Debt Maturity, Risk, and Asymmetric Information

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ABSTRACT

We test the implications of Flannery's (1986) and Diamond's (1991) models concerning the effects of risk and asymmetric information in determining debt maturity, and we examine the overall importance of informational asymmetries in debt maturity choices. We employ data on over 6,000 commercial loans from 53 large U.S. banks. Our results for low-risk firms are consistent with the predictions of both theoretical models, but our findings for high-risk firms conflict with the predictions of Diamond's model and with much of the empirical literature. Our findings also suggest a strong quantitative role for asymmetric information in explaining debt maturity.

WHY DO FIRMS WITH LONG-TERM PROJECTS often borrow on a short-term basis? One answer from the debt maturity literature emphasizes the importance of risk under conditions of asymmetric information. Flannery (1986), Diamond (1991), and others provide intuitive models that rely on low-risk and high-risk firms with long-term projects choosing different maturities to reduce their financing costs or liquidity risks. Although other theories of debt maturity focus on the roles of agency costs (e.g., Myers (1977), Barnea, Haugen, and Senbet (1980)), taxes (e.g., Brick and Ravid (1985), Lewis (1990)), and other market imperfections, we concentrate on the role of asymmetric information and how it interacts with firm risk. The importance of debt maturity has also recently been highlighted in the context of policy concerns relating to financial crises and credit availability (e.g., Diamond and Rajan (2001)).

In this paper, we test the empirical predictions of Flannery's and Diamond's theoretical models, and further explore the role of asymmetric information in debt maturity choices. Our data set provides an advantageous laboratory for these tasks. We match the maturities, risk ratings, and other contract terms of

The Journal of Finance

over 6,000 individual new loans to small businesses in 1997 from the Federal Reserve's Survey of Terms of Bank Lending (STBL) with Call Report data on the 53 large U.S. banks that extend these credits. We also include data from an Atlanta Federal Reserve survey on whether and how these banks employ small business credit scoring (SBCS) technology, which provides our measure of asymmetric information. Prior research supports the notion that SBCS can be used to reduce informational asymmetries (Berger, Frame, and Miller (2005)).

We perform two main tests based on regressions of loan maturity on the risk rating of the loan, use of the SBCS technology, and other bank characteristics and loan contract terms. In Test 1, we examine whether maturity is an upward-sloping function of the risk rating as predicted by Flannery's model versus a nonmonotonic function of the risk rating with the shortest maturities for the lowest and highest risk ratings as predicted by Diamond's model. We perform Test 1 using only observations for banks that do not use the SBCS technology, given that the models predict that the relationships between debt maturity and firm risk ratings should be strongest when informational asymmetries are greatest. In Test 2, we examine the effects of reduced informational asymmetries from SBCS on debt maturities for each different risk rating. Test 2 allows us to test the implications of the effects of asymmetric information in both models, and perhaps more important, to examine the quantitative importance of informational asymmetries in debt maturity generally. A number of empirical papers examine the relationship between risk ratings and debt maturity (Test 1), although none to our knowledge examine this relationship using only observations for which informational asymmetries are expected to be the greatest. Some empirical studies examine the effects of reduced informational asymmetries on debt maturities, but none to our knowledge examine these effects by risk ratings (Test 2).

Notably, our empirical tests are based on bank loans, rather than public debt securities as in the theoretical models and most of the empirical literature. The implications of the models are the same in both contexts—to the extent that value is created by maturity choice, it is similarly created whether the firm chooses from a menu of contract terms from a bank or from its expectations of market reactions.

By way of preview, the evidence supports the predictions of Flannery's and Diamond's models for low-risk firms—maturity is an upward-sloping function of risk ratings (Test 1) and a reduction in informational asymmetries is associated with increased maturities (Test 2) for these firms.[1] These findings for low-risk firms are also consistent with most of the empirical literature. However, our evidence for high-risk firms conflicts with the predictions of Diamond's model and with much of the extant empirical literature. The most likely explanation for our difference from the literature for high-risk firms may be our use of bank loans rather than publicly issued debt, as banks may be better able than public markets to use tools other than short maturities to resolve asymmetric

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[1] For convenience, we refer in this paper to firms or loans with low- and high-risk ratings as "low-risk" and "high-risk" firms or loans, although the risk ratings may not always correspond to the underlying risk of the firms or loans.

information problems for high-risk firms (Berlin and Loeys (1988)). We do find, however, that the predictions of Diamond's model for high-risk firms appear to hold for one group of small businesses—those without loan commitments—and we offer some possible explanations for this finding.

Our findings strongly support the quantitative importance of asymmetric information in the debt maturity decision. The results of Test 2 suggest a very substantial increase in average maturity for low-risk firms when informational asymmetries are lessened. As well, we find that the results of Test 1 would be substantially weakened if it were applied to observations for banks using the SBCS technology. Both findings are consistent with the predictions of the theoretical models. In Flannery's and Diamond's models, asymmetric information causes some firms to choose short maturities because they are less likely than other firms to have problems rolling over their short-term debt, either in terms of high interest rates (in Flannery's model) or liquidity risk (in Diamond's model). As shown below, reductions in informational asymmetries reduce these incentives and increase the average maturity for firms rated as low risk.

Section I of the paper provides the framework for our tests, delineating the intuition behind Flannery's and Diamond's models, connecting these theoretical models to the data, and motivating the empirical tests. Section II reviews the relevant empirical literature on debt maturity. Section III outlines the empirical tests. Section IV furnishes information on how the data samples are compiled, and Section V discusses the specific variables and their sample statistics. Section VI supplies the main empirical test results, while Section VII describes additional empirical checks. Section VIII presents some conclusions.

I. Framework for the Tests

Flannery's (1986) and Diamond's (1991) models are closely related in that they both explain why risky firms with long-term projects might borrow on a short-term basis in the presence of asymmetric information. However, they differ in important ways and have some distinct empirical predictions. In this section, we briefly describe the intuition underlying these theoretical models and show how they may be tested in the same empirical model.[2]

In both Flannery's and Diamond's models, firms have two-period projects about which they have private information. The projects could be financed either using long-term debt—a two-period security—or by short-term debt—a succession of two one-period securities. The longer maturity has a higher interest rate, but some firms may still choose it because of anticipated problems in rolling over short-term debt. In Diamond's model, some firms are not offered the option of long-term debt.

In Flannery's model, two types of firms that are initially observationally equivalent both have positive net present value (NPV) projects and private

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[2] The technical appendix to our working paper gives more explicit details about these models and the effects of reducing asymmetric information on debt maturity in the context of these models (Berger, Espinosa-Vega, Frame, and Miller (2005)).

information that one type is riskier than the other. At the end of one period, creditors learn whether projects were upgraded or not; firms with favorable private information (i.e., low-risk projects) have a higher probability of upgrade than those with unfavorable information (i.e., high-risk projects). At that time, all firms that initially chose short-term debt must roll it over at a new interest rate and incur additional transactions costs.

In this model, if transactions costs are sufficiently high, a separating equilibrium may exist in which firms with favorable private information issue short-term debt at a relatively low interest rate and roll it over, and those with unfavorable private information issue long-term debt at a relatively high rate. Firms with unfavorable private information are willing to pay the high rate on long-term debt to avoid the expected costs in rolling over short-term debt, that is, the transactions costs plus a relatively high probability of paying a high rate in the second period. Firms with favorable private information, in contrast, face a lower probability of a high rate in the second period and thus are willing to bear the transactions costs to obtain the lower rate on short-term debt in the first period. In equilibrium, creditors can infer some of what was initially firm-specific private information and use it in assigning risk ratings, assigning lower risk ratings to firms that choose short-term debt and higher risk ratings to those that choose long-term debt. As a result, debt maturity is predicted to be positively related to risk ratings. While we refer to this prediction as arising from Flannery's model, it is also consistent with related signaling models that do not rely on the presence of transactions costs (e.g., Kale and Noe (1990), Titman (1992)).

Diamond's model differs from Flannery's in that firms are not initially observationally equivalent and not all projects have positive NPVs. Firms have private information that their projects have positive or negative NPV. Creditors do not observe whether projects have positive or negative NPV, but are able to assign initial risk ratings based on other observational differences. No additional transactions costs are required for financing via short-term debt. As in Flannery's model, creditors learn whether projects were upgraded at the end of one period. Because some of the projects have negative NPV, creditors may refuse to roll over short-term debt at the end of one period, creating liquidity risk for firms with short-term debt.

In Diamond's model, firms with favorable private information (i.e., positive NPV projects) and sufficiently low-risk ratings may choose short-term debt at relatively low interest rates because of a high likelihood of being able to roll over their debt. Those with favorable private information and intermediate risk ratings may choose long-term debt at a higher rate to reduce their greater liquidity risk of being unable to roll over short-term debt after one period. Firms with unfavorable private information (i.e., negative NPV projects) and either low or intermediate risk ratings may mimic the actions of firms with favorable private information—otherwise, they may be identified by creditors as having negative NPV projects and be denied credit. Thus, all firms rated as low risk borrow short term and all those rated as intermediate risk borrow long term, whether their private information is favorable or unfavorable.

Firms that are initially rated as high risk in Diamond's model may be refused the option of long-term debt because of a high probability of a negative NPV project. This is consistent with the debt contracting literature, in which the most restrictive contract terms are often used with the high-risk borrowers under conditions of asymmetric information (e.g., Berlin and Loeys (1988), Berlin and Mester (1993), Carey et al. (1993)). However, if creditors can obtain sufficiently high returns from liquidation after the end of the first period, they may offer short-term debt to firms with projects rated as high risk. Thus, Diamond's model predicts debt maturity to be a nonmonotonic function of the risk ratings, with firms rated as low risk and high risk having short-term debt and firms rated as intermediate risk having long-term debt.

As discussed above, in Test 1, we examine whether maturity is an upward-sloping function of the risk rating as predicted by Flannery's model versus the nonmonotonic function predicted by Diamond's model. Thus, we test both theoretical models using the same empirical model. We argue that the use of the risk rating at the time the debt is issued gives appropriate tests of both theories. In Flannery's model, creditors draw inferences from debt maturity choices, and their risk ratings reflect some of what was initially private information of the firms. In Diamond's model, creditors' risk ratings reflect only the initial assessments based on observable differences because no private information is revealed by maturity choice. Thus, both theories have testable empirical implications for the relationship between maturity and risk ratings at the time the credits are issued when evaluated under their own assumptions.

As noted earlier, in Test 2, we examine the effects of reduced informational asymmetries from SBCS on debt maturities for each different risk rating as predicted by Flannery's and Diamond's models and further explore the quantitative impact of asymmetric information within the context of these models. Both models would predict an increase in average maturity for firms rated as low risk if informational asymmetries are reduced. In Flannery's model, this occurs because the benefits to a low-risk firm from distinguishing itself via costly signaling from riskier firms are lessened as transparency is improved. That is, low-risk firms need not bear the transactions costs of rolling over short-term debt if they are no longer in danger of being pooled with high-risk firms. In Diamond's model, the removal of asymmetric information would turn some firms into transparent, low-risk firms with positive NPV projects and others into transparent, high-risk firms with negative NPV projects. The former set of firms should be indifferent to short-term versus long-term debt, since the liquidity risk issue is resolved. Assuming that some choose long-term debt, the average maturity for low-risk firms would increase relative to the case of asymmetric information in which all firms rated as low risk choose short-term debt. The latter set of firms that are revealed to have negative NPV projects would be denied credit and so would have no effect on the observed relationship between maturity and risk ratings.

Test 2 also addresses a potential shortcoming of Test 1 both here and in the empirical literature, namely, that the observed relationship between debt maturity and risk ratings may reflect other factors. In particular, there may

be a problem if risk ratings are assigned, in part, on the basis of the risks associated with the amount of time that the funds are tied up, as opposed to the credit risks of the firms. Test 2 examines different maturities for a given risk rating, minimizing the effects of this potential problem.

II. Empirical Literature Review

This section first reviews the empirical evidence regarding debt maturity under conditions of asymmetric information. We focus on the relationship between maturity and risk ratings and the extent to which this relationship may be attributed to informational asymmetries as predicted by Flannery's and Diamond's models. We do not discuss findings with regard to other theories of debt maturity, such as agency costs and taxes. We then discuss how our empirical analysis differs from this literature.

A. *Tests of Flannery's and Diamond's Models*

Several studies examine the relationship between risk ratings and a firm's debt maturity structure, or the stock of debt that has been built up over time, to test the predictions of Diamond's model. Barclay and Smith (1995) find that among publicly traded industrial firms with bond ratings, those with higher bond ratings tend to use more short-term debt and those with lower bond ratings tend to have more long-term debt. Those without bond ratings generally have more short-term debt. If one interprets firms with high bond ratings as low risk, firms with low bond ratings as intermediate risk, and unrated firms as high risk, then their results as a whole may be considered to be consistent with Diamond's predicted nonmonotonic relationship. Subsequent studies by Stohs and Mauer (1996) using bond ratings for publicly traded industrial firms and Scherr and Hulburt (2001) using an accounting measure for risk ratings (Altman Z-Score) for small businesses also find evidence of a nonmonotonic relationship between firm risk ratings and debt maturity structure. Johnson (2003) studies nonfinancial traded firms and uses three different types of risk ratings, two based on accounting data (firm size and earnings volatility), and one based on whether the firm's debt is investment grade. Johnson's accounting indicators have the nonmonotonic relationship with debt maturity structure, but the indicator for investment-grade debt is negatively related to the proportion of short-term debt, which may be considered to be contrary to the predictions of Diamond's model, under which low-risk firms would have short-term debt.

These studies do not use the relationship between risk ratings and maturity to test the predictions of Flannery's model, although some inferences might be drawn using our framework for Test 1 discussed above. The nonmonotonic relationships in Barclay and Smith (1995), Stohs and Mauer (1996), and Johnson (2003) using bond ratings may be considered to be consistent with the predictions of Flannery's model for low-risk firms, but not for high-risk firms. The relationships using accounting measures for risk ratings in Scherr and Hulburt (2001) and Johnson (2003) do not have implications for Flannery's model. The

risk rating in Flannery's model is based at least in part on the revelation of private information by firm maturity choice. Although bond ratings may reflect such a revelation, accounting measures cannot.

It is unclear, however, how well these empirical studies of debt maturity structure test the theoretical models. Flannery's and Diamond's models deal with the maturity of new debt issues at the time of origination, not the remaining time on the stock of old contracts. The use of the maturity structure does not distinguish between, for example, a newly issued 1-year bond and a 30-year bond with 1 year remaining—both contribute to the stock of 1-year securities in the debt maturity structure. In addition, the debt maturity structure may reflect decisions made at different historical points in time when risk ratings and asymmetric information may have differed significantly from the sample period.[3]

Several studies avoid the potential problems with the use of maturity structure and focus on the maturity of new debt issues. Mitchell (1993), Guedes and Opler (1996), and Ortiz-Molina and Penas (2004) estimate the relationship between the maturity of new debt issues and risk ratings, although these studies do not use specifications that allow for the nonmonotonic function predicted by Diamond's model. Mitchell (1993) and Ortiz-Molina and Penas (2004) use linear functions and Guedes and Opler (1996) use only two categories of risk ratings (investment grade vs. noninvestment grade).

Mitchell (1993) uses data on publicly traded corporations and finds that those with higher bond ratings tend to have longer maturities. Ortiz-Molina and Penas (2004) use data on small businesses and specify an accounting measure for the risk rating (prior delinquency). They also find that firms rated as low risk tend to have longer maturities than those rated as high risk. The results presented in both papers may be consistent with Diamond's model for high-risk firms, but no strong conclusions may be taken because of the linear specifications. Finally, Guedes and Opler (1996) study traded corporations and find that firms with investment-grade ratings tend to issue shorter and longer term debt, while noninvestment-grade firms tend to issue debt with intermediate maturities, which would appear to conflict with some of the predictions of Diamond's model.

As above for the studies using debt maturity structure, the studies using new debt issues do not use the relationship between risk ratings and maturity to test the predictions of Flannery's model, but we may draw inferences based on our Test 1 framework. The relationships found in the bond ratings studies of Mitchell (1993) and Guedes and Opler (1996) appear to conflict with the upward-sloping function predicted by Flannery's model. The relationship in Ortiz-Molina and Penas (2004) does not have implications for Flannery's model because of the use of accounting data for risk ratings.

Most of the studies discussed here—using both debt maturity structure and new debt issues—also include measures of asymmetric information in their specifications. Some studies specify variables that may reflect the degree to

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[3] Barclay and Smith (1995, p. 629) make a similar point.

which a firm's ex ante private information is favorable versus unfavorable. Barclay and Smith (1995), Stohs and Mauer (1996), and Johnson (2003) include the ex post change in operating earnings per share, while Guedes and Opler (1996) include the ex post change in stock returns. To the extent that Flannery's model is important in determining debt maturity through a separating equilibrium, it may be expected that firms with favorable ex ante private information would tend to have short maturities and vice versa for those with unfavorable ex ante private information. However, the estimated effect of the ex post measures might be expected to be relatively weak because these measures are likely to be noisy gauges of ex ante private information. As well, the regression equations also include risk ratings as exogenous variables, which may also be indicators of favorable versus unfavorable private information under Flannery's model. Consistent with these arguments, the authors find relatively weak results in the application of these variables. Barclay and Smith (1995), Stohs and Mauer (1996), and Johnson (2003) find that ex post increases in earnings are associated with short-term debt, but the economic magnitudes are quite small, except in Johnson (2003). Guedes and Opler (1996) find no statistically significant relationship between maturity and a firm's ex post change in stock returns.

Many of these empirical studies also specify measures of asymmetric information or informational opacity of the firm regardless of whether the private information is favorable or unfavorable. Such measures are analogous to the SBCS variable that we use to measure asymmetric information in our Tests 1 and 2. Barclay and Smith (1995) find that firms with lower valuations, higher research and development spending, and more growth potential tend to issue more short-term debt, consistent with the notion that greater informational asymmetries are associated with shorter maturity. Analogously, three of the studies find that smaller firms—which are likely to be relatively opaque—tend to issue more short-term debt (Stohs and Mauer (1996), Scherr and Hulburt (2001), Ortiz-Molina and Penas (2004)). The evidence with regard to firm age is less clear. Scherr and Hulburt (2001) find that older firms issue less short-term debt, while Ortiz-Molina and Penas (2004) find that older firms issue more short-term debt. However, as noted above, none of the studies to our knowledge distinguish the effects of asymmetric information on maturity by risk rating.

B. How Our Empirical Analysis Differs from the Literature

Clearly, there is room for additional empirical work on debt maturity. Some of the studies use data on debt maturity structure, rather than new debt issues, and those using new debt issues employ specifications that do not allow for the nonmonotonic function predicted by Diamond's model. Moreover, none of the studies to our knowledge interact the effects of asymmetric information with risk ratings. In this paper, we use data on new debt issues, employ a specification that allows for the nonmonotonic function predicted by Diamond's model, and interact the effects of asymmetric information with the risk ratings. We also argue that our approach has several other advantages.

First, our focus on bank loans to small businesses is advantageous, since small businesses tend to fit the profile of risky firms under conditions of asymmetric information for which the theories are written. The small business loans used here have a broad range of maturities, from 1 day to 30 years. Most other empirical studies focus on corporations issuing debt in public markets, although two also use small business data, Scherr and Hulburt (2001) and Ortiz-Molina and Penas (2004).

Second, we include several additional loan contract terms in the regressions to help control for other important factors that may affect maturity. Other studies are often unable to control for all of these potentially confounding factors, which may be directly related to risk ratings, informational asymmetries, and debt maturity.

Third, our use of information about whether and how banks use the SBCS technology provides a very clean measure of asymmetric information that confers advantages to both of our tests. Test 1 focuses on loans made by banks that have not adopted the SBCS information technology, given that the relationships between debt maturity and firm risk ratings should be strongest when informational asymmetries are greatest. Other studies do not distinguish the effects of risk ratings given the level of informational asymmetries. Test 2 does differentiate the effects of the differences in asymmetric information by risk rating for the first time. We argue that it is important to conduct these tests by risk rating, given that the theoretical model predictions vary with firm ratings.

III. Brief Outline of the Empirical Tests

To test the theoretical models, we combine data on the maturities, risk ratings, and other contract terms of loans to small businesses with facts about the banks that extend these loans and information on whether and how these banks employ the SBCS lending technology. We base our two tests on a simple regression model of the maturities of the individual loans:

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\begin{aligned}
\ln(1 + \text{Maturity}) = {} & \alpha + \beta_1 \times \text{SCORE} + \gamma_2 \times \text{RISK2} + \gamma_3 \times \text{RISK3} + \gamma_4 \times \text{RISK4} \\
& + \delta_2 \times \text{SCORE} \times \text{RISK2} + \delta_3 \times \text{SCORE} \times \text{RISK3} \\
& + \delta_4 \times \text{SCORE} \times \text{RISK4} \\
& + \text{Control variables for the lending bank and loan contract} \\
& \quad \text{terms.} \tag{1}
\end{aligned}
$$

The dependent variable is the natural log of one plus Maturity, where Maturity is the time in years until full repayment of the loan is scheduled, with one included to avoid taking the log of a value close to 0. The variable SCORE takes a value of 1 if the SBCS technology is employed in conjunction with another lending technology to reduce informational asymmetries, and 0 if SBCS is not used. As discussed below, loan observations from banks that use SBCS in ways that are ambiguous with respect to reducing informational asymmetries, that is, use scores to automatically approve/reject applicants, are excluded. The variables RISK1 through RISK4 indicate the risk rating on the loan from safest

(RISK1) to riskiest (RISK4). We treat RISK1 as the base category and exclude the RISK1 and SCORE $\times$ RISK1 variables, that is, we set $\gamma_1 \equiv \delta_1 \equiv 0$. Thus, we estimate loan maturity as a function of measures of informational asymmetries, risk ratings, and their interactions, as well as some control variables. We provide more details on the data sources, variables, and estimation procedures below.

In Test 1, we examine whether maturity is an upward-sloping function of the risk ratings as predicted by Flannery's model versus the nonmonotonic function predicted by Diamond's model. We evaluate predicted maturities for RISK1, RISK2, RISK3, and RISK4 at SCORE = 0, that is, for loans made by banks that have not adopted SBCS. We focus on nonscoring banks for Test 1 because the relationships between maturity and risk ratings should be strongest when informational asymmetries are greatest. We test the difference in predicted maturity for the safest risk rating RISK1 versus the two intermediate risk ratings, RISK2 and RISK3. Thus, we test $H_0: \gamma_2 = 0$ and $H_0: \gamma_3 = 0$, where the subscript 0 refers to the null hypothesis. Similarly, we test the difference in predicted maturity for the highest risk rating RISK4 versus RISK2 and RISK3, that is, the null hypotheses $H_0: \gamma_4 - \gamma_2 = 0$ and $H_0: \gamma_4 - \gamma_3 = 0$. Although Flannery's original model had only two firm risk categories, the extension to incorporating intermediate categories is straightforward.

Thus, Test 1 examines whether the lowest risk and highest risk firms have shorter or longer maturities than intermediate-risk firms. Both Flannery's and Diamond's models predict the lowest risk firms to have shorter maturities than intermediate-risk firms, that is, $H_{A:F,D}: \gamma_2 > 0$ and $H_{A:F,D}: \gamma_3 > 0$, where subscript A refers to the alternative hypothesis, subscript F to Flannery's model, and subscript D to Diamond's model. Flannery's model also predicts the highest risk firms to have longer maturities than intermediate-risk firms, that is, $H_{A:F}: \gamma_4 - \gamma_2 > 0$ and $H_{A:F}: \gamma_4 - \gamma_3 > 0$. In contrast, Diamond's model predicts shorter maturities for the highest risk firms than for intermediate-risk firms, that is, $H_{A:D}: \gamma_4 - \gamma_2 < 0$ and $H_{A:D}: \gamma_4 - \gamma_3 < 0$. Thus, we test the following null versus alternative hypotheses in Test 1:

Test 1: (a) $H_0 : \gamma_2 = 0$ versus $H_{A:F,D} : \gamma_2 > 0$,
   (b) $H_0 : \gamma_3 = 0$ versus $H_{A:F,D} : \gamma_3 > 0$,
   (c) $H_0 : \gamma_4 - \gamma_2 = 0$ versus $H_{A:F} : \gamma_4 - \gamma_2 > 0$ and $H_{A:D} : \gamma_4 - \gamma_2 < 0$,
   (d) $H_0 : \gamma_4 - \gamma_3 = 0$ versus $H_{A:F} : \gamma_4 - \gamma_3 > 0$ and $H_{A:D} : \gamma_4 - \gamma_3 < 0$.   (2)

In Test 2, we examine the effects of reduced informational asymmetries from SBCS on debt maturity for each risk rating. As discussed, for a reduction in asymmetries, Flannery's model would predict an increase in maturity for low-risk firms and smaller increases in debt maturity for intermediate-risk firms. Diamond's model would predict a similar increase in maturity for low-risk firms.

We assess the effect of the reduction in informational asymmetries by testing for the difference in predicted maturity for SCORE = 1 versus SCORE = 0 for each risk rating. For the safest firms (RISK1 = 1), we test the null hypothesis $H_0: \beta_1 = 0$. Similarly, we test null hypotheses for the differences in predicted

maturity for SCORE = 1 versus SCORE = 0 for the other three risk ratings, RISK2 (H_0: $\beta_1 + \delta_2 = 0$), RISK3 (H_0: $\beta_1 + \delta_3 = 0$), and RISK4 (H_0: $\beta_1 + \delta_4 = 0$).[4] As well, we test the null of whether the predicted differences are equal for the intermediate risk ratings with the safest risk rating, that is, H_0: $\delta_2 = 0$ and H_0: $\delta_3 = 0$. Both Flannery's and Diamond's models would predict an increase in maturity for low-risk firms as informational asymmetries are reduced, that is, $H_{A:F,D}$: $\beta_1 > 0$. Flannery's model would also predict maturity increases for firms with intermediate risk ratings from reduced informational asymmetries, but these increases would be smaller than for the safest risk rating, that is, $H_{A:F}$: $\beta_1 + \delta_2 > 0$ and $\delta_2 < 0$, and $H_{A:F}$: $\beta_1 + \delta_3 > 0$ and $\delta_3 < 0$.[5] Thus, we test the following hypotheses in Test 2:

Test 2: (a) H_0: $\beta_1 = 0$ versus $H_{A:F,D}$: $\beta_1 > 0$,
(b) H_0: $\beta_1 + \delta_2 = 0$ and $\delta_2 = 0$ versus $H_{A:F}$: $\beta_1 + \delta_2 > 0$ and $\delta_2 < 0$,
(c) H_0: $\beta_1 + \delta_3 = 0$ and $\delta_3 = 0$ versus $H_{A:F}$: $\beta_1 + \delta_3 > 0$ and $\delta_3 < 0$,
(d) H_0: $\beta_1 + \delta_4 = 0$. (3)

We test the null hypothesis for RISK4 in (3d) for completeness, although neither of the theories predicts a significant effect of a change in asymmetric information on maturity for the highest risk firms.

IV. Compilation of the Data Set

We combine data from three sources to obtain the variables to estimate equation (1) and conduct Tests 1 and 2. The first source is the Federal Reserve's STBL, which contains details on the contract terms of all new domestic commercial and industrial (C&I) loans issued by surveyed banks during 1 or more days of the first week of the second month of each quarter. Starting in the second quarter of 1997, the banks report risk ratings on each loan as well. The STBL includes almost all of the largest U.S. banks plus a stratified random sample of smaller banks.

The second source is the set of regulatory reports on the banks that issue the loans. The Call Report and other regulatory files provide information on the balance sheets, income statements, ownership changes, markets, and so forth for all U.S. banks.

Our third data source is a January 1998 telephone survey conducted by the Federal Reserve Bank of Atlanta, which provides information on whether and how surveyed banks use the SBCS lending technology. The data include whether and when the technology is implemented, the sizes of credits that are scored, whether the credit scores are used in automated approval/rejection and pricing decisions, and whether the bank purchases credit scores. The survey

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[4] We test each of these coefficient sums separately, rather than the joint test (H_0: $\beta_1 = \delta_2 = \delta_3 = \delta_4 = 0$), because our focus is on the changes in maturity in each of the risk ratings from a reduction in informational asymmetries, rather than the general effect across the risk ratings.

[5] The δ_2 and δ_3 coefficients must be negative so that the increases in maturity for intermediate-risk firms ($\beta_1 + \delta_2$ and $\beta_1 + \delta_3$) are less than the increase for the low-risk firms (β_1).

queries 190 of the 200 largest U.S. banking organizations, of which 99 institutions respond. See Frame, Srinivasan, and Woosley (2001) for more details of the survey.

Our data set is compiled from the intersection of these three sources, so that complete information is available on the contract terms and risk ratings on each loan, the bank that extended the loan, and whether and how that bank uses the SBCS technology. The sample contains observations from the second, third, and fourth quarters of 1997, when the risk ratings are available from the STBL and the SBCS information is available from the credit scoring survey. We identify 53 banks that respond to the STBL during these three quarters and also respond to the January 1998 credit scoring survey.[6]

We include only loans with total credit size under $250,000 because SBCS models are generally only designed for credits up to this size. Total credit size is calculated as the maximum of the loan amount and the size of the commitment under which it is drawn, if any. As is standard procedure in bank lending research, we refer to these credits as small business loans, although in some cases they may be small credits to large businesses.[7]

We also divide the sample into credits under $100,000 (<$100K), and credits of $100,000 to $250,000 ($100K–$250K) because some banks only use SBCS to evaluate credits <$100K, while others use the technology to evaluate credits up to $250K. In the full SBCS survey, all of the banks that use SBCS (62 of the 99 responding banks) apply the technology to credits <$100K, and 74% of these banks (46 of the 62 SBCS users) also applied it to credits of $100K–$250K (Frame et al. (2001)). Other research also suggests that SBCS may have different effects for the two loan size classes (Berger et al. (2005)).

As noted earlier, we focus on the use of the SBCS technology when it is likely to reduce informational asymmetries. This is most likely to occur when the SBCS technology is used in conjunction with another lending technology, that is, when the credit score is added to the information set produced by financial statement lending, asset-based lending, relationship lending, or another lending technology.[8] Following this logic, we include loans from banks that use SBCS only if they also use another lending technology in the decision to accept or reject the credit application. Banks that report on the SBCS survey that they use the SBCS technology to automatically accept/reject credit applications are deleted from our samples because the effects of this use of the technology on informational asymmetries are ambiguous. Thus, our empirical treatment of a reduction in informational asymmetries is based on the difference between

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[6] Two banks that respond to both surveys are eliminated because they do not report risk ratings.

[7] We exclude fixed-rate loans (less than 2% of the observations) to construct a more homogeneous sample.

[8] It is theoretically possible that the banks adopting SBCS are those that tended to have worse loan quality, and hence even after implementing SBCS have more information asymmetry than their competitors. However, some of the other research using the SBCS data suggests that this is not the case. Investigations of the SBCS adoption decision find that it is unrelated to both the bank's prior commercial loan charge-off ratio (Frame et al. (2001)) and the bank's prior ratio of small business lending to assets (Berger et al. (2005)).

banks that use SBCS in conjunction with another lending technology to make the loan underwriting decision and banks that do not use SBCS at all. Consistent with this treatment, other research using these survey data finds evidence consistent with the hypothesis that the use of SBCS as a complement to other technologies improved accuracy in evaluating creditworthiness, resulting in significantly lower loan risk (Berger et al. (2005)).

V. Variables and Summary Statistics

Table I provides means and standard deviations of the variables used in the regressions and tests, shown separately for the two samples, credits < \$100K and credits of \$100K–\$250K. The variable Maturity is measured as the time in years before the scheduled repayment of all principal and interest, and ranges from 1 day to 30 years. For a significant minority of loans that have no stated maturity, we impute it as the time until the interest is first compounded or paid. If this date is not reported, we treat these as 1-day or overnight loans. We discuss altering these assumptions in the robustness section below. As shown, the average maturity is over 1 year for both samples.

The variable SCORE equals 1 if the bank reports that it employs SBCS for that size category of loans and does not use it for automatic accept/reject decisions (data from banks that use SBCS for automatic accept/reject decisions are deleted). We set SCORE = 0 if the bank does not use SBCS for that size category. As shown, more than half of the sample loans are made by banks that use SBCS.

The RISK1 through RISK4 variables are dummies for risk ratings on the loan assigned by the bank from safest (RISK1) to riskiest (RISK4): RISK1 equals 1 when the bank reports on the STBL that the loan carries "minimal" risk; RISK2 equals 1 when the loan carries "low" risk; RISK3 equals 1 when the loan carries "moderate" risk; and RISK4 equals 1 when the loan carries "acceptable" risk.[9] As shown, most of the loans have the two highest risk ratings.[10]

We control for bank size because different sized banks may treat small business borrowers differently. The regressions include ln(GTA), the natural log of bank gross total assets. There are no small banks in the samples because the SBCS survey queries only large institutions. The average GTA is about \$17 billion for credits < \$100K and about \$31 billion for credits of \$100K–\$250K,

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[9] The STBL instructions relate the rating of 1 with AA-rated corporate bonds and the rating of 2 with BBB corporate bonds. It is more difficult to provide a bond equivalent for ratings of 3 and 4. We exclude loans rated 5, "special mention or classified asset," because they are more likely renewals of problem loans rather than new, independent loans. We also exclude loans from banks that do not report comparable loan ratings.

[10] Extant research suggests that while these ratings provide a reasonable ordinal ranking of risks, they are far from perfect. Berger (2006) shows that higher risk ratings are generally associated with higher interest rate premiums (e.g., premiums of about 35 basis points more for RISK2 loans than RISK1 loans), but that some institutions may have problems translating their own ratings into the STBL categories. Morgan and Ashcraft (2003) find that the STBL risk ratings help predict future CAMEL downgrades as expected, but do not add much information to loan interest rates in predicting future nonperforming loans.

Table I

Variables and Summary Statistics for the Two Samples

Means and standard deviations for variables used in estimation. Both samples combine loan observations from banks that do not use credit scoring technology (SCORE = 0) with loan observations from banks that use credit scoring technology but not to automatically approve/reject loans (SCORE = 1). Maturity is the time in years before the repayment of principal and interest is scheduled to be completed. SCORE is a dummy variable that equals 1 if the bank adopted credit scoring technology before the loan was made. RISK1, RISK2, RISK3, and RISK4 are dummy variables that equal 1 if the loan is rated "minimal," "low," "moderate," and "acceptable" risk, respectively. RISK1 is excluded from the regressions as the base case. GTA is the gross total assets of the bank ($000). NPL is the bank's ratio of nonperforming loans (past due 30 days or more or nonaccrual) to total loans. GTA and NPL are measured from the previous year's December Call Reports to mitigate potential endogeneity problems. COLLAT is a dummy that equals 1 if the loan is secured. COMMIT is a dummy variable that equals 1 if the loan is made under commitment. CREDIT SIZE is the maximum of the loan amount and the amount of commitment, if any.

	Credits < $100K (N = 3,622)	Credits of $100K–$250K (N = 2,910)
Dependent variable		
Maturity	1.505	1.234
	(1.726)	(1.877)
Credit scoring and risk variables		
SCORE	0.624	0.528
	(0.484)	(0.499)
RISK1	0.035	0.019
	(0.185)	(0.136)
RISK2	0.118	0.073
	(0.323)	(0.260)
RISK3	0.610	0.488
	(0.488)	(0.500)
RISK4	0.237	0.421
	(0.425)	(0.494)
Bank variables		
GTA	17,048,837	30,832,584
	(34,625,844)	(45,515,624)
NPL	0.014	0.014
	(0.012)	(0.009)
Loan contract terms		
COLLAT	0.719	0.789
	(0.449)	(0.408)
COMMIT	0.610	0.815
	(0.488)	(0.389)
CREDIT SIZE ($000)	43.58	183.72
	(32.47)	(45.00)

and the overall range of banks is from about $1.5 billion to $245 billion. The difference in sample means occurs because the small banks use SBCS more often only on credits < $100K.[11]

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[11] We do not include bank fixed effects because they would be almost perfectly correlated with the SCORE variable. Only 2 of the 53 banks adopted SBCS during the sample period—the other 51 either have SCORE = 0 or SCORE = 1 for all observations.

We control for the loan portfolio health of the bank, which may affect the bank's proclivities to lend to risky firms, to lend at different maturities, or to make new loans. The regressions include NPL, the bank's ratio of nonperforming loans to total loans. The average NPL in both samples is 0.014, meaning that 1.4% of loans are past due 30 days or more, or are on a nonaccrual basis. Both GTA and NPL are constructed from the December 1996 Call Report. We use bank data from prior to the loans being issued to help mitigate potential endogeneity problems.

We control for three loan contract terms, a dummy for whether collateral is pledged (COLLAT); a dummy for whether the loan is drawn under a commitment (COMMIT); and the total credit size, including the amount of any commitment (CREDIT SIZE). These variables may be associated with asymmetric information, risk ratings, and maturity choice, so exclusion of these variables may create spurious relationships between maturity and the key exogenous variables. However, these variables could also introduce an endogeneity problem because the bank and the firm may trade off between maturity and other contract terms. As a consequence, we run all regressions with and without contract terms to evaluate the robustness of our results.[12] Table I shows that most of the loans are secured and drawn under commitments. The means of CREDIT SIZE are about $44,000 for credits < $100K and about $184,000 for credits of $100K–$250K.

Finally, the regressions include Q3 and Q4, two seasonal dummy variables that indicate whether the loan was made in the third and fourth quarters of 1997, respectively (not shown in tables). A dummy for the second quarter dummy is excluded as the base case.

VI. Empirical Test Results

A. Main Regression Results

Table II shows our main regressions for loan maturity based on the specification in equation (1). We run ordinary least squares regressions separately for credits < $100K and for credits of $100K–$250K, and run each regression both with and without the potentially endogenous loan contract terms, COLLAT, COMMIT, and ln(CREDIT SIZE). Robust standard errors are calculated using a clustering correction that accounts for heteroskedasticity and for correlations among observations from the same bank.[13]

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[12] Prior research offers empirical evidence that contract terms are endogenous based on a sample of revolving bank loans to large firms (Dennis, Nandy, and Sharpe (2000)). These authors provide a structural model that incorporates a number of firm-level characteristics, which allows them to identify the system and to construct instrumental variables. Unfortunately, our data have no firm-specific information that would allow for such an approach.

[13] We use the Huber–White sandwich estimator to compute standard errors (Huber (1967), White (1982)). Independence is relaxed for loan observations from the same bank, but maintained for loan observations from different banks. The results are materially unchanged when we use random effects or the standard White correction instead of clustering.

Table II

Maturity Regressions

Ordinary least squares regressions for $\ln(1 + \text{Maturity})$, where Maturity is the time in years before the repayment of principal and interest is scheduled to be completed. Both samples combine loan observations from banks that do not use credit scoring technology (SCORE = 0) with loan observations from banks that use credit scoring technology but not to automatically approve/reject loans (SCORE = 1). Regressions include RISK2, RISK3, and RISK4, dummy variables that equal 1 if the loan is rated "low," "moderate," and "acceptable" risk, respectively (RISK1 or "minimal" risk is excluded as the base case); ln(GTA), the natural log of gross total assets of the bank ($000); NPL, the bank's ratio of nonperforming loans (past due 30 days or more or nonaccrual) to total loans; COLLAT, a dummy that equals 1 if the loan is secured; COMMIT, a dummy variable that equals 1 if the loan is made under commitment; and ln(CREDIT SIZE), the natural log of the maximum of the loan amount and the amount of commitment ($000), if any. Regressions also include Q3 and Q4, which indicate the quarter in which the loan was made; Q2 is excluded as the base case (our sample includes the final three quarters of 1997). Robust t-statistics are calculated using a clustering correction for correlations among observations from the same bank (we impose a zero correlation across banks), and for heteroskedasticity. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Credits < $100K				Credits of $100K–$250K			
	Contract Terms		No Contract Terms		Contract Terms		No Contract Terms	
Variables	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Intercept	2.901***	4.11	2.999***	3.93	1.092	1.53	1.137**	2.05
Credit scoring and risk								
SCORE	0.251***	2.97	0.167**	2.26	0.403***	3.05	0.387***	3.08
RISK2	0.345***	3.27	0.236**	2.29	0.151	1.15	0.143	1.10
RISK3	0.436***	8.38	0.285***	5.60	0.247**	2.44	0.236**	2.32
RISK4	0.470***	4.82	0.312***	3.44	0.307***	2.69	0.300***	2.72
SCORE × RISK2	−0.156	−1.19	−0.143	−1.15	−0.226	−1.31	−0.211	−1.20
SCORE × RISK3	−0.352***	−3.57	−0.260***	−2.82	−0.442***	−3.13	−0.428***	−3.05
SCORE × RISK4	−0.390***	−2.72	−0.318**	−2.62	−0.550***	−3.42	−0.542***	−3.31
Bank size and loan portfolio health								
ln(GTA)	−0.158***	−3.52	−0.155***	−3.12	−0.053	−1.50	−0.048	−1.36
NPL	−1.914	−1.02	−2.221	−1.03	−1.702	−0.68	−1.831	−0.73
Loan contract terms								
COLLAT	0.184***	4.13			−0.041	−0.74		
COMMIT	−0.264***	−3.36			−0.004	−0.02		
ln(CREDIT SIZE)	0.001	0.05			0.029	0.47		
Adj. R^2	0.160		0.100		0.029		0.030	
N	3,622		3,622		2,910		2,910	

For expositional convenience, we first briefly discuss the control variable results. The data suggest that larger bank size is associated with shorter maturities, consistent with theories that larger banks have a comparative disadvantage in small business lending, all else equal. Higher nonperforming loan-to-asset ratios are also associated with shorter maturities, consistent with the expectation that banks with portfolios in poor condition may be more cautious with the contract terms on new loans. Collateral is associated with shorter maturities for credits < $100K, consistent with the expectation that banks may

require both that collateral be pledged and that maturity be short for firms subject to significant moral hazard or adverse selection problems. Collateral has no statistically significant effect for credits of $100K–$250K. Commitments are associated with shorter maturities for smaller credits, perhaps because commitments are substitutes for long maturities on the loans themselves. Finally, total credit size is not strongly associated with loan maturity, although this finding may in part reflect the fact that there is relatively little variation in credit size within each sample (< $100K, $100K–$250K).

We show the main results of our key exogenous variables graphically in Figure 1. Using the parameter estimates from the regressions, we map the predicted maturities for the four different risk ratings, holding the control variables at their sample means in each case. We evaluate the predictions separately for SCORE = 0 (solid lines) and for SCORE = 1 (dashed lines). We use the predictions for SCORE = 0 in Test 1 to determine the effect of risk on maturity when informational asymmetries are at their greatest. We use the predicted differences for each risk rating between SCORE = 1 and SCORE = 0 in Test 2 to ascertain how the effects of reducing informational asymmetries affect maturity by risk rating.

B. Test 1 Findings—The Effects of Risk on Debt Maturity

Turning first to the Test 1 findings, loan maturity appears to be an upward-sloping function of risk in Figure 1. As shown in Panel A of the figure (and replicated in the first column of Table III), for credits < $100K with loan contract terms included, the predicted maturities for nonscoring banks for RISK1, RISK2, RISK3, and RISK4 are 0.67, 1.36, 1.58, and 1.67 years, respectively. Thus, maturity goes up by a full year, more than doubling, as firms move from the low-risk to the high-risk ratings, with most of the increase occurring between RISK1 and RISK2. We test below whether this large increase is statistically significant. The upward slope for SCORE = 0 is also apparent in the other three panels, with the largest increase always being between RISK1 and RISK2. The upward slope throughout is consistent with Flannery's model, and the upward slope between low risk and intermediate risk is also consistent with Diamond's model. However, the finding that maturity does not fall for high-risk firms does not appear to be consistent with Diamond's model, which would predict relatively short maturities for these firms.

We show the formal statistical tests of Test 1 in Table III for the two samples, credits <$100K and $100K–$250K, using the regressions with and without the contract terms included. For each of these four cases, we first show the predicted maturity for each risk rating, evaluated at SCORE = 0 and the sample means for the control variables. As shown in equation (2) and discussed in Section III above, we then test the difference in predicted maturity for the safest risk rating RISK1 versus the two intermediate risk ratings, RISK2 and RISK3, evaluated at SCORE = 0, that is, the null hypotheses $H_0: \gamma_2 = 0$ and $H_0: \gamma_3 = 0$. We also test the difference in predicted maturity for the highest risk rating, RISK4, versus RISK2 and

The Journal of Finance
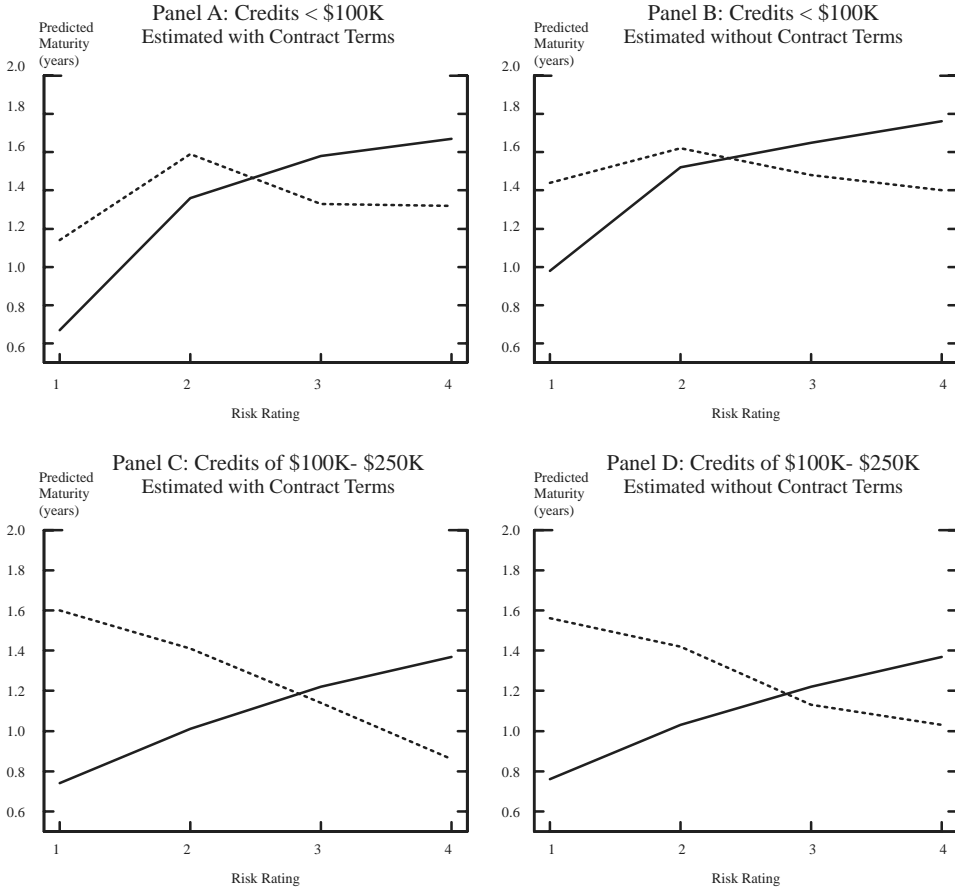
Figure 1. Predicted maturities by risk rating for SCORE = 0 and SCORE = 1. This figure maps the predicted loan maturities for the four different risk ratings, holding the control variables at their sample means. The predictions are evaluated separately for observations from banks that do not use the credit scoring technology (SCORE = 0, solid lines) and for observations from banks that use the credit scoring technology, but not to automatically approve/reject loans (SCORE = 1, dashed lines).

RISK3, that is, the null hypotheses $H_0: \gamma_4 - \gamma_2 = 0$ and $H_0: \gamma_4 - \gamma_3 = 0$. We are able to reject the null hypothesis in favor of the alternative that the lowest risk loans (RISK1) have shorter maturities than the intermediate-risk loans (RISK2, RISK3) in six of eight cases, consistent with the predictions of Flannery's and Diamond's models. Notably, we are able to reject the null in favor of the alternative that RISK1 loans have shorter maturities than either or both of RISK2 and RISK3 loans in all four regressions. These findings are also consistent with most of the findings in the empirical literature.

However, we cannot reject the null hypothesis that the highest risk loans (RISK4) have the same maturities as the intermediate-risk loans (RISK2, RISK3). Thus, although the predicted values for RISK4 at SCORE = 0 are

Table III

Test 1: The Effects of Risk on Debt Maturity

The measured effects of loan risk on predicted loan maturity, evaluated at SCORE = 0 (not using the credit scoring technology) for each loan risk rating, holding the control variables at the sample mean. We include a correction for the mean of the error on the assumption of normality (values are multiplied by $\exp(0.5 \times MSE^2)$). Rows (a) and (b) also show the difference in predicted maturities between low-risk loans (RISK1) and intermediate-risk loans (RISK2 and RISK3, respectively). Rows (c) and (d) show the difference in predicted maturities between high-risk loans (RISK4) and intermediate-risk loans (RISK2 and RISK3, respectively). RISK1 through RISK4 indicate the risk rating on the loan from safest (RISK1) to riskiest (RISK4). Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

		Contract Terms				No Contract Terms		
Row	Risk Rating	Predicted Maturity, SCORE = 0	Differences between Risk Ratings		t-Stat	Predicted Maturity, SCORE = 0	Differences between Risk Ratings		t-Stat
			Credits < $100K						
(a)	RISK1	0.67	RISK1, RISK2	−0.69***	−3.27	0.98	RISK1, RISK2	−0.54**	−2.29
(b)	RISK2	1.36	RISK1, RISK3	−0.91***	−8.38	1.52	RISK1, RISK3	−0.68***	−5.60
(c)	RISK3	1.58	RISK4, RISK2	0.31	0.89	1.65	RISK4, RISK2	0.24	0.54
(d)	RISK4	1.67	RISK4, RISK3	0.09	0.33	1.76	RISK4, RISK3	0.11	0.26
			Credits of $100K–$250K						
(a)	RISK1	0.74	RISK1, RISK2	−0.27	−1.15	0.76	RISK1, RISK2	−0.27	−1.10
(b)	RISK2	1.01	RISK1, RISK3	−0.48**	−2.44	1.03	RISK1, RISK3	−0.46**	−2.32
(c)	RISK3	1.22	RISK4, RISK2	0.34	1.06	1.22	RISK4, RISK2	0.34	0.48
(d)	RISK4	1.35	RISK4, RISK3	0.13	0.32	1.37	RISK4, RISK3	0.15	0.10

the highest in Figure 1, they are not statistically significantly different than the predicted values for RISK2 and RISK3. This finding conflicts with the predictions of Diamond's model and contrasts with most of the empirical literature that uses historically based debt maturity structure. Importantly, this finding does not suggest that Diamond's model does not apply to any of the high-risk firms, but rather that such effects could be empirically dominated by other high-risk firms for which maturity does not increase with risk ratings.

We also note that the results of Test 1 would be substantially weaker if this test was applied to observations for which SCORE = 1, with reduced informational asymmetries from SBCS. As shown by the dashed lines in Panel A of Figure 1 (and replicated below in Table IV), for credits <\$100K with loan contract terms included, the predicted maturities for RISK1, RISK2, RISK3, and RISK4 are 1.14, 1.59, 1.33, and 1.32 years, respectively, for SCORE = 1 banks. Thus, predicted maturity rises less between RISK1 and RISK2 for SCORE = 1 than for SCORE = 0 (0.45 years vs. 0.69 years), and then falls for the higher risk ratings. The statistical significance is also weaker and in some cases nonexistent for SCORE = 1 (not shown in tables). These results highlight the importance of informational asymmetries in the theoretical models and in the determination of debt maturity.

C. Test 2 Findings—The Effects of Reducing Informational Asymmetries on Debt Maturity

Turning next to the Test 2 findings, in Figure 1 loan maturity appears to increase when shifting from SCORE = 0 to SCORE = 1 for the lower risk ratings, but decrease for the higher risk ratings. As shown in Panel A of the figure (and replicated in Table IV) for credits < \$100K with loan contract terms included, the predicted maturity for RISK1 increases from 0.67 years for SCORE = 0 to 1.14 years for SCORE = 1. This predicted increase of 0.48 years, or about 72%, for the low-risk firms from employing the credit scoring technology in conjunction with another lending technology is substantial in magnitude. For RISK2, the predicted maturity increase is 0.23 years, from 1.36 to 1.59 years. However, for RISK3 and RISK4, the predicted maturities actually fall when moving from SCORE = 0 to SCORE = 1. The same qualitative pattern appears in the other three panels. Notably, for the low-risk credits of \$100K–\$250K, the predicted maturity more than doubles from SCORE = 0 to SCORE = 1, suggesting an even larger quantitative role for asymmetric information in explaining debt maturity for these larger credits. The increase in maturity for lower risk firms from a reduction in informational asymmetries is consistent with Flannery's and Diamond's models, but the fall in maturity for the higher risk firms is not consistent with these models.

Turning to formal statistical tests of Test 2, we test the difference in predicted maturity for SCORE = 1 versus SCORE = 0 by risk rating as shown in equation (3) above. We test the null hypotheses of no effect of SCORE for each of the risk ratings, that is, we test $H_0: \beta_1 = 0$, $H_0: \beta_1 + \delta_2 = 0$, $H_0: \beta_1 + \delta_3 = 0$, and

Table IV

Test 2: The Effects of Reduced Informational Asymmetries from SBCS on Debt Maturity

The measured effects of credit scoring and loan risk on predicted loan maturity, evaluated at SCORE = 0 (not using the credit scoring technology) and SCORE = 1 (using the credit scoring technology, but not to automatically approve/reject loans) for each loan risk rating, holding the control variables at the sample mean. We include a correction for the mean of the error on the assumption of normality (values are multiplied by $\exp(0.5 \times \text{MSE}^2)$). Rows (a), (b), (c), and (d) also show the difference in predicted maturity between SCORE = 1 and SCORE = 0 for RISK1, RISK2, RISK3, and RISK4 loans, respectively. RISK1 through RISK4 indicate the risk rating on the loan from safest (RISK1) to riskiest (RISK4). Significance at the 10%, 5% , and 1% levels is denoted by *, **, and ***, respectively.

Row	Risk Rating	Contract Terms				No Contract Terms			
		Predicted Maturity, SCORE = 0	Predicted Maturity, SCORE = 1	Difference	*t*-Stat	Predicted Maturity, SCORE = 0	Predicted Maturity, SCORE = 1	Difference	*t*-Stat
				Credits < $100K					
(a)	RISK1	0.67	1.14	0.48***	2.97	0.98	1.44	0.46**	2.26
(b)	RISK2	1.36	1.59	0.23	0.69	1.52	1.62	0.10	0.17
(c)	RISK3	1.58	1.33	−0.25	−0.97	1.65	1.48	−0.18	−0.77
(d)	RISK4	1.67	1.32	−0.35	−0.95	1.76	1.40	−0.36	−1.15
				Credits of $100K–$250K					
(a)	RISK1	0.74	1.60	0.86***	3.05	0.76	1.56	0.80***	3.08
(b)	RISK2	1.01	1.41	0.40	1.29	1.03	1.42	0.39	1.24
(c)	RISK3	1.22	1.14	−0.08	−0.39	1.22	1.13	−0.09	−0.40
(d)	RISK4	1.37	0.86	−0.51	−1.10	1.37	1.03	−0.34	−1.13

H_0: $\beta_1 + \delta_4 = 0$, for RISK1, RISK2, RISK3, and RISK4, respectively. These tests are shown in Table IV. For the intermediate risk ratings, RISK2 and RISK3, we also test null hypotheses of no difference in effect from the safest firms, RISK1, that is, we test H_0: $\delta_2 = 0$ and H_0: $\delta_3 = 0$ for RISK2 and RISK3, respectively. These tests are easily culled from the regression equation results shown in Table II. As shown in Table IV, we are able to statistically reject the null hypothesis in favor of the alternative that SBCS increases maturities for the lowest risk loans (RISK1) for all four estimations. The large, statistically significant increase in maturity is consistent with the predictions of Flannery's and Diamond's models that reductions in informational asymmetries reduce the benefit for low-risk firms from borrowing short term. However, we cannot statistically reject the null hypothesis that the movement from SCORE = 0 to SCORE = 1 has no effect for the other risk ratings. As shown in Table II, none of the estimates of δ_2 are statistically significant. The estimates of δ_3 are negative and statistically significant, consistent with a predicted reduction in maturity for RISK3 firms relative to RISK1 firms from a reduction in informational asymmetries. However, as shown above, the total effect for this risk rating, $\beta_1 + \delta_3$, is not statistically significant.

VII. Additional Empirical Checks

We conduct some additional empirical checks to ensure that our main findings are robust, are not the product of particular choices of samples, variables, or specifications, and do not reflect spurious outcomes due to endogeneity problems.

A. Sample and Specification Changes

We first perform a number of checks based on changes in sample and specification. We try to alter the sample by excluding loans with the longest 1% and 5% of Maturity to investigate whether outliers drive our results. In both cases, our findings remain materially unchanged. We also try altering the dependent variable by replacing ln(1 + Maturity) with the level of Maturity, and the main results continue to hold. Similarly, we try replacing the dependent variable with ln(1 + Duration), where Duration is the weighted-average time until all scheduled principal and interest payments are made. Again the main results hold, with somewhat weaker statistical significance. In addition, we try including more control variables for the lending bank and its market, specifically, the bank's age, dummies indicating whether the bank survived a merger or was acquired by a different holding company in the previous 3 years, and the weighted-average market Herfindahl index of deposit concentration and both the weighted-average personal income growth in all of the bank's local markets; there is no qualitative effect on the main results. To control for potential asset-liability maturity matching, we include the proportion of the bank's time deposits that mature in less than 1 year, again with no qualitative effect on the main results.

We also try to alter our maintained hypothesis regarding the effects of SBCS on informational asymmetries. In our main specification, we include loans from banks that use SBCS only if they do not use the technology to automatically accept/reject credit applications, so that we have only observations in which another lending technology is used in the key underwriting decision. We partially relax this constraint by also including observations from banks that do not use SBCS to set loan terms, and from banks that develop their own SBCS models, which are also indicators that the bank is using SBCS in conjunction with another lending technology. Again, the test results are materially unchanged.

As noted above, for loans with no stated maturity (18.5% of credits < $100K and 29.5% of credits of $100K–$250K), we impute Maturity as the time until the interest is first compounded or paid if reported, or assign Maturity a value of 1 day otherwise. Our results are robust to an alternative imputation that assigns a maturity of 0 for all of these loans. When we exclude the loans with no stated maturity from the sample of credits < 100K, the Test 1 results retain economic and statistical significance, but the Test 2 results do not. When we exclude these loans from the sample of credits of $100K–$250K, both the Test 1 and the Test 2 results retain economic and statistical significance. Our results are also robust to the exclusion of all overnight loans.

For a sizable minority of the credits in our samples (16.8% of credits < $100K, 26.3% of credits of $100K–$250K), the bank maintains an unqualified ability to call the credit at any time. One possible explanation of our lack of support for Diamond's model for high-risk firms is that the bank offers these firms callable loans with long maturities, using the call option instead of short maturity to address asymmetric information problems. To test this possibility, we redefine Maturity to equal 0 if the loan is callable, regardless of the stated maturity. For both credit size samples, the Test 1 and Test 2 results hold with essentially unchanged economic and statistical significance. The main results are also robust to the exclusion of all callable loans.

In addition, we run Test 1 for larger credits of $250,000 to $1 million ($250K–$1M) and $1 million to $10 million ($1M–$10M). Since SBCS technology is generally not used on these larger credits, we can run Test 1 using all banks that respond to the STBL survey, whether or not they respond to the SBCS survey. However, we cannot run Test 2 for these larger credits, since we cannot examine the effect of SBCS on these loans. We run Test 1 on these two credit size classes separately and also run these tests by bank size class to avoid confounding the effects of differences in size with difference in risk. We also run these tests for the full STBL sample and for the 53 large banks included in our main samples here for which we have SBCS information to be sure that sample selection does not explain the findings. That is, we run Test 1 for larger credits for several different samples of larger credits using the same hypothesis specification as in equation (2) and using the same regression specification as in equation (1) except that the SCORE variable and interactions are deleted. In all cases, we find no statistically significant relationship between maturity and risk rating for either low-risk or high-risk firms, so the findings are not consistent with either Flannery's or Diamond's models for larger bank credits.

This may suggest that asymmetric information problems are less severe on these larger loans or that the banks have methods other than maturity to help resolve information problems on larger loans.[14]

Finally, we analyze subsamples delineated by whether the credits were secured with collateral (COLLAT = 1) or not (COLLAT = 0), and drawn under a commitment (COMMIT = 1) or not (COMMIT = 0). Like maturity, collateral and commitments are loan contracting tools that may be used to help mitigate information problems. The subsample regressions may give insight into whether collateral or commitments may substitute for maturity in reducing information problems. These regressions may also yield inferences about clientele effects, or how the use of maturity may vary for different types of firms.[15]

For the COLLAT = 1, COLLAT = 0, and COMMIT = 1 subsamples, the main results generally hold with similar coefficients, albeit with weaker statistical significance apparently due to the reduced degrees of freedom in estimation.[16] The findings that the results generally hold for the COLLAT = 1 and COMMIT = 1 subsamples suggest that these contract terms more likely complement, rather than substitute, for maturity in dealing with asymmetric information problems.

However, we do find different results for the COMMIT = 0 subsample that are consistent with Diamond's model for both low-risk and high-risk firms. In Test 1 for the credits < \$100K that are not commitment draws, the predicted

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[14] For purposes of comparability, we also rerun Test 1 for the credits < \$100K and credits of \$100K–\$250K, and delete the SCORE variable and interactions. The deletion of SCORE and interactions in effect removes our distinction between firms that are likely to have greater versus lesser informational asymmetries (SCORE = 0 vs. SCORE = 1) within the pool of firms in a given credit size sample. We find the results for low-risk firms to be robust for the credits < \$100K, but statistical significance is lost for the credits of \$100K–\$250K. Again, this is consistent with the hypothesis that the informational opacity problems are greater for smaller credits, although the distinction is less sharp without the use of the SCORE variable.

[15] Most of the theoretical research on collateral suggests that safer firms tend to pledge collateral to signal their quality (e.g., Bester (1985), Chan and Kanatas (1985)); however, most of the empirical literature finds that riskier firms tend to pledge collateral more often (e.g., Berger and Udell (1990)). These results are consistent with the hypothesis that firms rated as the most risky may not be offered a credit alternative without collateral requirements, similar to Diamond's argument for firms rated as high risk. Similarly, commitment contracts may help banks resolve information problems by offering various sets of contract terms—up-front fees, usage fees, unused line charges, interest rates, and so forth—that induce firms to reveal their types or to choose higher net present value projects (e.g., Boot, Thakor, and Udell (1987), Berkovitch and Greenbaum (1991)).

[16] In most cases, the coefficient estimates are similar, but statistical significance declines as the estimated standard errors increase. To check whether this is due primarily to the reduction in degrees of freedom, we note that under the standard classical assumptions of i.i.d. random errors, reducing the sample size should increase the standard errors at the rate $(n - k)^{1/2}$, where $n - k$ is the degrees of freedom (subsample size n minus number of regressors k). We find that the estimated standard errors for the subsamples generally increase at approximately this rate. For example, the estimated standard error on RISK2 is 0.225 in the COLLAT = 0 subsample for credits < \$100K, and takes the value 0.103 in the full sample, creating a ratio of 0.225/0.103 = 2.18. This ratio is close to what would be predicted by the ratio of the square roots of degrees of freedom as the subsample size is reduced from 3,622 to 1,016, with 11 regressors, or $[(3,622 - 11)/(1,016 - 11)]^{1/2} = 1.92$.

maturities for RISK1, RISK2, RISK3, and RISK4 at SCORE = 0 are 1.00, 1.64, 2.38, and 1.53, respectively. The predicted values for RISK1 and RISK4 are considerably shorter than the predicted value for RISK3, and the differences are statistically significant (*t*-statistics of 10.30 and 2.99, respectively). For the credits of \$100K–\$250K, the curve also has the nonmonotonic shape for the COMMIT = 0 subsample, although the differences are not statistically significant. Thus, for Test 1, we find a nonmonotonic relationship between risk and maturity that is consistent with Diamond's model for this subsample. In Test 2, there is little change from the main results for the COMMIT = 0 subsample.

The collateral and commitment subsample findings support the robustness of our main findings in most cases, although the exception for COMMIT = 0 is the most interesting. The finding of short maturity for high-risk firms without loan commitments—as in Diamond's model—is consistent with a clientele effect in which these firms may be offered only short maturities to help mitigate their information problems because they tend to be relatively opaque. This may also occur because firms without commitments tend to be those without strong banking relationships to help address their information problems.

B. The Potential Endogeneity of the Loan Risk Ratings

A potential endogeneity problem in our main results could occur because to some extent, the measured risk ratings may be endogenous to the SCORE variable. In particular, the significant maturity increase for RISK1 firms when shifting from SCORE = 0 to SCORE = 1 in Test 2 could be driven by a reassessment of firm risk following SBCS adoption. That is, the finding could reflect a migration of firms with generally longer maturities from the RISK2, RISK3, or RISK4 ratings being relabeled as RISK1 because they are thought to be lower risk as a result of credit scoring instead of our interpretation that credit scoring reduced informational asymmetries and led to longer maturities. To examine this possibility, we show in Table V the results of logit regressions for the probability that RISK1 = 1 for the same samples and with the same explanatory variables other than RISK as in the main regressions. If a reassessment of risk due to credit scoring explained our Test 2 result, we would expect a positive coefficient on SCORE as firms with relatively high maturities from the other risk ratings move into the low-risk rating. As shown, the coefficient of SCORE is not statistically different from 0 in any of the four logit equations, making the alternative explanation of our main Test 2 finding relatively unlikely.

C. The Potential Endogeneity of SBCS

Alternatively, our test results could be driven, in part, by the potential endogeneity of the choice to adopt the SBCS technology. Some conditions that face the lending bank for which we are unable to control may affect both the maturity of its newly issued loans and its probability of adopting SBCS. In this event, the observed associations between SCORE and Maturity may be spuriously determined. To mitigate this potential problem, we try excluding

Table V

Risk Rating Regressions

Logit regressions for the probability that the risk rating equals 1 ("minimal" risk loans) versus the probability that the risk rating equals 2, 3, or 4 ("low," "moderate," and "acceptable" loans, respectively). Both samples combine loan observations from banks that do not use credit scoring technology (SCORE = 0) with loan observations from banks that use credit scoring technology but not to automatically approve/reject loans (SCORE = 1). Regressions include ln(GTA), the natural log of gross total assets of the bank ($000); NPL, the bank's ratio of nonperforming loans (past due 30 days or more or nonaccrual) to total loans; COLLAT, a dummy that equals 1 if the loan is secured; COMMIT, a dummy variable that equals 1 if the loan is made under commitment; ln(CREDIT SIZE), the natural log of the maximum of the loan amount and the amount of commitment ($000), if any. Regressions also include Q3 and Q4, which indicate the quarter in which the loan was made; Q2 is excluded as the base case (our sample includes the final three quarters of 1997). Regressions for Credits of $100K–$250K exclude NPL because the variable has an unreasonably large coefficient when it is included. Significance at the 10%, 5% and 1% levels is denoted by *, **, and ***, respectively.

	Credits < $100K				Credits of $100K–$250K			
	Contract Terms		No Contract Terms		Contract Terms		No Contract Terms	
Variables	Coefficient	*t*-Stat	Coefficient	*t*-Stat	Coefficient	*t*-Stat	Coefficient	*t*-Stat
Intercept	11.372***	4.94	8.196***	4.31	−3.732	−1.00	3.170	1.38
Credit scoring								
SCORE	0.093	0.41	−0.197	−0.94	0.113	0.40	0.035	0.13
Bank size and loan portfolio health								
ln(GTA)	−0.920***	−6.23	−0.708***	−5.70	−0.454***	−3.20	−0.417***	−2.97
NPL	−1.879	−0.30	−5.066	−0.74				
Loan contract terms								
COLLAT	1.458***	4.91			−0.140	−0.40		
COMMIT	−1.456***	−6.76			0.104	0.26		
ln(CREDIT SIZE)	−0.210**	−2.00			1.438**	2.44		
Pseudo-R^2	0.132		0.050		0.035		0.022	
N	3,622		3,622		2,910		2,910	

observations from banks that adopt SBCS within 1 year of the time the loan is issued. That is, we create a time barrier of at least 1 year between the conditions under which SBCS is adopted and the conditions under which the maturity is chosen to reduce any spurious association. The main results are robust to this change.[17]

VIII. Conclusions

We test the implications of the theoretical models of Flannery (1986) and Diamond (1991) concerning the effects of risk and asymmetric information on

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[17] We also attempt to deal with this potential endogeneity with a Heckman correction, using banks' past small business loans/GTA ratio as the instrument. However, this instrument does not have a significant effect on the probability of adopting SBCS in the first-stage regression, making the results unreliable.

debt maturity, and further explore the importance of asymmetric information in debt maturity choices. The theoretical models, empirical tests of these models, and recent international financial crises have raised significant academic and policy interests in issues related to debt maturity.

The extant empirical literature does not come to a consensus regarding these theories, which may be due to several factors. Many of the studies use data on debt maturity structure, but the theoretical models are based on the maturity of new debt issues at the time of origination, not the remaining time on the stock of old contracts. The studies that use data on new debt issues employ specifications that do not allow for the nonmonotonic function predicted by Diamond's model. In addition, none of the empirical studies distinguish the effects of asymmetric information on maturity by risk rating, as implied by the theories. In this paper, we use data on new debt issues, employ a specification that allows for the nonmonotonic function predicted by Diamond's model, and interact the effects of asymmetric information with the risk ratings. Other advantages of our approach include the use of a clean measure of asymmetric information based on the use of credit scoring technology.

We test the theories using data on the maturities, risk ratings, and other contract terms of over 6,000 newly issued individual loans to small businesses, data on the banks that extend these loans, and information on whether and how these banks employ SBCS, a lending technology that may reduce informational asymmetries. Our Test 1 examines the effects of the banks' risk ratings on maturity under conditions in which informational asymmetries are expected to be great (no credit scoring), while our Test 2 examines the effects of a reduction in informational asymmetries (the use of credit scoring in conjunction with another lending technology) on maturity for each of the different risk ratings. Both the performance of Test 1 under conditions of greatest informational asymmetries and the performance of Test 2 by different risk ratings are unique to the literature. We also perform a number of robustness checks to verify that our findings are not the product of particular choices of samples, variables, or specifications, and do not reflect spurious outcomes due to endogeneity problems.

Our test results are consistent with the predictions of both Flannery's and Diamond's models for low-risk firms. All else equal, these firms tend to have significantly shorter maturities than other firms (Test 1), and these maturities tend to increase significantly when informational asymmetries are reduced (Test 2). The latter result also suggests a strong quantitative role for asymmetric information in the determination of debt maturity. For high-risk firms, our main test results conflict with the predictions of Diamond's model and with many of the prior empirical studies. All else equal, high-risk firms do not have significantly different maturities than intermediate-risk firms, whereas Diamond's theory would predict that banks would impose short maturities on the riskiest firms.

Our finding for high-risk firms may reflect, in part, an important difference between banks and public debt markets. Banks may have comparative advantages over public markets in gathering information, renegotiating loans, and enforcing other loan contract terms, such as collateral and restrictive covenants.

Thus, banks may be better able than public markets to use tools other than short maturities to help resolve moral hazard and adverse selection problems for risky firms. Some additional checks of the data are consistent with this possibility and suggest that within the category of bank loans, the results differ with the degree of informational asymmetries.

REFERENCES

Barclay, Michael J., and Clifford W. Smith, 1995, The maturity structure of corporate debt, *Journal of Finance* 50, 609–631.

Barnea, Amir, Robert A. Haugen, and Lemma W. Senbet, 1980, A rationale for debt maturity structure and call provisions in the agency theoretic framework, *Journal of Finance* 35, 1223–1234.

Berger, Allen N., 2006, Potential competitive effects of Basel II on banks in SME credit markets in the United States, *Journal of Financial Services Research* (forthcoming).

Berger, Allen N., Macro A. Espinosa-Vega, W. Scott Frame, and Nathan H. Miller, 2004, Debt maturity, risk, and asymmetric information." Finance and Economics Discussion Series 2004–60, Federal Reserve Board, http://www.federalreserve.gov/pubs/feds/2004/200460/200460abs.html.

Berger, Allen N., W. Scott Frame, and Nathan H. Miller, 2005, Credit scoring and the availability, price, and risk of small business credit, *Journal of Money, Credit, and Banking* 37, 191–222.

Berger, Allen N., and Gregory F. Udell, 1990, Collateral, loan quality, and bank risk, *Journal of Monetary Economics* 25, 21–42.

Berkovitch, Elazar, and Stuart I. Greenbaum, 1991, The loan commitment as an optimal financing contract, *Journal of Financial and Quantitative Analysis* 26, 83–95.

Berlin, Mitchell, and Jan Loeys, 1988, Bond covenants and delegated monitoring, *Journal of Finance* 43, 397–412.

Berlin, Mitchell, and Loretta J. Mester, 1993, Debt covenants and renegotiation, *Journal of Financial Intermediation* 2, 95–133.

Bester, Helmut, 1985, Screening vs. rationing in credit markets with imperfect information, *American Economic Review* 75, 850–855.

Boot, Arnoud, Anjan V. Thakor, and Gregory F. Udell, 1987, Competition, risk neutrality and loan commitments, *Journal of Banking and Finance* 11, 449–471.

Brick, Ivan E., and S. Abraham Ravid, 1985, On the relevance of debt maturity structure, *Journal of Finance* 40, 1423–1437.

Carey, Mark, Stephen A. Prowse, John Rea, and Gregory F. Udell, 1993, The economics of the private placements: A new look, *Financial Markets, Institutions & Instruments* 2, 1–67.

Chan, Yuk-Shee, and George Kanatas, 1985, Asymmetric valuation and the role of collateral in loan agreements, *Journal of Money, Credit, and Banking* 17, 85–95.

Dennis, Steven, Debarshi Nandy, and Ian G. Sharpe, 2000, The determinants of contract terms in bank revolving credit agreements, *Journal of Financial and Quantitative Analysis* 35, 87–110.

Diamond, Douglas W., 1991, Debt maturity structure and liquidity risk, *Quarterly Journal of Economics* 106, 709–738.

Diamond, Douglas W., and Raghuram G. Rajan, 2001, Banks, short-term debt and financial crises: Theory, policy implications and applications, *Carnegie-Rochester Conference Series on Policy* 54, 37–71.

Flannery, Mark J., 1986, Asymmetric information and risky debt maturity choice, *Journal of Finance* 41, 19–37.

Frame, W. Scott, Aruna Srinivasan, and Lynn Woosley, 2001, The effect of credit scoring on small business lending, *Journal of Money, Credit, and Banking* 33, 813–825.

Guedes, Jose, and Tim Opler, 1996, The determinants of the maturity of corporate debt issues, *Journal of Finance* 51, 1809–1833.

Huber, Peter J., 1967, The behavior of the ML estimates under nonstandard conditions, *Proceedings of the Fifth Berkeley Symposium in Mathematical Statistics*, vol. 1 (Berkeley: University of CA Press).

Johnson, Shane A., 2003, Debt maturity and the effects of growth opportunities and liquidity risk on leverage, *Review of Financial Studies* 16, 209–236.

Kale, Jayant R., and Thomas H. Noe, 1990, Risky debt maturity choice in a sequential game equilibrium, *Journal of Financial Research* 13, 155–165.

Lewis, Craig M., 1990, A multi-period theory of corporate financial policy under taxation, *Journal of Financial and Quantitative Analysis* 25, 25–43.

Mitchell, Karlyn, 1993, The debt maturity choice: An empirical investigation, *Journal of Financial Research* 16, 309–320.

Morgan, Donald P., and Adam B. Ashcraft, 2003, Using loan rates to measure and regulate bank risk: Findings and an immodest proposal, *Journal of Financial Services Research* 24, 181–200.

Myers, Stewart C., 1977, Determinants of corporate borrowing, *Journal of Financial Economics* 5, 147–176.

Ortiz-Molina, Hernan, and Maria Fabiana Penas, 2004, Lending to small businesses: The role of loan maturity in addressing information problems, Working paper, Tilburg University.

Scherr, Frederick C., and Heather M. Hulburt, 2001, The debt maturity structure of small firms, *Financial Management* 30, 85–111.

Stohs, Mark Hoven, and David C. Mauer, 1996, The determinants of corporate debt maturity structure, *Journal of Business* 69, 279–312.

Titman, Sheridan, 1992, Interest rate swaps and corporate financing choices, *Journal of Finance* 47, 1503–1515.

White, Halbert, 1982, Maximum likelihood estimation of misspecified models, *Econometrica* 50, 1–25.