3703	<.0001	-0.3719	<.0001	-0.3661	<.0001
LOANAGE(4,5)	1.4850	<.0001	1.4847	<.0001	1.4850	<.0001
LOANAGE(6,7)	1.7037	<.0001	1.7031	<.0001	1.7036	<.0001
LOANAGE(8,9)	1.8043	<.0001	1.8037	<.0001	1.8043	<.0001
LOANAGE(10,12)	1.7527	<.0001	1.7519	<.0001	1.7527	<.0001
LOANAGE(13,15)	1.7034	<.0001	1.7018	<.0001	1.7034	<.0001
LOANAGE(16,20)	1.6204	<.0001	1.6176	<.0001	1.6197	<.0001
LOANAGE(21+)	1.3822	<.0001	1.3771	<.0001	1.3817	<.0001
Marginal effects:						
SBA%	0.00499		0.00460		0.00511	
lnDISTANCE	0.00030		0.00031			
DIST2550					0.00097	
DIST50UP					0.00195	
SCORER	0.00198		0.00151		0.00196	
lnDISTANCE(SCORER=0)	0.00036		0.00034			
lnDISTANCE(SCORER=1)	-0.00014		-0.00019			
DIST2550 (SCORER=0)					0.00109	
DIST2550 (SCORER=1)					-0.00016	
DIST50UP (SCORER=0)					0.00225	
DIST50UP (SCORER=1)					-0.00063	

Appendix Table A4a

Corresponds to Table 4a, but includes SPREAD on right-hand-side of regressions.

Variable	[4] Survey years only 1984 -1998 Coefficient	p>Chi Sq.	[5] First half 1984 -1992 Coefficient	p>Chi Sq.	[6] Second half 1993 -2001 Coefficient	p>Chi Sq.	[7] Second half 1993-2001 Coefficient	p>Chi Sq.
SBA%	0.3219	0.1857	0.2526	0.5457	0.7998	0.0006	0.8801	0.0002
lnDISTANCE	0.0408	<.0001	0.0577	0.0003	0.0199	0.0643	0.0287	0.0197
SCORER	0.3755	0.0005					0.2981	0.0022
SCORER*lnDISTANCE	-0.0489	0.0858					-0.0462	0.0560
SPREAD	0.0609	0.2492	-0.8236	<.0001	0.3854	<.0001	0.3833	<.0001
N	435,305		166,933		324,579		324,579	
D=1	3,935		1,412		2,992		2,992	
D=0	431,370		165,521		321,587		321,587	
% SCORER=1	7.59%		0.00%		17.17%		17.27%	
Marginal effects:								
SBA%	0.00288		0.00211		0.00728		0.00801	
lnDISTANCE	0.00032		0.00048		0.00018		0.00018	
lnDISTANCE(SCORER=0)	0.00036						0.00026	
lnDISTANCE(SCORER=1)	-0.00009						-0.00019	
SCORER	0.00246						0.00172	

Appendix Table A4b

Corresponds to Table 4b, but includes SPREAD on right-hand-side of regressions.

Variable	[8] Loan ≤ $100,000 Coefficient	p>Chi Sq.	[9] Loan ≤ $250,000 Coefficient	p>Chi Sq.	[10] Loan > $100,000 Coefficient	p>Chi Sq.
SBA%	0.8343	0.0014	0.7619	0.0007	-0.0353	0.9224
lnDISTANCE	0.0347	0.0056	0.0389	0.0002	0.0505	0.0010
SCORER	0.2269	0.0481	0.3319	0.0009	0.5860	0.0004
SCORER*lnDISTANCE	-0.0257	0.3620	-0.0470	0.0554	-0.1070	0.0091
SPREAD	0.1453	0.0087	0.1201	0.0093	0.0667	0.3219
N	271,307		409,390		220,205	
D=1	2,746		3,775		1,658	
D=0	268,561		405,615		218,547	
% SCORER=1	13.22%		12.11%		9.17%	
Marginal effects:						
SBA%	0.00833		0.00694		-0.00026	
lnDISTANCE	0.00031		0.00030		0.00029	
lnDISTANCE(SCORER=0)	0.00034		0.00035		0.00037	
lnDISTANCE(SCORER=1)	0.00010		-0.00009		-0.00059	
SCORER	0.00172		0.00211		0.00262	

Appendix Table A4c

Corresponds to Table 4c, but includes SPREAD on right-hand-side of regressions.

Variable	[11] Bank assets ≤ $1 billion in growth-adjusted 2001 dollars Coefficient	p>Chi Sq.	[12] Bank assets > $1 billion in growth-adjusted 2001 dollars Coefficient	p>Chi Sq.
SBA%	0.2140	0.5400	0.7566	0.0028
lnDISTANCE	0.0530	<.0001	0.0248	0.0892
SCORER	0.8755	0.0019	0.2525	0.0148
SCORER*lnDISTANCE	-0.3432	0.0042	-0.0343	0.1858
SPREAD	-0.0552	0.4199	0.2318	<.0001
N	224,492		267,019	
D=1	2,049		2,355	
D=0	222,444		264,664	
% SCORER=1	0.61%		20.48%	
Marginal effects:				
SBA%	0.00193		0.00659	
lnDISTANCE	0.00045		0.00015	
lnDISTANCE(SCORER=0)	0.00048		0.00021	
lnDISTANCE(SCORER=1)	-0.00407		-0.00009	
SCORER	0.00249		0.00145	

Appendix Table A4d

Corresponds to Table 4d, but includes SPREAD on right-hand-side of regressions.

Variable	[13] DISTANCE between 0 and 10 miles Coefficient	p>Chi Sq.	[14] DISTANCE between 10 and 25 miles Coefficient	p>Chi Sq.	[15] DISTANCE between 25 and 50 miles Coefficient	p>Chi Sq.	[16] DISTANCE greater than 50 miles Coefficient	p>Chi Sq.
SBA%	0.5923	0.0544	0.3406	0.4386	0.1651	0.8026	0.7641	0.0753
lnDISTANCE	0.0102	0.5322	0.0383	0.7732	0.2927	0.2612	0.0843	0.1384
SCORER	0.4090	0.0006	0.8666	0.4410	4.0023	0.1098	-0.2048	0.6522
SCORER*lnDISTANCE	-0.0551	0.4290	-0.3009	0.4618	-1.0755	0.1305	0.0514	0.5444
SPREAD	-0.0439	0.4788	0.1522	0.0936	0.1686	0.2091	0.4207	0.0001
N	269,057		110,674		46,507		65,274	
D=1	2,346		977		436		645	
D=0	266,711		109,697		46,071		64,629	
% SCORER=1	7.85%		12.36%		16.29%		48.71%	
Marginal effects:								
SBA%	0.00510		0.00297		0.00153		0.00744	
lnDISTANCE	0.00005		0.00009		0.00143		0.00101	
lnDISTANCE(SCORER=0)	0.00009		0.00033		0.00264		0.00080	
lnDISTANCE(SCORER=1)	-0.00054		-0.00240		-0.00882		0.00136	
SCORER	0.00313		0.00042		0.00196		0.00060	