FEDERAL RESERVE BANK *of* ATLANTA

Why Do Borrowers Pledge Collateral? New Empirical Evidence on the Role of Asymmetric Information

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Abstract: An important theoretical literature motivates collateral as a mechanism that mitigates adverse selection, credit rationing, and other inefficiencies that arise when borrowers hold ex ante private information. There is no clear empirical evidence regarding the central implication of this literature—that a reduction in asymmetric information reduces the incidence of collateral. We exploit exogenous variation in lender information related to the adoption of an information technology that reduces ex ante private information, and compare collateral outcomes before and after adoption. Our results are consistent with this central implication of the private-information models and support the empirical importance of this theory.

JEL classification: G21, D82, G32, G38

Key words: collateral, asymmetric information, banks, small business, credit scoring

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Why Do Borrowers Pledge Collateral?
New Empirical Evidence on the Role of Asymmetric Information

I. Introduction

Although collateral is a widely observed debt contracting feature, the underlying motivation for collateral is not well understood. An important set of theoretical models explains collateral as arising from information gaps between borrowers and lenders. Specifically, when borrowers hold private information regarding their project quality, equilibrium may be characterized by adverse selection and credit rationing (Stiglitz and Weiss 1981, Wette 1983). Collateral requirements may allow lenders to sort observationally equivalent loan applicants and mitigate these inefficiencies. In particular, lenders may offer a menu of contract terms such that applicants with higher-quality projects choose secured debt at lower premiums, while those with lower-quality projects select unsecured debt at higher premiums (e.g., Bester 1985, 1987, Besanko and Thakor 1987a, 1987b, Chan and Thakor 1987, Boot, Thakor and Udell 1991, Beaudry and Poitevin 1995, Schmidt-Mohr 1997).

Recent research, however, suggests that collateral may not always be optimal within the private information framework (Carlier and Renou 2005, 2006). Furthermore, an expansive theoretical literature invokes alternative frictions that motivate collateral as part of an optimal contract. These frictions include risk-shifting, reduced effort, and other moral hazard concerns (e.g., Holmstrom and Tirole 1997, Aghion and Bolton 1997), limited contract enforceability (e.g., Banerjee and Newman 1993, Albuquerque and Hopenhayn 2004, Cooley, Marimon, and Quadrini 2004), or an inability of lenders to monitor project outcomes at sufficiently low cost (e.g., Townsend 1979, Gale and Hellwig 1985, Williamson 1986, Border and Sobel 1987, Mookherjee and Png 1989, Boyd and Smith 1994, Krasa and Villamil 2000, Lacker 2001, Hvide and Leite 2006).

In this paper, we isolate and test a central empirical prediction that is distinctly generated by the private-information models. In particular, we test whether a reduction in information gaps between borrowers and lenders is associated with a lower incidence of collateral. Our test exploits variation in *ex ante* lender information created by the adoption of an information-enhancing loan underwriting technology**.** The test isolates the private-information models by focusing only on the *ex ante* information environment (i.e., information gaps that are present when the loan is made), rather than the *ex post* frictions featured in other theoretical models. Thus, a finding that the technology is associated with a lower incidence of collateral may be interpreted as consistent with the central implication of the private-information literature. By contrast, a finding that the technology is not associated with a significantly lower incidence of collateral may suggest that *ex post* frictions – such as moral hazard, limited contract enforceability, and/or costly monitoring – are empirically dominant.[1]

Our data set provides an advantageous laboratory in which to test the empirical prediction. We match the contract terms of nearly 14,000 individual newly-issued loans to small businesses between 1993 and 1997 from the Federal Reserve's Survey of Terms of Bank Lending Technology (STBL) with Call Report data on the 37 large U.S. banks that extended these credits. We also include data from a 1998 Atlanta Federal Reserve survey on whether, when, and how these banks employ small business credit scoring technology (SBCS), which provides our measure of asymmetric information. The combined data set allows for a rich set of

[1] Inderst and Mueller (forthcoming) suggest an alternative model in which collateral arises due to informational advantages of the lending bank vis-à-vis its competitors. The model shares the prediction that an increase in the information available to the lending bank reduces the incidence of collateral.

controls at both the loan and bank level, as well as for bank and time fixed effects to account for unobserved bank heterogeneity and changes in the lending environment, respectively.

Small business credit scoring combines data on the personal credit history of the small business owner with firm financial data to generate a "score" which reflects repayment probabilities.[2] The SBCS technology may be used exclusively or in a way that augments other lending technologies – such as financial statement lending, asset-backed lending, and/or relationship lending. To isolate those cases in which SBCS technology is most likely to reduce informational asymmetries, our analysis focuses on banks that use this technology in conjunction with other lending technologies. Recent research suggests that SBCS improves the lender's information set when the technology is used in this fashion (e.g., Berger, Frame, and Miller 2005, Berger, Espinosa-Vega, Frame, and Miller 2005). The extant research also finds the use of SBCS to be exogenous in that it is unrelated to the bank's prior portfolio composition, financial condition, and market characteristics (e.g., Frame, Srinivasan, and Woosley 2001, Akhavein, Frame, and White 2005).

By way of preview, the data suggest that the employment of the SBCS technology in a fashion that supplements information from other lending technologies is associated with a reduction in the use of collateral, consistent with the private-information models. The result is both statistically and economically significant and is robust to a number of alternative specifications and samples. We also present some evidence that the results are not driven by compositional shifts in the pool of borrowers served by SBCS adopters, and are not due to the endogenous adoption of the technology. We believe that our analysis provides the first clear-cut

[2] The personal information used in SBCS models (obtained from consumer credit bureaus) may include the owner's monthly income, outstanding debt, financial assets, employment tenure, home ownership, and previous loan defaults or delinquencies (Mester 1997). Although credit scoring models were applied to consumer loans well before the sample period, their application to business loans was delayed due to concerns regarding firm heterogeneity and nonstandardized documentation across firms (Berger and Frame 2007).

empirical evidence regarding the implications of the private-information models.[3] Previous findings have been mixed and may be hampered by issues relating to endogenous selection and other biases.

Identifying the specific informational frictions that underlie the observed widespread use of collateral is important because collateral pledges often impose costs on both lenders and borrowers, reducing the efficiency of debt markets. This contracting mechanism requires that lenders incur the screening costs of valuing the pledged assets; the costs of monitoring the secured assets; and any enforcement/disposal expenses in the event of repossession (e.g., Leeth and Scott 1989). The use of collateral may also impose opportunity costs on borrowers to the extent that it ties up assets that might otherwise be put to more productive uses. Borrowers may also suffer fluctuations in their credit availability as the values of their securable assets vary.

The common application of collateral may also have macroeconomic consequences. Changes in the values of pledgeable assets that are correlated across borrowers – due to external shocks such as interest rate spikes, oil price increases, or real estate bubbles – may amplify the business cycle through procyclical changes in access to credit (e.g., Bernanke and Gertler 1989, 1990, Kiyatoka and Moore 1997). Indeed, recent empirical evidence suggests that the significant decline in real estate collateral values in Japan in the early 1990s played an important role in reducing debt capacity and investment in that nation (Gan forthcoming).

We acknowledge that the focus here on small business loans may limit the generality of our results. However, the use of these data also conveys a potentially important advantage in evaluating the theoretical literature because small businesses tend to fit the profile of firms under conditions of asymmetric information featured in the theoretical models. The small business

[3] The findings may also underscore the importance of investigating the effects of *ex ante* information gaps on other loan contract features, for example as in Diamond (1989) and Chatterjee, Corbae, and Rios-Rull (2007).

data may also yield the most insight regarding the policy issue of credit availability, given that these firms are likely to suffer the greatest reductions in funding when their collateral values are impaired due to external shocks.

The remainder of the paper is structured as follows. Section II reviews the existing empirical evidence and Section III outlines our econometric methodology. Section IV describes the data and variables used in these econometric tests, respectively. We present the test results in Section V and conclude in Section VI.

II. Empirical Literature Review

A number of studies examine the empirical relationship between asymmetric information and the incidence of collateral. These papers use the strength of the lender-borrower relationship – as measured by length or breadth, or whether the lender is the borrower's main or only lender – as an inverse proxy for the degree of asymmetric information. Lenders may gather proprietary information about the borrower's project choice, effort, and risk as their relationship with the borrower strengthens (e.g., Petersen and Rajan 1994, Berger and Udell 1995, Degryse and van Cayseele 2000). The empirical association between collateral and relationship strength is sometimes found to be negative as predicted by the private-information models (e.g., Berger and Udell 1995, Harhoff and Korting 1998, Chakraborty and Hu 2006); in other cases it is found to be positive (e.g., Machaer and Weber 1998, Elsas and Krahnen 2000, Ono and Uesegi 2005); while a third set of studies finds mixed signs (e.g., Degryse and van Cayseele 2000, Jiminez, Salas, and Saurina 2006, Menkhoff, Neuberger, and Suwanaporn 2006, Voordeckers and Steijvers 2006).

These analyses may have problems that diminish their usefulness for testing the implications of the private-information theory, which could also help explain the mixed empirical findings. First, the results could be biased towards a positive association between collateral and relationships to the extent that lenders sort borrowers into different lending arrangements based on their opacity. In particular, one could generate a positive coefficient if lenders use relationships to evaluate more opaque small businesses (e.g., Berger and Udell 2002) – precisely those borrowers that pledge collateral in models based on moral hazard and other *ex post* frictions. Second, the results could be biased toward a negative association to the extent that collateral and relationships are substitute methods of dealing with opacity problems. For example, lenders may often require that borrowers pledge fixed assets such as real estate, motor vehicles, or equipment as collateral to resolve information problems instead of using evidence acquired through strong relationships (e.g., Manove, Padilla, and Pagano 2001, Berger and Udell 2006). Our methodology sidesteps these complications by exploiting exogenous variation in *ex ante* private information.[4]

Another set of studies examine the empirical association between risk and collateral, rather than that between asymmetric information and collateral. The private-information models suggest that borrowers with low unobservable risk may signal this through the pledging of collateral. The private-information models do not have a prediction regarding the relationship between observed risk and collateral, though the empirical literature finds that collateral is associated with higher risk (e.g., Leeth and Scott 1989, Berger and Udell 1990, 1995, Booth

[4] The empirical association between collateral and relationship strength may also in part reflect the exercise of market power through a non-price term of credit. Some of the theoretical literature on relationship lending predicts that loan rates rise over the course of a relationship as a borrower becomes "locked-in" to its current lender because of its informational advantage over other potential lenders (e.g., Greenbaum, Kanatas, and Venezia 1989, Sharpe 1990, Rajan 1992). It is also possible that lenders may use this market power to extract collateral pledges more often from borrowers with strong relationships.

1992, Degryse and Van Cayseele 2000, Ono and Uesegi 2005). Some of these studies find that collateral is positively related to risk premiums among small business loans (e.g., Berger and Udell 1990, Degryse and Van Cayseele 2000). To the extent that the risk premiums reflect unobserved risk that is signaled through the sorting mechanism of the private-information models, these data are not consistent with the prediction of lower unobserved risk for secured credits. The data rather suggest that an association between collateral and higher observed risk may empirically dominate the findings.[5]

In another article of evidence on the private-information models, Jiminez, Salas, and Saurina (2006) show that collateral is negatively related to *ex post* defaults on debt issued to young firms. The authors argue that *ex post* defaults may reflect high unobserved risk and hence *ex ante* private information.[6] However, because collateral may raise the cost of default, one might expect to find that secured debt is less likely to default, irrespective of whether *ex ante* asymmetric information is important. Moreover, defaults may reflect moral hazard or other frictions, and thus may not isolate the effects of *ex ante* private information. Our methodology, which exploits an exogenous shock to the level of *ex ante* informational asymmetries, avoids the problems that characterize tests based on the collateral-risk relationship. In particular, our methodology allows us to isolate the specific effect of *ex ante* private information from those of *ex post* frictions and other potentially confounding factors.

[5] Interestingly, Weill and Godlewski (2006) show that collateral and risk premiums may be negatively related in nations characterized by higher levels of asymmetric information – as measured by variables such as accounting standards and the level of financial development of the nation – a result that is consistent with the private-information models.

[6] Abbring, Chiappori, Heckman, and Pinquet (2002) discuss the merits of inferring *ex ante* private information from *ex post* claims in insurance markets.

III. Outline of the Econometric Methodology

We test the central prediction of the private-information models regarding collateral and asymmetric information using data on the terms of individual small business loan contracts, the banks that extend these loans, and whether and how these banks employ the SBCS lending technology. We base the test on a logit model of whether collateral was pledged on the individual loans:

$$ln\ [P(COLLAT_{ijt}) \,/\, (1 - P(COLLAT_{ijt}))] = b_1\, SCORE_{jt} + x_{ijt}'b_2 + a_j + g_t\ , \qquad (1)$$

where $P(\cdot)$ indicates probability, $COLLAT_{ijt}$ is a dummy variable that equals 1 if the loan is secured, and i, j, and t index loans, banks, and time, respectively. The key exogenous variable is $SCORE_{jt}$, which takes a value of one if bank j employs SBCS in a manner that reduces informational asymmetries in time t, and zero otherwise. The vector x_{ijt} includes other loan and bank control variables. The scalars a_j and g_t capture differences in the probability that collateral is pledged due to fixed effects for bank j and time t, respectively.

A negative, statistically and economically significant estimate for the parameter b_1 would be consistent with the prediction of the private-information models that a reduction in asymmetric information lowers the probability that collateral is pledged. By contrast, an estimate that is not significantly negative would be consistent with the notion that *ex post* frictions – such as moral hazard, limited contract enforceability, and/or costly monitoring – empirically dominate any effect of *ex ante* private information on collateral. As discussed below, we remove loan observations from the data set when the employment of SBCS has ambiguous implications with respect to reducing asymmetric information. In all cases, our empirical results are robust to changing the inclusion rules.

In equation (1), the estimate of b_1 is primarily determined by loans from banks for which *SCORE* takes on values of both 0 and 1 within the data set – i.e., banks that adopted SBCS during the sample period and have both before- and after- adoption observations available. Loans by other banks in the sample have no direct influence on the estimate of b_1 because they have no variation in *SCORE*. These other banks are of three types. First, some banks had not adopted SBCS by the end of the sample period ($SCORE_{jt}$ = 0 for all *t*). Second, some banks had adopted the technology prior to the sample period and therefore had experienced any information benefits at some earlier time ($SCORE_{jt}$ = 1 for all *t*). Finally, some sample banks adopted SBCS during the sample period, but have no observations available prior to adoption because one of the underlying data sets had no observations for these institutions prior to adoption ($SCORE_{jt}$ = 1 for all *t* after adoption, no observations for $SCORE_{jt}$ prior to adoption). The inclusion of loans by banks with no variation in *SCORE* directly improves the estimation efficiency of the loan and bank control variables and the time fixed effects, and thereby indirectly contributes to improving the estimation efficiency of b_1, the *SCORE* effect.

Our empirical test is essentially equivalent to differences-in-differences estimation and presents two important econometric issues. First, the parameters are consistently estimated despite our use of fixed effects within a discrete-choice framework. The ratio of observations to parameters tends to infinity as the number of loans per bank-quarter grows large, and as the number of banks and quarters rise together. Our sample features 19 loans per bank-quarter, 37 banks, and 20 quarters. As a result, we are able to use nearly 14,000 observations to estimate 65 total parameters, including one parameter for $SCORE_{jt}$ (b_1), seven parameters for the control variables (b_2), 37 bank effects (a_j), and 20 time effects (g_t).

Second, we use a clustering correction that provides consistent estimates of the *t* statistics in the presence of arbitrary correlation patterns (including autocorrelation) among loan observations from the same bank. Bertrand, Duflo, and Mullainathan (2004) show that autocorrelation may cause differences-in-differences estimators to yield upwardly-biased *t* statistics that over-reject the null. However, they also note that the clustering correction we employ works well when then number of sample states – the number of sample banks in our case – is large, on the order of 50. Our baseline sample includes data on 37 banks.

IV. Data and Variables Employed in the Tests

We combine data from three sources to estimate equation (1) and test the main hypothesis about the effects of asymmetric information on the probability that collateral is pledged. The first source is the Federal Reserve's Survey of Terms of Bank Lending (STBL). Respondents to this survey include virtually all of the largest U.S. banks plus a stratified random sample of smaller institutions. The STBL contains details on the loan contract terms of all newly-issued domestic commercial and industrial (C&I) loans by surveyed banks during one or more days of the first week of the second month of each quarter. The terms include whether collateral is pledged – the basis for the dependent variable in equation (1) – as well as information on whether the loan is issued under commitment, the amount of the loan and commitment (if any), and whether the loan has a floating interest rate.

Our second data source is the January 1998 Survey of Small Business Credit Scoring conducted by the Federal Reserve Bank of Atlanta. This survey targeted many of the same large institutions as the STBL, including 99 of the largest 200 U.S. banking organizations operating at that time. The available information includes whether lenders employed SBCS as of 1997:Q4, and if so, the date that they initially adopted the technology. The survey responses also provide data on how the adopting institutions employ the technology – specifically whether they simply use credit scores to automatically approve/reject loan applications versus using SBCS in a manner that supplements their existing underwriting techniques (Frame, Srinivasan, and Woosley 2001). The SBCS Survey data are used to construct the *SCORE* variable, and to determine whether and when this technology likely reduced asymmetric information.

Finally, we gather statistics from regulatory reports on the banks that issue the loans – items from Call Reports, Summary of Deposits, and the National Information Center. These regulatory files provide information on the financial statements, ownership, and market characteristics for virtually all U.S. banks. We use these data to construct control variables for the bank's size, age, financial condition, recent merger activity, and local market concentration.

Our regression sample is compiled by matching data from these three sources, so that each observation includes loan contract information from the STBL, data on whether, when, and how large U.S. banking organizations employed small business credit scoring from the SBCS Survey data, and statistics on the banks themselves from the regulatory files. The sample contains observations over the period 1993:Q1-1997:Q4. As noted above, SBCS was introduced to many U.S. large banks during this interval.

We exclude observations from the regression sample when there are ambiguities about whether the use of SBCS reduces informational asymmetries. First, we exclude loans made in the two quarters following a bank's adoption of SBCS to lessen the effects of any learning curves associated with implementing this new technology. Second, we omit observations from banks that use SBCS to automatically accept/reject credit applications, rather than to supplement the information from other loan evaluation methods. Third, we exclude loans for which the total credit is over $100,000 because SBCS is often applied by lenders only on loans up to this size, and so would have no informational effect for larger credits. Finally, we omit data on loans not issued under commitment. Prior research finds that commitment loans are more often relationship-based and therefore are likely to be associated with greater asymmetric information problems (e.g., Berger and Udell 1995). We show below that our empirical results are robust to altering all of these exclusion rules.

Our main regression sample includes 13,973 loans made by 37 different large banks, 19 of which use SBCS to supplement other loan evaluation methods and 18 of which do not use this technology in any way over the sample interval. As discussed above, the estimated effect of *SCORE* is primarily determined by loans from banks that adopted the technology during the sample period and have both before- and after- adoption observations available. In our sample, 16 of the 19 adopting banks are in this category – one bank had adopted prior to the sample period and two banks adopted during the sample interval, but were added to the STBL data set only after adoption. As discussed above, the inclusion of the three adopting banks for which *SCORE* = 1 for all observations and the 18 non-adopters for which *SCORE* = 0 for all observations improve estimation efficiency.

Table 1 provides the means and standard deviations of the variables used in our main regressions. The dependent variable, *COLLAT*, is a dummy variable that equals 1 if the loan is secured. The key exogenous variable is *SCORE*, a dummy that equals one if the bank adopted SBCS at least two quarters before the loan was made. As shown, more than 80 percent of the sample loans have collateral pledged, and about 50 percent are made by banks that use SBCS in a way that is likely to reduce asymmetric information.

We control for two loan contract terms in our analysis: total loan size, including the amount of any commitment (*SIZE*), and a dummy variable indicating whether the loan has a floating interest (*FLOAT*). Table 1 shows that most of the loans carry floating rates and that the average loan size is just below $50,000. Recall that we limit *SIZE* to $100,000 or less because many banks use SBCS only for credits below this limit. We also control for five bank characteristics, gross total assets (*GTA*), bank age (*AGE*), the ratio of nonperforming loans (past due at least 30 days or nonaccrual) to gross total assets (*NPL*), whether the bank was involved in a merger in the previous year (*MERGED*), and the weighted-average market Herfindahl index of deposit concentration (*HERF*). The characteristics are constructed from the previous year's regulatory reports to mitigate potential endogeneity problems. The average *GTA* is about $16.5 billion and the average *AGE* is almost 120 years. There are no small or young banks in the sample because the SBCS survey queries only large institutions. The means of *NPL, MERGED* and *HERF* are 0.014, 0.429, and 0.203 respectively.

V. Empirical Results

A. Main Regression Results

Table 2 presents our main regression results examining the effects of *SCORE* on the likelihood that collateral is pledged. The logit regression represented by equation (1) is estimated for four specifications that alternatively exclude or include the loan and bank control variables. Each regression includes bank and time fixed effects. Robust *t* statistics are calculated using a clustering correction for heteroskedasticity and arbitrary correlations among loan observations from the same bank.

The estimates for b_1, the coefficient on *SCORE*, are negative and statistically significant at the 1% level in all four of the specifications in Table 2. These findings are consistent with the central prediction of the private-information models that a reduction in asymmetric information lowers the probability that collateral is pledged. For the specification in column (4), which includes all of the loan and bank control variables, the *SCORE* coefficient is -0.449. The corresponding estimates in columns (1), (2), and (3) – which exclude all of the control variables, just the bank variables, and just the loan variables, respectively – the coefficients are quite similar, -0.530, -0.534, and -0.438.

To evaluate whether these effects are economically significant, we convert the coefficients from the nonlinear logit model into predicted changes in the probability that collateral is pledged. In the second row of the table, we show *Predicted ? P(COLLAT)*, which is the predicted change in the probability that collateral is pledged from changing *SCORE* from 0 to 1 at the sample means of the other exogenous variables.[7] For the full specification in column (4), *Predicted ? P(COLLAT)* = -0.057, suggesting that the use of SBCS to augment other loan underwriting methods reduces estimated collateral incidence by roughly 6 percent. This result is robust – the figures for the other specifications shown in Table 2 are all close to 6 percent. Thus, for a loan at the sample mean *P(COLLAT)* of about 83%, the likelihood that collateral would be pledged falls to about 77% when SBCS is used to reduce asymmetric information. This finding appears to be highly economically significant because the use of SBCS to supplement other lending technologies almost surely closes only a small portion of information gap between the

[7] The formula for *Predicted ? P(COLLAT)* is as follows. Let μ_X be the vector of sample means of control variable vector x_{ijt} over all i, j, and t; q_j be the proportion of loans in the sample made by bank j, and r_t be the proportion of sample loans made in year t. Define d_1 as $b_1 + \mu_X' b_2 +$? $q_j a_j +$? $r_t g_t$, and define d_0 as $d_1 - b_1$. The values shown for *Predicted ? P(COLLAT)* are given by $[exp(d_1)/(1 + exp(d_1))] – [exp(d_0)/(1 + exp(d_0))]$, where d_1 and d_0 replace the actual coefficients with the estimated coefficients in d_1 and d_0, respectively.

bank and borrower. That is, the estimated 6 percentage point effect likely represents only a minor fraction of the full effect of private information on collateral decisions.

Turning briefly to the control variables, only three of these variables are statistically significant in the full specification in column (4). The coefficients on *ln(SIZE)*, *ln(GTA)*, and *NPL* suggest that larger credits and larger and financially healthier banks tend to be associated with a higher incidence of collateral. In addition, Wald tests for the fixed effects (not shown) reject the null hypotheses that both the bank and the time effects are jointly zero at the 1% level in all four specifications.[8]

In the remaining discussion, we refer to the findings for the full specification shown in column (4) of Table 2 as our baseline results. These represent our best efforts at choosing the specification and sample that reflect the effects of a reduction in asymmetric information on the likelihood that collateral is pledged.

B. Alternative Specifications and Samples

In Table 3, we alter the specification of equation (1) in ways other than changing the control variables to examine further the robustness of the baseline results. We show the consequences of excluding the fixed effects and of using conventional, uncorrected *t* statistics in place of robust *t* statistics calculated using the clustering correction. Specifically, column (1) excludes the time effects, column (2) excludes the bank effects, column (3) excludes both sets of effects, and column (4) replicates the baseline regression without the clustering correction for robust *t* statistics. The loan and bank control variables are included in all of these regressions, but their coefficients are not shown in the interest of brevity.

[8] The results are also statistically and economically similar when controls for loan maturity and the bank's internal loan risk rating are added to the specification. We omit maturity from the main regressions due to potential endogeneity concerns, and we exclude the risk ratings because they are available only for the final three quarters of our sample.

The results in the first three columns suggest that the main results are robust with respect to excluding the time fixed effects, but not the bank fixed effects. When only the time effects are excluded in column (1), the estimated coefficient on *SCORE* is -0.423, similar to the baseline coefficient of -0.449, and is statistically significant at the 1% level. The economic significance is also maintained, with only a small change in *Predicted ? P(COLLAT)* to -0.045. In contrast, the exclusion of bank fixed effects (with or without the time fixed effects) in columns (2) and (3) results in relatively small, statistically insignificant *SCORE* coefficient estimates, and much lower pseudo R-squared statistics. These findings suggest that systematic differences across banks may exist that are not captured by observables. For example, some institutions may require collateral more often than others due to their internal policies and procedures or because these banks tend to specialize in certain lending technologies that rely more heavily on collateral.

The results in column (4) of Table 3 show that when uncorrected *t* statistics are used in place of robust *t* statistics that correct for correlations among loan observations from the same bank, the coefficient on *SCORE* is again statistically significant at the 1% level. The uncorrected statistic is much larger in absolute value than the robust statistic, consistent with the potential autocorrelation bias discussed above.

In Table 4, we examine the robustness of our baseline results with respect to the use of alternative data samples. Specifically, we examine the effects of using different bank samples, different loan samples, and excluding different numbers of quarters after SBCS adoption. Columns (1) and (2) show the effects of altering the set of banks included in the sample. In column (1), we include 22 additional banks that use credit scores to automatically approve/reject loan applications. In column (2), we restrict the sample to include only those banks present in the data in both 1993 and 1997, reducing the number of sample banks by 11. The STBL bank panel changes somewhat over the sample period due to mergers, bank growth, and other factors, which could potentially introduce sample selection issues. The results in columns (1) and (2) suggest that our baseline results are robust to these changes in bank samples. In both cases, the coefficients on *SCORE* remain negative and statistically significant at the 1% level, and the value of *Predicted ? P(COLLAT)* is reasonably close to the -0.057 found for the baseline regression.

We next show the results from regressions using alternative loan samples. Specifically, we use observations on loans not issued under commitment in column (3), loans of total size up to $50,000 in column (4), and loans of total size between $50,000 and $100,000 in column (5). As discussed above, the sample in our baseline regression includes only loans issued under commitment which are expected to be associated with greater asymmetric information problems, and credits of all sizes up to $100,000, the maximum size on which many lenders use the SBCS technology. In all three alternative samples, the coefficients on *SCORE* are negative, statistically significant, and of economically significant magnitude – actually notably greater magnitude for loans not issued under commitment. Again, the findings support the robustness of the baseline results and suggest that our finding that the adoption of SBCS is associated with less collateral is not due to specific loan sample restrictions.

Columns (6), (7), and (8) give the findings when we exclude different numbers of quarters after SBCS adoption: zero quarters (column (6)), one quarter (column (7)), and four quarters (column (8)). The sample used in the baseline regression excludes two quarters to reduce the effects of any learning curve associated with implementing the technology. The *SCORE* coefficients are all again negative and statistically significant, consistent with the baseline regression. However, the value of *Predicted ? P(COLLAT)* is smaller when zero quarters are excluded, which suggests that the new technology may take some time to significantly improve lender information.

C. Alternative Explanations

One alternative explanation for the results is that banks may experience compositional shifts in their pools of borrowers after adopting the SBCS technology. In particular, if the SBCS technology improves the ability to screen marginal credits, then the reduction in collateral may reflect overall changes in borrower risk rather than changes in the level of asymmetric information. To address this issue, we regress the banks' internal loan risk ratings on *SCORE*, the bank and loan control variables, and the time fixed effects. The risk rating characterizes loans as being of "minimal," "low," "moderate," and "acceptable" risk, and we use ordered logit to capture the effect of SBCS on risk accordingly. The risk ratings are available only starting in 1997:Q2, so we restrict the sample to the final three quarters of data.[9] The resulting *SCORE* coefficient is small (0.089) and not statistically significant (*t* statistic of 0.110). The finding suggests that composition shifts do not drive the main results of the paper.

A second alternative explanation for the results is that the adoption of SBCS technology is not truly exogenous. For example, if a bank's borrowers become less able to provide collateral, then one might expect the bank to adopt technology that allows it to better evaluate unsecured loans. In this interpretation, the SBCS technology results from movements in demand away from collateralization, rather than causes changes in collateral requirements. Three articles of evidence suggest that this does not describe our results. First, the extant research finds the timing of SBCS adoption is unrelated to the bank's prior portfolio composition, financial condition, and market characteristics (Frame, Srinivasan, and Woosley 2001, Akhavein, Frame,

[9] Given the shorter sample period, the *SCORE* coefficient is not identifiable in the presence of bank fixed effects (only two banks adopt during these quarters), and we exclude bank fixed effects from the regression.

and White 2005). Second, if borrowers become less able to provide collateral over time and this causes SBCS adoption, then one might also expect SBCS technology to be associated with changes in borrower risk. The risk rating regressions discussed above suggest that this did not occur. Third, our main results include bank and time fixed effects, so any source of endogeneity bias must vary both across banks and across time. In an attempt to account directly for such factors, we run the main regressions adding bank-specific time trends to the bank and time fixed effects. The *SCORE* coefficient remains negative, although it is somewhat smaller and no longer statistically significant. Together, these findings suggest that the main results are not likely due to endogenous SBCS adoption.

VI. Conclusions

The theoretical literature identifies collateral as a key contracting tool employed by lenders to reduce problems associated with asymmetric information. In particular, an important set of models suggests that collateral may mitigate adverse selection and reduce credit rationing when borrowers have *ex ante* private information regarding the quality of their project. The central implication of these private-information models is that an attenuation of the information gap between borrowers and lenders should reduce the incidence of collateral. Previous findings regarding this implication are mixed and may be hampered by issues relating to endogenous selection and other biases.

In this paper, we sidestep the potential endogeneity and other problems of the existing empirical literature by employing data on an exogenous technological innovation that was not introduced to most large U.S. banks until the mid-1990s. Specifically, we use data on whether, when, and how large U.S. banks employed small business credit scoring (SBCS) over the period

1993:Q1-1997:Q4, focusing on cases in which this technology supplements other loan evaluation techniques to reduce asymmetric information. We combine the SBCS data with information on collateral and other contract terms on about 14,000 newly-issued small business loans and data on the banks themselves.

The empirical results support the central prediction of the private-information models. The data are consistent with a fall in the use of collateral when banks adopt SBCS and use it to supplement information from other lending technologies. The findings are both statistically and economically significant and are robust to a number of alternative specifications and changes in sample. The results suggest that banks that used the new technology to reduce information gaps during our sample interval lessened their need for collateral on a significant number of small business loans. The findings further imply that the employment of SBCS may have reduced lender and borrower costs and improved the efficiency of a segment of the small business lending market.

Our empirical application examines the effects of just one new lending technology on credits to one class of borrower over one time interval. Nonetheless, our findings may have more general implications. The results suggest that any market advances (e.g., new technologies, financial contracting tools) or policy innovations (e.g., improved disclosure rules/enforcement) that appreciably reduce information gaps between borrowers and lenders may improve the efficiency of debt markets by reducing reliance on costly collateral. Such developments may also bring about substantially greater credit availability for some potential borrowers – particularly those with severe asymmetric information problems or without access to pledgeable collateral – as collateral requirements are reduced. Any improvements in information that substantially reduce dependence on collateral may also reduce procyclicality and other adverse macroeconomic consequences associated with external shocks to asset values.

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Table 1
Variables and Summary Statistics

Means and standard deviations for variables used in subsequent estimation. The sample combines loan observations from 19 large banks that use small business credit scoring technology over 1993:Q1-1997:Q4, but not to automatically approve/reject loans, with loan observations from 18 large banks that do not use this technology in any capacity during this interval. Loan observations from the first two quarters following credit scoring adoption are excluded. *COLLAT* is a dummy that equals 1 if the loan is secured. *SCORE* is a dummy that equals 1 if the bank uses small business credit scoring technology when the loan is made. *SIZE* is the maximum of the loan amount and the amount of commitment. *FLOAT* is a dummy that equals one if the loan has a floating interest rate. *GTA* is the gross total assets of the bank. *AGE* is the age of the bank. *NPL* is the bank's ratio of nonperforming loans (past due at least 30 days or nonaccrual) to *GTA*. *MERGED* is a dummy that equals one if the bank was involved in a merger the previous year. *HERF* is the bank's weighted-average market Herfindahl index of deposit concentration. Bank variables are constructed from the previous year's regulatory reports. The loans considered have *SIZE* less than or equal to $100,000 and are issued under commitment. The total sample size is 13,973. Sources: Federal Reserve's Survey of Terms of Bank Lending (STBL) for *COLLAT*, *SIZE* and *FLOAT*; January 1998 Federal Reserve Bank of Atlanta survey on the use of credit scoring for *SCORE*; bank regulatory reports (Call Reports, Summary of Deposits, National Information Center) for *GTA*, *AGE*, *NPL*, *MERGED* and *HERF*.

Variable	Description	Mean	Std Dev	25%	50%	75%
Dependent variable:						
COLLAT	Loan is secured (1=yes)	0.825	0.380	1.000	1.000	1.000
Credit scoring dummy:						
SCORE	Bank uses credit scoring (1=yes)	0.505	0.500	0.000	1.000	1.000
Loan variables						
SIZE	Loan size ($000)	48.544	28.734	24.466	47.087	72.005
FLOAT	Floating interest rate (1=yes)	0.917	0.277	1.000	1.000	1.000
Bank variables						
GTA	Gross total assets ($000)	16,718,600	20,827,050	3,878,491	9,558,315	27,057,860
AGE	Age of the bank (years)	119.062	23.332	112.000	119.000	130.000
NPL	Nonperforming loans ÷ *GTA*	0.015	0.008	0.010	0.013	0.019
MERGED	Merged last year (1=yes)	0.445	0.497	0.000	0.000	1.000
HERF	Average market Herfindahl	0.203	0.051	0.180	0.193	0.224

Table 2

Main Collateral Regressions

Logit regressions for *COLLAT*, a dummy variable that equals one if the loan is secured. The sample combines loan observations from 19 large banks that use small business credit scoring technology over 1993:Q1-1997:Q4, but not to automatically approve/reject loans, with loan observations from 18 large banks that do not use this technology in any capacity during this interval. The loans considered have *SIZE* of less than or equal to $100,000 and are issued under commitment. Loans made during the first two quarters following credit scoring adoption are excluded. Robust *t* statistics are calculated using a clustering correction for heteroskedasticity and arbitrary correlations among loan observations from the same bank. *Predicted ? P(COLLAT)* indicates the predicted change in the probability that collateral is pledged from changing *SCORE* from 0 to 1 at the means of the other exogenous variables. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Credit scoring dummy:				
SCORE	-0.530***	-0.534***	-0.438***	-0.449***
	(-3.42)	(-3.60)	(-2.91)	(-3.10)
Predicted ? P(COLLAT)	-0.066	-0.066	-0.056	-0.057
Loan variables:				
ln(SIZE)		0.356***		0.353***
		(3.95)		(3.88)
FLOAT		-0.374*		-0.321
		(-1.74)		(-1.44)
Bank variables:				
ln(GTA)			0.393***	0.384***
			(3.55)	(3.67)
ln(AGE)			15.488	15.379
			(1.58)	(1.62)
NPL			-8.374**	-7.560*
			(-2.03)	(-1.72)
MERGED			-0.035	-0.064
			(-0.33)	(-0.63)
HERF			0.340	0.672
			(0.20)	(0.41)
Bank fixed effects	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes
Pseudo R-Squared	0.096	0.106	0.098	0.108
Number of obs.	13,973	13,973	13,973	13,973

Table 3

Robustness Tests: Additional Alternative Specifications

Logit regressions for *COLLAT*, a dummy variable that equals one if the loan is secured. The sample combines loan observations from 19 large banks that use small business credit scoring technology over 1993:Q1-1997:Q4, but not to automatically approve/reject loans, with loan observations from 18 large banks that do not use this technology in any capacity during this interval. The loans considered have *SIZE* of less than or equal to $100,000 and are issued under commitment. Loans made during the first two quarters following credit scoring adoption are excluded. Where indicated, robust *t* statistics are calculated using a clustering correction for heteroskedasticity and arbitrary correlations among loan observations from the same bank. Otherwise, uncorrected *t* statistics are used. *Predicted ? P(COLLAT)* indicates the predicted change in the probability that collateral is pledged from changing *SCORE* from 0 to 1 at the means of the other exogenous variables. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Credit scoring dummy:				
SCORE	-0.423***	0.085	0.274	-0.449***
	(-2.83)	(0.27)	(0.76)	(-4.27)
Predicted ? P(COLLAT)	-0.045	0.012	0.038	-0.057
Loan variables	Yes	yes	yes	Yes
Bank variables	Yes	yes	yes	Yes
Bank fixed effects	Yes	no	no	yes
Time fixed effects	No	yes	no	yes
Robust *t* statistics	Yes	yes	yes	no
Pseudo R-Squared	0.106	0.033	0.026	0.108
Number of obs.	13,973	13,997	13,997	13,973

Table 4
Robustness Tests: Alternative Samples

Logit regressions for *COLLAT*, a dummy variable that equals one if the loan is secured. The baseline sample combines loan observations from 19 large banks that use small business credit scoring technology over 1993:Q1-1997:Q4, but not to automatically approve/reject loans, with loan observations from 18 banks that do not use this technology in any capacity during this interval. Unless otherwise noted, loans have *SIZE* less than or equal to $100,000, are issued under commitment, and are not made during the first two quarters following credit scoring adoption. Robust *t* statistics are calculated using a clustering correction for heteroskedasticity and arbitrary correlations among loan observations from the same bank. *Predicted ? P(COLLAT)* indicates the predicted change in the probability that collateral is pledged from changing *SCORE* from 0 to 1 at the means of the other exogenous variables. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Different bank samples:		Different loan samples:			Different # of quarters excluded after adoption:		
	Includes banks that use credit scoring to automatically approve/reject	Includes only banks that are present in both 1993 and 1997	Loans not issued under commitment	Loans of up to $50,000	Loans of $50,000-$100,000	None	One	Four
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit scoring dummy:								
SCORE	-0.422***	-0.458***	-0.532**	-0.397***	-0.567***	-0.327**	-0.405***	-0.445***
	(-2.81)	(-3.06)	(-2.49)	(-3.01)	(-2.76)	(-2.26)	(-2.71)	(-2.81)
Predicted ? P(COLLAT)	-0.072	-0.055	-0.114	-0.044	-0.077	-0.032	-0.050	-0.052
Loan variables	yes	Yes	yes	yes	yes	yes	yes	yes
Bank variables	yes	Yes	yes	yes	yes	yes	yes	yes
Bank fixed effects	yes	Yes	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	Yes	yes	yes	yes	yes	yes	yes
Pseudo R-Squared	0.238	0.105	0.179	0.165	0.053	0.105	0.107	0.107
Number of obs.	21,980	12,858	8,807	8,582	5,339	14,780	14,357	13,087