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

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Abstract

An impressive theoretical literature motivates collateral as a mechanism that reduces equilibrium credit rationing and other problems arising from asymmetric information between borrowers and lenders. However, there is no clear empirical evidence regarding the central implication of this theory – that a reduction in asymmetric information reduces the incidence of collateral. We provide such evidence by exploiting exogenous variation in lender information sets related to their adoption of a new information technology, and comparing collateral outcomes before and after adoption. Our results are consistent with the central implication of the theoretical models, and may also have efficiency and macroeconomic implications.

JEL Classification Numbers: G21, D82, G32, G38
Keywords: Collateral, Asymmetric Information, Banks, Small Business, Credit Scoring

The views expressed do not necessarily reflect those of the Federal Reserve Board, Federal Reserve Bank of Atlanta, the International Monetary Fund, or their staffs. The authors thank Lamont Black for helpful comments and Phil Ostromogolsky and Shalini Patel for outstanding research assistance.

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I. Introduction

Collateral is one of the most widely-used features of debt contracts. An impressive theoretical literature – dating back at least to Stiglitz and Weiss (1981) – motivates collateral as arising from information gaps between borrowers and lenders. While the theoretical models are well-developed, to our knowledge there is no clear empirical evidence that either confirms or refutes the central implication of these models – that a reduction in asymmetric information should reduce the incidence of collateral. The primary goal of this paper is to provide such evidence.

The theoretical models explain the use of collateral as a mechanism to reduce equilibrium credit rationing and other problems that arise due to asymmetric information between borrowers and lenders. Most of this literature invokes two particular frictions. The first is *ex ante* private information regarding project quality held by borrowers that may result in adverse selection problems. The second is *ex post* risk shifting, reduced effort, and other moral hazard problems due to costly monitoring or incomplete contracting. Some models consider environments in which *ex ante* private information is the only friction (e.g., Bester 1985, 1987, Besanko and Thakor 1987a,b, Beaudry and Poitevin 1995, Schmidt-Mohr 1997); others incorporate only *ex post* moral hazard (e.g., Gale and Hellwig 1985, Stulz and Johnson 1985, Williamson 1986, Boot and Thakor 1994, Lacker 2001); while a third set features both types of informational frictions (e.g., Chan and Thakor 1987, Boot, Thakor, and Udell 1991, Carlier and Renou 2005, 2006). Thus, the theoretical models suggest that collateral may induce borrowers to sort themselves *ex* *ante* and/or improve their incentives *ex post*, potentially mitigating problems generated by information gaps between borrowers and lenders.[1]

The central implication of these theoretical models is that a shrinking of the information gap between borrowers and lenders should lower the incidence of collateral. We are unaware of any previous empirical studies that provide persuasive evidence on this causal link, although as discussed below, the relationship lending literature may shed some light on the topic. One reason for the dearth of such empirical research may be the fundamental problem associated with identifying asymmetric information, which by its nature is difficult to measure.

We confront this identification problem directly by exploiting variation in the information sets of lenders related to their adoption and use of a new information technology. In particular, we use data on whether, when, and how large U.S. banks employed small business credit scoring (SBCS) technology over the period 1993:Q1-1997:Q4. Credit scoring was applied to consumer loans well before these dates, but SBCS – which combines statistics on the personal credit history of the small business owner with data on the firm – was not introduced to most large U.S. banks until the mid-1990s. Recent research suggests that SBCS improves the lender's information set when this technology supplements other loan evaluation techniques, which makes it a valuable tool for evaluating the role of asymmetric information (e.g., Berger, Frame, and Miller 2005, Berger, Espinosa-Vega, Frame, and Miller 2005). The extant research also finds the adoption 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).

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[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.

We combine the SBCS data with a large database of small business loans issued by some of these banks, as well as descriptive statistics on the banks themselves. To examine the effect of a reduction in asymmetric information on the incidence of collateral, our econometric method in effect compares collateral outcomes from banks that use SBCS in conjunction with other loan evaluation techniques with outcomes from these same institutions prior to their adoption of the technology. Our method also includes observations from some banks without before-and-after observations to improve estimation efficiency. The combined dataset allows for a rich set of 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 over time, respectively.

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 key empirical implication of the theoretical models. The result is both statistically and economically significant and is robust to a number of alternative specifications and samples. To our knowledge, this is the first clear evidence that either confirms or refutes the central prediction of the theoretical models.

This issue is important because the pledging of collateral often imposes 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 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 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 briefly reviews the evidence on collateral from the relationship lending literature. Section III outlines our econometric methodology for testing the central implication of the theoretical models, and 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. Collateral in the Relationship Lending Literature

As discussed above, we are not aware of any research that provides clear empirical findings on the causal connection between asymmetric information and collateral implied by the theoretical models. Nonetheless, the relationship lending literature may provide some evidence on this issue. The strength of the lender-borrower relationship – as measured by relationship length or breadth, or whether the lender is the borrower's main or only lender – may be viewed as an inverse proxy for the degree of asymmetric information. This is because the lender gathers additional proprietary information about the firm's project choice, effort, and risk as the relationship strengthens (e.g., Petersen and Rajan 1994, Berger and Udell 1995, Degryse and van Cayseele 2000).

A number of papers examine the effect of relationship strength on collateral, with mixed findings. The empirical association between collateral and relationship strength is sometimes found to be negative as predicted by the theory (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 theory, which could also help explain the mixed empirical findings. One potential problem is that relationship strength may be an endogenous outcome because lenders sort borrowers into different lending arrangements depending on their opacity. The conventional wisdom in small business lending research is that financial institutions tend to use relationship lending to lend to more opaque firms (e.g., Berger and Udell 2002). These are also the borrowers that the theoretical models predict should more often pledge collateral. The endogenous sorting process may introduce correlation between unobserved firm opacity and relationship strength that could confound attempts to measure the effect of relationship strength on the incidence of collateral. That is, collateral and relationship strength may be positively associated because both variables are positively related to unobserved firm opacity.

A second source of endogeneity may drive the findings in the opposite direction. The pledging of collateral and the use of a strong relationship may be 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 (Berger and Udell 2006). This may occur because of the "lazy bank hypothesis" in which collateral is used as a substitute for the effort of building a strong relationship (Manove, Padilla, and Pagano 2001). To the extent that lenders use collateral and strong relationships as substitute tools for lending to opaque borrowers, the association between collateral and relationship strength may be negatively biased.

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.

Before proceeding with our new approach, we note that much of the empirical literature focuses on the association between risk and collateral, rather than on the link between asymmetric information and collateral. However, the theoretical models do not provide a consistent empirical prediction for the sign of the association between risk and collateral. The models with only *ex ante* private information predict that lower-risk firms pledge collateral; the models with only *ex post* moral hazard predict that higher-risk firms pledge collateral, and the models with both types of information problems have ambiguous empirical implications. The empirical research generally find that collateral is associated with higher risk (e.g., Leeth and Scott 1989, Berger and Udell 1990, 1995, Booth 1992, Ono and Uesegi 2005), although at least one recent study obtains the result that collateral is associated with lower risk (Jiminez, Salas, and Saurina 2006).

III. Outline of the Econometric Methodology

We test the central prediction of the theoretical 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:

$$ln\,[P(COLLAT_{ijt}) / (1 - P(COLLAT_{ijt}))] = \beta_1 SCORE_{jt} + x_{ijt}'\beta_2 + \alpha_j + \gamma_t \qquad (1)$$

where $P(\bullet)$ 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 α_j and γ_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 β_1 would be consistent with the prediction of the theoretical models that a reduction in asymmetric information lowers the probability that collateral is pledged. 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 β_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 β_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 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 8 parameters for $SCORE_{jt}$ and the control variables (β_1 and β_2) plus 37 bank effects and 20 time effects (α_j and γ_t).

Second, we use a clustering correction that provides consistent estimates of *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, and 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 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 significant 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. We make this omission because the effects of employing SBCS as a stand-alone technology are ambiguous with respect to reducing asymmetric information. 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. The inclusion of the three adopting banks for which *SCORE* = 1 for all observations plus the 18 non-adopters for which *SCORE* = 0 for all observations improve the estimation of the coefficients of the control variables and time fixed effects, and thereby indirectly improve the estimation of the *SCORE* parameter.

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*). These variables may be associated with both the likelihood of collateral being pledged and the degree of asymmetric information, so exclusion of these variables could create spurious relationships between collateral and the use of SBCS. 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 that may be associated with a bank's average degree of asymmetric information and its policies and procedures regarding collateral. These include 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. There are no small or young banks in the sample because the SBCS survey queries only large institutions. The average *GTA* is about $16.5 billion and the average *AGE* is almost 120 years. The means of *NPL*, *MERGED* and *HERF* are 0.014, 0.429, and 0.203 respectively.

V. Empirical 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 β_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 theoretical 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 Δ 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.[2] For the full specification in column

[2] The formula for *Predicted Δ 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 δ_1 as $\beta_1 + \mu_X'\beta_2 + \sum q_j \alpha_j + \sum r_t \gamma_t$, and define δ_0 as $\delta_1 - \beta_1$. The values shown

(4), *Predicted Δ 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 bank and borrower. That is, the estimated 6 percentage point effect likely represents only a minor fraction of the full effect of asymmetric 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.

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.

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

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for *Predicted Δ 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 δ_1 and δ_0, respectively.

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.

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 Δ 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 Δ 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 Δ P(COLLAT)* is noticeably smaller when zero quarters are excluded, which suggests that the new technology may take some time to significantly improve lender information.

VI. Conclusions

The theoretical literature identifies collateral as an important contracting tool employed by lenders to reduce problems associated with asymmetric information. The central implication of the theoretical models is that an attenuation of the information gap between borrowers and lenders should reduce the incidence of collateral, but the evidence in the literature does not clearly confirm or refute this causal link. The relationship lending literature provides some limited evidence on this issue, as the strength of the lender-borrower relationship may be viewed as an inverse proxy for the degree of asymmetric information. However, this research yields mixed findings, possibly due to endogeneity or other problems.

In this paper, we try to 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 theoretical 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 much 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 Δ 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 Δ 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 Δ 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 Δ 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 Δ 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 Δ 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