Credit Ratings and Stock Liquidity

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ABSTRACT

We analyze contemporaneous and predictive relations between debt ratings and measures of equity market liquidity, and find that common measures of adverse selection, which reflect a portion of the uncertainty about future firm value, are larger when debt ratings are poorer. This relation holds even after controlling for many other observable factors. We also show that ratings changes can be predicted using current levels of adverse selection, which suggests that credit rating agencies sometimes react slowly to new information. Collectively, our results offer new insights into the value of debt ratings, the specific nature of the information they contain, and the speed with which they reflect changes in uncertainty.

In the wake of some of the worst corporate disasters in U.S. history, credit rating agencies have come under fire. Critics argue that the agencies are too slow to respond to signs of trouble. For example, they maintained an investment grade rating for Enron's debt until just days before the company filed for bankruptcy. These recent events raise questions about the value of bond ratings. Do the ratings actually contain information beyond that contained in published financial data? If so, do the rating agencies uncover and react to problems in a timely manner? Answers to these questions are of critical importance to individuals and institutions making investment decisions, to firms raising capital through debt issuances, and to regulators who rely on ratings when evaluating risk.

In this paper, we develop a simple model in which the value of a firm's assets changes in response to both publicly observed and privately observed shocks. Since default becomes more likely as the value of the assets approaches the value of the outstanding debt, debt ratings will be inversely related to both the current ratio of debt to assets and the level of uncertainty about the assets' future value. The model predicts that, all else equal, firms with greater risk of private shocks will have lower debt ratings. The market microstructure literature contains several measures of adverse selection, which are designed to capture the privately observed component of uncertainty. Accordingly, our model predicts that there should be a negative association between debt ratings and these standard measures of adverse selection. Our model also suggests ways to decompose these standard adverse selection measures into components that better isolate the uncertainty parameters that are related to debt ratings.

We test the model by analyzing contemporaneous and predictive relations between debt ratings and measures of adverse selection, using the standard measures from the literature and the decompositions of these measures suggested by our model. We demonstrate in panel data regressions that debt ratings are in fact poorer when several common measures of adverse selection – including quoted and effective spreads, Hasbrouck's (1991) information-based price impact measure, Glosten and Harris' (1988) adverse selection component of the spread, and Easley, Kiefer, O'Hara, and Paperman's (1996) probability of informed trading – are larger. When we decompose these measures, we find that the components related to the amount of private information are significantly negatively related to debt ratings, as predicted by the model.

For all but one of the measures, the statistical significance of the relation between adverse selection and debt ratings holds even after controlling for the observable factors used by the rating agencies to determine debt ratings, as well as for other factors related to debt ratings and liquidity. This implies that the ratings contain information beyond that in other published financial data, which supports the rating agencies' assertion that quantitative financial analysis is merely one component of a complex process.[1] It is also consistent with studies documenting significant relationships between bond ratings and returns on debt and equity after controlling for other factors.[2]

The regression results validate the model and extend the existing literature by linking the information contained in debt ratings to equity market microstructure-based measures of uncertainty about the firm's prospects. They do not directly assess the speed with which the rating agencies respond to new information, however. If ratings respond to changes in uncertainty with a lag, then adverse selection measures should have predictive power for the probability of future ratings changes. More specifically, we would expect increases in the adverse selection measures (which should impound uncertainty very quickly through the trading process) to be followed by ratings downgrades. Likewise, we would expect periods with

[1] See Standard and Poor's (2002).

[2] See, for example, Ederington, Yawitz, and Roberts (1987), Hand, Holthausen, and Leftwich (1992), Goh and Ederington (1993), Hite and Warga (1997), Kliger and Sarig (2000), and Dichev and Piotroski (2001).

decreases in adverse selection to be followed by upgrades. We test these hypotheses by estimating ordered probit models using an indicator of future ratings changes as the dependent variable. The results show that future ratings changes can be predicted using recent changes in the levels of adverse selection and the debt-to-asset ratio, which suggests that the agencies are sometimes slow to react.

Collectively, our results offer new insights into the value of debt ratings, their relationship to firm-value uncertainty, and the speed with which they reflect changes in uncertainty. In addition, the regression results validate the adverse selection measures, which are used extensively in the microstructure literature and elsewhere, by showing that they behave as would be expected from microstructure theory.

The remainder of the paper is organized as follows. Section I provides a simple theoretical model that establishes the link between debt ratings and the adverse selection measures. Section II discusses the data and methods employed, including descriptions of the adverse selection measures used in the study. Section III presents the tests of the contemporaneous relation between debt ratings and the adverse selection measures, Section IV investigates the prediction of future ratings changes, and Section V concludes.

I. A Model of Credit Ratings and Adverse Selection

In this section we present a simple model of the uncertainty facing a firm, and show how this uncertainty translates into debt credit ratings and equity adverse selection costs. Let t denote time in days, where t=0 is the current date. The total value of the firm's assets is A_t. The face value of the firm's debt, which is assumed to remain constant in the future, is D.

Assumption 1: Asset-Value Uncertainty

We assume that the natural logarithm of the value of the assets changes each day in response to three different sources of uncertainty:

$$\ln(A_t) = \ln(A_{t-1}) + \beta\gamma_t + \eta_t + I_t\iota_t.$$

γ_t is the economy-wide ("systematic") shock in day t, and β is the firm's sensitivity to that economy-wide shock. η_t is a publicly-observed unsystematic shock. The third source of uncertainty is observed at the start of the trading day by a small set of "informed" investors and is observed by the rest of the market participants at the start of the next trading day. This uncertainty has two components: a Bernoulli random variable, I_t, which equals 1 if an information event occurs on day t, and the conditional value of the event, ι_t. α denotes the probability that an event occurs on day t. We assume that γ_t, η_t and ι_t are normally distributed with mean zero and standard deviations σ_γ, σ_η and σ_ι, respectively. We also assume that γ_t, η_t, ι_t and I_t are jointly and serially independent.

It is convenient to subsume the debt level D into a new state variable, defined as $X_t = \ln(A_t) - \ln(D)$. Note that $-X_t$ is the log of the ratio of debt to total firm value, and that X_t has the same transition equation as $\ln(A_t)$. We define insolvency as the condition $\ln(A_t) < \ln(D)$, or equivalently $X_t<0$. We assume that debt ratings are related to the probability of insolvency at some time in the future. The form of this relation may be quite complex, but we merely need to assume that a higher probability of insolvency at every date in the future translates into a lower debt rating.

Assumption 2: Debt Ratings

For any two firms A and B, if $P[X_t^A<0] < P[X_t^B<0]$ for every t>0, then A has a higher debt rating than B.

With the above two assumptions, we can show that higher debt ratings are associated with lower levels of adverse selection, as measured by the parameters α and σ_ι. The proofs of both of the following propositions are contained in the appendix.

Proposition 1: A lower α implies a higher debt rating.

For any two firms A and B, if $\alpha^A<\alpha^B$ and the remaining parameters are equal ($X_0^A=X_0^B=X_0$, $\beta^A=\beta^B=\beta$, $\sigma_\eta^A = \sigma_\eta^B = \sigma_\eta$, and $\sigma_\iota^A = \sigma_\iota^B = \sigma_\iota$) then the debt rating of A is higher than the debt rating of B.

Proposition 2: A lower σ_ι implies a higher debt rating.

For any two firms A and B, if $\sigma_\iota^A < \sigma_\iota^B$ and the remaining parameters are equal ($X_0^A=X_0^B=X_0$, $\beta^A=\beta^B=\beta$, $\sigma_\eta^A = \sigma_\eta^B = \sigma_\eta$, and $\alpha^A=\alpha^B=\alpha$) then the debt rating of A is higher than the debt rating of B.

The above propositions are quite intuitive. Additional uncertainty of any type is likely to reduce debt ratings. The obvious question is whether the magnitude of the private information events will be large enough to be an important determinant of debt ratings. Hasbrouck (1988) showed that approximately 34% of total stock price changes could be explained by order flow, so there is reason to believe that private information that is impounded into the stock price through the trading process can be quite important.

In the next section, we describe the data and introduce the various adverse selection measures that we examine. After describing the measures, we discuss their linkage to the model presented above.

II. Data and Methods

A. Sample Selection and Firm Characteristics

Our sample period covers the 24 calendar quarters from January 1995 through December 2000. As of the last trading day of each May, we determine the 3000 largest U.S. common stocks traded on the NYSE, Nasdaq, or Amex based on market capitalization.[3] For the subsequent quarters beginning July 1, October 1, January 1, and April 1, we select all NYSE-listed common stocks that have publicly-traded debt that is rated by at least one nationally recognized statistical ratings organization at the start of the quarter.[4]

Company attributes, such as market capitalization and book-to-market ratio, are calculated using data from the Center for Research in Securities Prices (CRSP) and from the COMPUSTAT database maintained by Standard and Poor's. For each measure, we use the most recent information available as of the start of the quarter. Matching between CRSP and COMPUSTAT is accomplished using the PERMNO/GVKEY tables maintained by CRSP. Because this match is imperfect, our approach fails to find COMPUSTAT data for approximately

[3] This is identical to the procedure used by the Frank Russell Company when forming the Russell 3000 index, but because they deviate from their own procedure on rare occasions, our list may not match the Russell 3000 perfectly.

[4] We limit our sample to NYSE stocks because our various measures depend on accurate synchronization of trade and quote data, which is more difficult for Nasdaq stocks. For example, Porter and Weaver (1998) show that a substantial number of Nasdaq trades are reported more than 90 seconds late through the early 1990's and that the problem persists through the end of their sample in mid-1995. We reran all of our tests including the Nasdaq and AMEX firms with rated debt and the results are similar.

1% of the firm/quarter observations in our sample. In addition, some of the COMPUSTAT data items are missing for some of the observations. In our regression tests, we replace missing values for variables other than the adverse selection measures with the sample median.[5]

Table 1 shows summary statistics (based on non-missing values) for the firms included in our sample for January 1998, and compares our sample firms with the others in the largest 3000 (i.e., Nasdaq firms, Amex firms, and NYSE firms without rated debt). Not surprisingly, the firms in our sample tend to be substantially larger than both the NYSE-listed firms without rated debt and the Nasdaq and Amex firms. In addition, whether they have rated debt or not, NYSE-listed stocks appear to be less risky than the Amex and Nasdaq stocks, as measured by both beta and standard deviation of returns. The firms are reasonably similar in other dimensions, including book-to-market ratios and industry classification.[6]

B. Debt Ratings

Debt ratings are taken from the Fixed Income Securities Database, which was obtained from LJS Global Information Services.[7] We include only U.S.-dollar denominated issues with at least two years to maturity, and we match firms with debt issues based on CUSIP, so we tend to exclude issues made by a firm's subsidiaries. We assign a numerical score to each rating category as shown in Table 2. To calculate ratings for the firms in our sample, we compute a weighted average of the numerical ratings across all issues and rating agencies at the start of each quarter, using the amount outstanding of each debt issue to determine the weights. As can be seen in Table 2, debt ratings for the firms in our sample tend to cluster between A+ and BBB-

[5] Firms with missing COMPUSTAT data are included in the "manufacturing" industry category.
[6] Table 1 shows that the sample contains a relatively high fraction of utilities. We ran all of our tests excluding both utilities and financials to ensure that the results are not driven by features of regulation. The results are similar.
[7] This database is now distributed by Mergent, Inc.

(using the S&P and Fitch categorization), and show a slight downward trend over the sample period.

Table 3 shows the distribution of the numbers of issues and the average ratings across our sample, as well as the degree of agreement across the three rating agencies. These statistics demonstrate that Moody's and Standard and Poor's rate many of the same debt issues and tend to assign similar ratings. Fitch, on the other hand, rates fewer issues and tends to assign slightly higher ratings.

In addition to calculating average ratings at a point in time, we calculate rating changes during each quarter. In some cases, the average rating changes because amounts outstanding change or because a rating agency initiates or drops coverage of a particular issue. We do not include such events in our sample of changes, because they do not represent a clear reassessment of the firm's prospects. Rather, we define changes by the first change (from the start of the quarter) of an individual rating agency's rating of an individual issue. Table 4 examines firms with issues rated by both Standard and Poor's and Moody's. Panel A shows that while the rating changes are clearly correlated across the two agencies, it is fairly common for one agency to change ratings during the quarter while the other does not. Panel B shows that when an agency changes the rating of one of the firm's issues, that agency almost always changes the ratings of all the firm's other issues on the same day.

C. Adverse Selection Measures

Adverse selection measures seek to quantify the impact of uncertainty or asymmetric information in the market. Several adverse selection measures have been proposed in the literature, and each takes a slightly different approach to capturing this risk. Dennis and Weston

(2001) find that the various measures behave in a largely consistent manner but are not always highly (or even positively) correlated. Since differences among the measures may lead to different conclusions, we take a comprehensive approach by utilizing a variety of common measures. Each is described in more detail below.

C.1. Quoted and Effective Spreads

Beginning with work by Bagehot (1971), bid-ask spreads have been viewed not merely as a reflection of the fixed costs of trading, but also as a direct result of asymmetric information. When market makers realize that the investors with whom they trade may possess better information, they set bid-ask spreads that allow them to offset their loses to informed traders with gains from the uninformed. Consequently, the width of the quoted spread provides an indication of the severity of adverse selection risk. We focus on what is sometimes called the "relative" quoted spread, which simply divides the difference between the ask and bid quotes by the quote midpoint.

Effective spreads measure adverse selection risk for identical reasons. The only difference between quoted and effective spreads is that the latter takes price improvement into account, meaning that effective spreads are computed using transaction prices (which may differ from quoted prices). Specifically, the ("relative") effective spread is calculated as twice the absolute difference between the transaction price and the midpoint of the quoted bid-ask spread, divided by the quote midpoint.

C.2. Information-Based Price Impact

Although quoted and effective spreads are a natural measure of adverse selection risk, they may reflect other costs as well. Hasbrouck (1991) used a vector autoregressive (VAR) model to dissect a trade's price impact into a permanent portion, which reflects the information contained in the trade, and a transient portion, which captures order processing costs and inventory risk. The novelty of this approach is the recognition that information is conveyed not by total transaction volume but through trade *innovations* – the unexpected portion of order flow.

Our estimates of the information-based price impact follow Brennan and Subrahmanyam's (1996) adaptation of Hasbrouck's (1991) model. The model is described by the following system of equations:

$$Z_t = a_Z + \sum_{i=1}^{5} b_i \Delta P_{t-i} + \sum_{i=1}^{5} c_i Z_{t-i} + \tau_t \quad (1)$$

$$\Delta P_t = a_P + d\Delta Q_t + \lambda \tau_t + e_t, \quad (2)$$

where P is the transaction price, Q is a buy/sell indicator variable, and Z is the signed trade size (Q times trade volume). The residuals (τ) from the first equation reflect the unexpected portion of each trade, so the λ in the second equation captures the information-based price impact.

We normalize λ in two ways. First, we multiply it by the standard deviation of the residuals (τ) from the first regression to convert it from impact per share to impact per trade. This makes it more comparable to the Glosten and Harris (1988) measure described below. We also divide by the share price at the start of the estimation interval (in our case a calendar quarter) to convert it to a relative measure.

C.3. Adverse Selection Component of the Spread

Another common approach to measuring the risk of informed trading involves dissecting the bid-ask spread into components reflecting some combination of adverse selection risk, order processing costs, and inventory risk. This measure is conceptually similar to the information-based price impact measure, but stems from a somewhat different estimation method. Models by Roll (1984), Glosten and Harris (1988), Stoll (1989), George, Kaul, and Nimalendran (1991), and Huang and Stoll (1997), among others, use price changes and buy-sell indicator variables to estimate the effective spread and its components.

We estimate the adverse selection component of the spread using Huang and Stoll's (1997) version of the Glosten and Harris (1988) two-component model[8]:

$$\Delta P_t = (1-\lambda)\frac{S}{2}\Delta Q_t + \lambda\frac{S}{2}Q_t + e_t \tag{3}$$

where P and Q are defined as above, S is the size of the "traded" spread (which can differ from the quoted spread due to price improvement or disimprovement), and λ is the fraction of the traded spread due to adverse selection. In our application, we are interested in the quantity $\lambda\frac{S}{2}$, which we simply refer to as the adverse selection component. As with the other spread measures described above, we divide by the share price at the start of the quarter to convert it to a relative measure.

[8] Two-component models are often used in lieu of three-component models, which separately capture inventory effects, in light of the unreasonable component estimates that can arise in the latter framework. See, for example, Brennan and Subrahmanyam (1996) and Dennis and Weston (2001).

C.4. Probability of Informed Trading

The final approach, developed by Easley, Kiefer, O'Hara, and Paperman (1996), yields a measure of the probability that a trader possesses private information. It exploits the fact that market makers update their quotes in response to patterns in the order flow. In this model, the probability of informed trading is equal to:

$$PI = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}, \tag{4}$$

where α is the probability of an information event, μ is the arrival rate of informed buys or sells (conditional on an information event having occurred), and 2ε is the arrival rate of uninformed buys and sells. These parameters are estimated by maximizing the following likelihood function:

$$L(B,S \mid \alpha,\varepsilon,\delta,\mu) = \prod_{i=1}^{I} \left\{ \begin{array}{l} (1-\alpha)\left[e^{-\varepsilon T} \frac{(\varepsilon T)^{B_i}}{B_i!} e^{-\varepsilon T} \frac{(\varepsilon T)^{S_i}}{S_i!} \right] \\ + \alpha\delta\left[e^{-\varepsilon T} \frac{(\varepsilon T)^{B_i}}{B_i!} e^{-(\mu+\varepsilon)T} \frac{[(\mu+\varepsilon)T]^{S_i}}{S_i!} \right] \\ + \alpha(1-\delta)\left[e^{-(\mu+\varepsilon)T} \frac{[(\mu+\varepsilon)T]^{B_i}}{B_i!} e^{-\varepsilon T} \frac{(\varepsilon T)^{S_i}}{S_i!} \right] \end{array} \right\}. \tag{5}$$

B_i and S_i represent the number of buys and sells during a period of length T on day i, and δ represents the probability that a given event is bad news.

D. The Linkage Between the Measures and the Model

Our model, described in Section I, is similar to that of Easley, Kiefer, O'Hara, and Paperman (1996); the only difference is that we assume the value impact of privately observed events has a normal distribution, whereas they assume a Bernoulli distribution in which the value is either high or low. Accordingly, our α parameter, which captures the probability of an information event, is analogous to theirs.

The Glosten and Harris (1988) adverse selection component measures the average amount of private information per trade, as a fraction of share price. To define this quantity in terms of the parameters of our model, we must relate the amount of information per trade to the amount of private information per day. We begin by making two assumptions about the way trading incorporates the private signal into the share price in our model:

1) Each trade moves the log asset value by an amount ϕQ_t, where Q is the buy sell indicator for the trade
2) By the end of the day, trading has incorporated the full impact of any information event (up to the point where the bid and ask prices bracket the true value).

The assumption of constant value impact (assumption 1) is consistent with the use of the Glosten and Harris estimation technique, but it is not fully rational behavior on the part of the market maker. As in Easley, Kiefer, O'Hara, and Paperman (1996), a sophisticated market maker who knew the full structure of the information in the model would update the estimated probability that an information event had occurred on a particular day, and the price impact would be smaller in the later part of days where the updated probability of an information event was low.

As is standard in microstructure models, it is natural to assume that some of the orders each day come from uniformed traders, and that this part of the order flow will have random imbalance between buyers and sellers. The informed traders, however, respond to this random order flow with their own orders, and under assumption 2 they do so until the net total order flow in the market fully reveals their private information, which occurs when the following equation is satisfied:

$$I_t \iota_t = \phi \sum_{t=1}^{N} Q_t \text{ , where N= the number of trades during the day.} \quad (6)$$

These two quantities won't be exactly equal because ι_t is a continuous random variable and the trade imbalance is discrete.

In our model, information events are normally distributed and occur on α of the days. Note that the average absolute value of a normal random variable with mean 0 and standard deviation σ is $\sigma\sqrt{2/\pi}$, so since I_t and ι_t are independent, $E[|I_t\iota_t|]=\alpha\sigma_\iota\sqrt{2/\pi}$. Using equation (6), this implies $\phi = \alpha\sigma_\iota\sqrt{2/\pi}/N^I$ where $N^I = E\left[\left|\sum_{t=1}^{N} Q_t\right|\right]$ is the average daily absolute trade imbalance (measured in number of trades).

Also, note that for small percentage changes, the change in the log value is approximately equal to the percentage change in the value, so ϕ is approximately equal to the percentage change in asset value ($\Delta A/A$) per trade. Since the value of the debt is fixed, the change in the equity value is the same as the change in the asset value. Thus, the relative Glosten and Harris measure, which estimates the percentage change in price per share for each trade, is equal to $\Delta A/E \approx \phi(A/E)$, where (A/E) is the ratio of asset value to equity value. Combined with the above results, this means the Glosten and Harris measure is proportional to $\alpha\sigma_\iota(A/E)/N^I$. In summary, an increase in either α or σ_ι will both increase the Glosten and Harris measure and decrease the firm's debt rating.

Our version of the Hasbrouck measure is constructed to be similar to the Glosten and Harris measure, although the Hasbrouck measure's dependence on the unexpected portion of the order flow makes an explicit comparison to our model more complex. Nonetheless, it seems clear that the measure should respond positively to an increase in either α or σ_ι. Likewise, the quoted and effective spreads contain the adverse selection component, so they should respond positively to an increase in either α or σ_ι, as well.

Although we focus on the measures as defined in other studies, the above discussion suggests new, related measures that would isolate the effects of the parameters α and σ_ι. In Section III, we run separate tests where we first multiply all of the spread measures by N^I(E/A). In the case of the Glosten and Harris measure, the model predicts that this new measure will be proportional to $\alpha\sigma_\iota$ and purged of the effects of trading frequency and capital structure. By including trading frequency and capital structure as separate variables in these tests, we attempt to isolate the impact of α and σ_ι on debt ratings. In these separate tests, we also use the α parameter instead of the probability of informed trading (PI) from the Easley, Kiefer, O'Hara, and Paperman estimation procedure.

E. Intraday Trade and Quote Data and Estimation issues

We estimate the adverse selection measures for the stocks in our sample using intraday trade and quote data from the TAQ database, distributed by the NYSE. All measures are computed using three-month intervals (beginning in January, April, July, and October of each year), consistent with Easley, Kiefer, and O'Hara (1997).[9] Trade direction is determined using the Lee and Ready algorithm (1991), which compares trade prices to the midpoint of the quote as of 5 seconds prior to the trade report and uses the tick test to classify midpoint trades. As recommended by Odders-White (2000), we repeat all of our tests after eliminating midpoint transactions and find that the results are robust. Since NYSE trades are often reported in two or more pieces, we follow Easley, Kiefer, O'Hara, and Paperman (1996) (and others) by combining trades at the same price that occur within 5 seconds of one another.

Quoted spreads for each firm quarter are computed as time-weighted averages over the period, and effective spreads are weighted by trade size. The information-based price impact measure and the adverse selection component of the spread are estimated using ordinary least squares. The probability of informed trading is estimated via maximum likelihood.[10]

III. Tests of the Relation between Debt Ratings and Adverse Selection Measures

We examine the relation between adverse selection risk and debt ratings by running panel data regressions of the following general form:

$$\text{Rating}_{it} = \beta' x_{it} + \varepsilon_{it}, \tag{6}$$

where i denotes the stock, t denotes calendar quarter, y represents the mean debt rating, and x contains the chosen adverse selection measure and control variables. Because our panel includes repeated estimates from each firm, and because we can never be sure that we have identified all

[9] Firm quarters with fewer than 25 trades are omitted because the number of degrees of freedom in the estimation procedure seems unreasonably low.

[10] The maximum likelihood estimation procedure used to estimate the probability of informed trading failed to converge for a small fraction of the stocks in our sample. For example, 11 of the 730 total firms in the first quarter of 1998 failed to converge. The convergence rate is similar to that reported by Easley, Hvidkjaer, and O'Hara (2002). Our estimation yielded more boundary solutions (147 of 730 in the first quarter of 1998) than the Easley et al. (2002) analysis, most likely because we estimate the measure quarterly rather than annually. All tests exclude cases in which the estimation failed to converge or converged to a boundary.

relevant explanatory variables, we expect the residuals from regression (6) to be correlated across time for the same firm. Accordingly, we allow the residuals to have the following "random effects" structure:

$$\varepsilon_{it} = u_i + v_{it} \, , \qquad (7)$$

where the ϕ_i terms are independent across firms and the v_{it} terms are independent across observations. We estimate (6) and (7) using restricted maximum likelihood. T-statistics are calculated using a method that allows for heteroscedasticity in the residuals that is related to the explanatory variables.

Although our model predicts a monotonic relation between debt ratings and various adverse selection measures, it does not offer any direction as to the particular functional form of this relation. For tractability, we choose the separable linear form in equation (6). We use natural logarithm transformations for the adverse selection variables for two reasons. First, it allows us to decompose the variables in a natural way. For example, in the previous section we argued that the Glosten and Harris measure is proportional to $\alpha\sigma_\iota(A/E)/N^I$. The fact that $\ln(\alpha\sigma_\iota(A/E)/N^I) = \ln(\alpha\sigma_\iota) - \ln(E/A) - \ln(N^I)$ leads to an alternative linear specification that can be compared to the original specification using a standard likelihood ratio test. The second reason for our logarithmic transformation is that it allows us to use changes in the same (log) adverse selection measures in our ordered probit model. Without the natural logarithm adjustment, firms with large (not logged) values for the adverse selection component might have undue influence on the results.

In addition to the adverse selection measures, the natural logarithm of debt to assets is included in the regression because it is the state variable in our model. We use the book value of debt and the market value of equity to calculate the debt-to-asset ratio. To make the coefficient on the logged debt-to-asset ratio more readily interpretable, we subtract the cross-sectional median and divide the result by the difference between the 75th percentile and the median. This normalization has no effect on the significance of any variables or on the fit of the regression as we are simply subtracting and dividing by a constant.

Because our model is simple, it does not capture all of the features that we believe will be important to debt ratings. Consequently, we include extra explanatory variables to help control for some of the features of debt ratings that are outside of our model. We include industry dummy variables to reflect the fact that debt ratings may not be comparable across industries due to differences in asset tangibility and marketability. Intercept terms are allowed to vary by year to eliminate any estimated relation that might result if both debt ratings and adverse selection levels changed systematically through time.

As in Table 2, the debt-rating variable is a weighted average (as of the first day of each quarter) of the numerical ratings across all issues and rating agencies, using the relative value of each debt issue to determine the weights. Recall that a higher quality debt rating corresponds to a higher numerical score. Consequently, if poorer debt ratings are associated with higher adverse selection risk as we expect, then the coefficients on the adverse selection measures will be negative and significant.

Table 5 shows the results from our first set of regressions of debt ratings on the adverse selection variables. The first column contains the results for the quoted spread. Consistent with intuition, debt ratings worsen as the quoted spread and the debt-to-asset ratio increase. In both cases, the coefficients are statistically significant. The same holds in the regressions including the effective spread, the information-based price impact measure, and the adverse selection component (columns two through four). This demonstrates that the association between spreads and debt ratings is at least in part a reflection of the increased uncertainty captured by wider spreads and not simply the result of higher fixed costs.[11] The results in the final column of Table 5 provide additional evidence of the strong relation between adverse selection and ratings by showing that decreases in credit ratings are associated with increases in the probability of informed trading.

The results in Table 5 demonstrate that debt ratings provide a simple, readily available indication of the uncertainty captured by common adverse selection measures. This confirms that debt ratings do in fact contain information related to asset-value uncertainty, and in particular, to the level of uncertainty associated with private information events. These findings establish a natural link between two previously distinct lines of research and, in so doing, validate that debt ratings and adverse selection measures are both reasonable metrics of uncertainty and behave in ways consistent with intuition.

Because the panel data regressions impose a fairly restrictive structure (e.g., slope coefficients are restricted to be the same for all observations in the sample), we conduct an event study of ratings changes to confirm the robustness of our results. Given the association between debt ratings and adverse selection in the panel data regressions, we would expect adverse selection to increase around downgrades and decrease around upgrades.

We examine the 313 downgrades and 352 upgrades for which we have data for the three quarters surrounding the change (before, during, and after) and for which no other ratings changes take place during the pre- or post-event quarter. We compute differences in (logged)

[11] Panel data regressions using logged *dollar* adverse selection measures (with price included as a control variable) confirm that the results are not driven by the presence of price in the denominator of the relative adverse selection measures. In addition, separate regressions for firms with average ratings below the investment grade cutoff and firms with average ratings above the cutoff reveal that our results are not driven entirely by non-investment grade firms.

adverse selection measures from the quarter preceding the change to the quarter following the change and examine the statistical significance of these differences using paired t-tests.

The event study results (not reported) support those in Table 5. All adverse selection measures decrease surrounding ratings upgrades, and all but the probability of informed trading increase surrounding downgrades. The magnitudes and statistical significance of the changes are somewhat weaker than might be expected given the panel data regressions, perhaps due in part to the "stickiness" of ratings documented in Section IV below. Overall, the event study results validate our earlier findings, providing further evidence that debt ratings contain valuable information, and linking this information to uncertainty.

While Table 5 shows that the standard adverse selection measures are related to debt ratings in ways that are consistent with our model, we recognize that these standard measures impound factors beyond the parameters contained in our model, like trading frequency and capital structure. In Table 6, we decompose the adverse selection measures into linear components that attempt to isolate the effects of the uncertainty described in the model from the other factors. Specifically, we modify each of the four (logged) spread measures by adding the log of the average absolute trade imbalance per day, N^I, and the log of the ratio of equity to assets, E/A.[12] We then include the modified measure, as well as $\ln(N^I)$ and ln(E/A), as separate variables in the regression. As discussed above, the modified adverse selection measure in these four regressions should be related to $\alpha\sigma_\iota$. In the fifth regression, we decompose ln(PI) into $\ln(\alpha)$ and $\ln(\mu/(\alpha\mu+2\varepsilon))$.

Table 6 shows that the modified adverse selection measures are related to debt ratings as predicted by the model, and the results are all statistically significant. Likelihood ratio tests

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[12] This is mathematically equivalent to multiplying by the average absolute trade imbalance per day and dividing by the ratio of equity to assets prior to taking logs.

reject the model in Table 5 in favor of the model in Table 6 at the 1% level in all cases. The results for the four spread-based measures also show that debt ratings are positively related to the absolute daily trade imbalance. The average imbalance is strongly positively correlated with the total number of trades, so this positive relation is consistent with the idea (outside of our model) that firms with more liquidity may find it easier to avoid financial distress. The final column of Table 6 demonstrates that, as expected, debt ratings are negatively related to the probability of an information event (α). The negative coefficient on $\ln(\mu/(\alpha\mu+2\varepsilon))$ suggests that this measure, which represents the fraction of trades that are informed when an event occurs, also reflects the uncertainty captured by debt ratings. Finally, Table 6 seems to indicate that the log of the equity-to-asset ratio, which is equal to the log of one minus the debt-to-asset ratio, provides a better specification for predicting debt ratings than does the log of the debt-to-asset ratio, at least in regressions that include the modified adverse selection measures.

The results above demonstrate that debt ratings reflect the type of uncertainty captured by our model and by the various adverse selection measures. Several existing studies have found that other factors are useful in explaining debt ratings.[13] The question as to whether adverse selection measures contain incremental information beyond these other factors naturally arises. We address this question by adding a comprehensive set of control variables to our panel data regressions from Table 6. Our choices are guided by both the prior literature and Standard and Poor's description of its debt rating criteria. In "Corporate Ratings Criteria 2002," Standard and Poor's describes its bond-rating process in depth, including detailed discussions of the qualitative analysis it conducts and of the specific financial ratios it uses for quantitative analysis.

[13] See, for example, Horrigan (1966), Pogue and Soldofsky (1969), West (1970), Pinches and Mingo (1973, 1975), Kaplan and Urwitz (1979), Ederington (1985), Blume, Lin, and MacKinlay (1998), Chan and Jegadeesh (2001), and Kamstra, Kennedy, and Suan (2001).

When determining a firm's debt rating, S&P begins with an assessment of business risk. Although much of this analysis is qualitative, some quantitative factors emerge at this stage. According to Standard and Poor's, industry risk "goes a long way toward setting the upper limit on the rating" and "sets the stage for analyzing specific company risk factors." Accordingly, we continue to include industry dummy variables in our regressions. Firm size (captured by market capitalization in our regressions) is another critical input that "provides a measure of diversification and often affects competitive issues" (S&P 2002). Upon completing the analysis of business risk, S&P turns to measuring financial risk, which is accomplished "largely through quantitative means, particularly by using financial ratios" (S&P 2002). Key ratios include measures of profitability and cash flow adequacy, interest coverage ratios, and leverage ratios. In addition to the debt-to-asset ratio mentioned above, our regressions include several explanatory variables to control for the effects of these factors. Specifically, we include return on assets (measured as net operating income over total assets), profit margin (defined as the ratio of net operating income to total sales), free cash flow ratio (defined as free cash flow over total debt), and times interest earned (computed as net operating income over total interest charges). Since the effects of negative cash flows could be different from those of positive cash flows, we separate the cash flow ratio into two variables and add a dummy variable that allows the intercepts to differ across these two cases. The necessary data for all variables come from COMPUSTAT.

Work by Chan and Jegadeesh (2001) indicates that market-related variables may also be relevant for debt ratings. Accordingly, we include book-to-market ratio to capture growth potential, and dividend yield (equal to most recent quarterly dividend as a fraction of stock price) and stock return over the past six months to reflect profitability. Furthermore, existing research on determinants of liquidity (see, e.g., Chordia, Roll, and Subrahmanyam (2001) and Breen, Hodrick, and Korajczyk (2002)) suggests several additional control variables. These include share price, volatility (computed as the standard deviation of monthly returns over the most recent 60 months), and beta (estimated from a monthly market model regression over the most recent 60 months). Finally, we include time-specific intercepts and, of course, the chosen adverse selection measure, decomposed as in Table 6.

Because the raw measures of market capitalization, stock price, volatility, and free cash flow have high skewness, we transform these variables using a logarithmic function. In addition, we subtract the cross-sectional median from each continuous control variable and divide the result by the difference between the 75th percentile and the median (the interquartile range) as we did for the debt-to-asset ratio in Tables 5 and 6.[14] The components of the adverse selection measures, which are the parameters of interest, have not been scaled.

The results, which are presented in Table 7, demonstrate that even after controlling for other observable determinants of debt ratings and liquidity, lower quality debt ratings are still significantly associated with higher adverse selection risk captured by quoted spreads, effective spreads, the Hasbrouck measure (marginally significant), and the probability of informed trading. There is also a negative, but insignificant, relation between debt ratings and the Glosten and Harris measure. As in Table 6, absolute trade imbalance and capital structure remain important determinants of debt ratings as well. The magnitudes of the adverse selection coefficients are smaller in Table 7 than in Table 6, which is consistent with previous findings that debt ratings

[14] As above, if a control variable is missing for a particular firm quarter, we replace the missing value with the median for that variable (i.e., the scaled variable is set to zero).

are predictable by other factors. Likelihood ratio tests confirm that the specification in Table 7 dominates the more restrictive model in Table 6.[15]

As expected, many of the control variables are also statistically significant. Consistent with intuition, larger firms and less volatile firms tend to have higher debt ratings. Debt ratings are also positively associated with interest coverage and, surprisingly, negatively related to the past 6-month return. The fact that many of the control variables are correlated with one another makes interpretation of some of these results more difficult.

The result that ratings contain incremental information is consistent with the rating agencies' assertion that quantitative financial analysis is merely one component of a complex undertaking. According to Standard and Poor's "Corporate Ratings Criteria," the ratings process involves "quantitative, qualitative, and legal analyses," including an evaluation of business fundamentals, industry characteristics, and "vulnerability to technical change, labor unrest, or regulatory actions" (S&P 2002). S&P characterizes this process as "an art as much as a science" and emphasizes that "subjectivity is at the heart of every rating" (S&P 2002). The fact that firms often reveal private forecasts or other information to the rating agencies also supports this view.

IV. Prediction of Future Ratings Changes

We now address the question as to whether rating agencies uncover and react to problems in a timely manner by examining the ability of adverse selection measures to predict future ratings changes. We would expect the adverse selection measures to impound changes in uncertainty very quickly through the trading process. If the rating agencies react with a lag to

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[15] We also estimate the model in Table 5 (rather than Table 6) after adding the control variables and the results are similar to those presented here.

these changes, then periods with higher (lower) adverse selection are likely to be followed by ratings downgrades (upgrades) in the future.

We study the effects of adverse selection on the probability of subsequent ratings changes using an ordered probit model. For all firm/quarters in which the debt rating remained unchanged, we create an indicator variable that is equal to –1 if a ratings downgrade occurs during the following quarter, equal to 1 if a ratings upgrade occurs during the following quarter, and equal to zero otherwise. For each firm/quarter observation we compare the logged values of the debt-to-asset ratio and the adverse selection measure in the *current* quarter to those from the *previous* quarter. We estimate ordered probit regressions of the ratings change indicator variable on the lagged changes in logged values of the debt-to-asset ratio and the adverse selection measure.

The sample used in our ordered probit regressions contains 14,211 firm/quarter observations, of which 5.0% are downgraded in the following quarter and 5.3% are upgraded. The number of observations in this sample is smaller than the sample summarized in Panel A of Table 4, which shows statistics for all firm quarters with debt rated by both Standard and Poor's and Moody's. Although our ordered probit analysis includes observations where there is a single rating agency, we delete any observations with a rating change in the current quarter, and we eliminate the first and last quarters because we need one future quarter to define the rating change variable and one past quarter to measure the changes in the independent variables. For firms with issues rated by multiple agencies, we consider the firm to have been upgraded or downgraded if any of the agencies take action in the quarter, so our sample frequencies of upgrades and downgrades are larger than the single-agency frequencies reported in Panel B of Table 4.

Panel A of Table 8 contains the estimated parameters. The estimation procedure models the probability of a ratings downgrade. The significant positive coefficients reported in the first line of Table 8 indicate that increases in the debt-to-asset ratio are associated with increased likelihood of a downgrade and a reduced likelihood of an upgrade. The second line of Table 8 shows that even after controlling for changes in the debt-to-asset ratio, firms with increased adverse selection risk, as measured by the quoted spread, effective spread, Hasbrouck price impact measure, or Glosten and Harris adverse selection component, are significantly more likely to have their debt downgraded in a subsequent quarter, and firms with lower adverse selection risk are more likely to have subsequent upgrades. The final column shows that results for the Easley, Kiefer, O'Hara, and Paperman measure of the probability of informed trading have the predicted sign, but the coefficient is not statistically significant.

The results suggest that the rating agencies do not immediately reflect the information contained in the adverse selection measures in their ratings. Instead, the agencies incorporate this information with a lag, consistent with the anecdotal and academic evidence that agencies are slow to react.[16] As a result, adverse selection measures provide an indication of the probability of future ratings changes.

Panels B and C of Table 8 show the changes in the probabilities of upgrades and downgrades associated with an increase in each adverse selection measure. The first line in Panel B reports the standard deviation of percentage changes in the adverse selection measures. The next two lines show the changes in predicted probabilities that result from a one standard-

[16]Weinstein (1977), Hand, Holthausen, and Leftwich (1992), and Hite and Warga (1997) show that rating changes can be predicted using changes in bond prices. Chan and Jegadeesh (2001) show that rating changes can be predicted from accounting information and find this predictability can provide information beyond that contained in bond prices (they examine bond trading strategies and find small abnormal profits). Johnson (2003) finds that Standard and Poor's rating changes tend to follow those of Egan-Jones. Egan-Jones does not have Nationally Recognized Statistical Ratings Organization (NRSRO) status, so they may face less pressure than Standard and Poor's to hold their ratings constant.

deviation increase in adverse selection (i.e., moving from no change in adverse selection to a one standard-deviation change). Panel C of Table 8 shows the changes in the predicted probabilities associated with a 0.20 (approximately 20%) increase in each measure. The results in Panels B and C indicate that quoted and effective spreads are particularly useful in predicting ratings changes, with a 20% increase in the spread translating into a roughly 30% increase (0.015 divided by the initial predicted probability of 0.05) in the probability of a downgrade and 25% decrease in the probability of an upgrade, even with no change in the debt-to-asset ratio. Although the other measures can also be used to predict ratings changes, their results are less striking, possibly because these measures contain additional estimation error. The first line of Panel B indicates that the quoted and effective spreads are much more stable than the other three measures.

V. Conclusion

This study addresses two critical questions regarding the value of bond ratings. Do the ratings actually contain information beyond that contained in published financial data? If so, do the rating agencies uncover and react to problems in a timely manner? We take a novel approach to these questions by relating debt ratings to equity measures of adverse selection. We present a model that links the two and guides our empirical framework. The idea behind the model is simple: firms that have high probability of large changes in total firm value should have both poorer debt ratings and higher adverse selection costs in trading their equity.

We find that debt ratings do in fact contain information related to adverse selection. Specifically, in panel data regressions, we show that several common measures of adverse selection are larger when debt ratings are poorer. For all but one of measures, this relation holds even after controlling for the observable factors used by the rating agencies to determine bond ratings, as well as for other factors known to affect adverse selection and liquidity. The results provide evidence that debt ratings contain information about underlying uncertainty that is not captured by other observable variables. In addition, the results validate the adverse selection measures, which are used extensively in the microstructure literature and elsewhere, by showing that they behave as would be expected from microstructure theory.

We also show that future ratings changes are related to past changes in the level of adverse selection, which suggests that the agencies often fail to react to changes in uncertainty immediately. This delay may stem from the potential conflict of interest that exists because the agencies are paid by the issuing firms. Moreover, rating agency critics argue that the present system in which the Securities and Exchange Commission (SEC) determines whether agencies are "nationally recognized statistical ratings organizations" (NRSROs) has created artificial barriers to entry that limit competition and reduce the agencies' incentives to respond quickly. Alternatively, the lagged response may reflect the rating agencies' desire to avoid making changes that will later be reversed. In any case, we show that adverse selection measures can be used to predict future ratings changes.

The fact that ratings changes are predictable is of potential concern to market regulators, who would presumably want to see more timely and accurate information provided to investors. On the other hand, the adverse selection information that we use to predict ratings changes is already available to market participants. Accordingly, regulatory actions designed to cause more responsive ratings would only be beneficial to the extent these more timely ratings included more information than already provided by other sources. Furthermore, more responsive ratings might lead to more frequent revisions, so if ratings changes are disruptive to markets, then there may be a potential benefit to the lagged response.

Appendix

<u>Lemma 1</u>: Let Q(k,p,n)=the probability of k or more successes in n Bernoulli trials with success probability p. For fixed k, and n, Q(k,p,n) is an increasing function of p.

<u>Proof:</u>

$$Q(k,p,n) = \sum_{r=k}^{n} \left\{ \frac{n!}{(n-r)!r!} p^r(1-p)^{n-r} \right\}$$

$$= \sum_{r=k}^{n-1} \left\{ \frac{n!}{(n-r)!r!} p^r(1-p)^{n-r} \right\} + p^n$$

$$\frac{d\,Q(k,p,n)}{dp} = \sum_{r=k}^{n-1} \left\{ \frac{n!}{(n-r)!r!} \left[rp^{r-1}(1-p)^{n-r} - (n-r)p^r(1-p)^{n-r-1} \right] \right\} + np^{n-1}$$

$$= \sum_{r=k}^{n-1} \left\{ \frac{n!}{(n-r)!(r-1)!} p^{r-1}(1-p)^{n-r} \right\} - \sum_{r=k}^{n-1} \left\{ \frac{n!}{(n-r-1)!r!} p^r(1-p)^{n-r-1} \right\} + np^{n-1}$$

combining the final term with the first sum and changing the index on the second sum gives:

$$\frac{d\,Q(k,p,n)}{dp} = \sum_{r=k}^{n} \left\{ \frac{n!}{(n-r)!(r-1)!} p^{r-1}(1-p)^{n-r} \right\} - \sum_{r=k+1}^{n} \left\{ \frac{n!}{(n-r)!(r-1)!} p^{r-1}(1-p)^{n-r} \right\}$$

canceling terms leaves

$$\frac{d\,Q(k,p,n)}{dp} = \frac{n!}{(n-k)!(k-1)!} p^{k-1}(1-p)^{n-k} > 0 \qquad ///$$

Lemma 2:

Let r be a binomial random variable with parameters p and n, and let F(k) be any increasing function of k defined on integers k=0,1,2,…,n. Then E[F(r)] is an increasing function of p.

Proof:

Define d_k = F(k)-F(k-1) for k=1,2,3,…,n. As in Lemma 1, let Q(k,p,n)=P[r≥k].

$$E[F(r)] = F(0) + \sum_{k=1}^{n} d_k Q(k,p,n), \text{ so}$$

$$\frac{d\,E[F(r)]}{dp} = \sum_{k=1}^{n} d_k \frac{d\,Q(k,p,n)}{dp}$$

By the fact that F is increasing, $d_k \geq 0$ for all k and $d_k > 0$ for at least one k. In combination with the fact that $\frac{d\,Q(k,p,n)}{dp}$ is greater than zero by Lemma 1, this gives $\frac{d\,E[F(r)]}{dp} > 0$. ///

Proposition 1: A lower α implies a higher debt rating.

For any two firms A and B, if $\alpha^A < \alpha^B$ and the remaining parameters are equal ($X_0^A = X_0^B = X_0$, $\beta^A = \beta^A = \beta$, $\sigma_\eta^A = \sigma_\eta^B = \sigma_\eta$, and $\sigma_\iota^A = \sigma_\iota^B = \sigma_\iota$) then the debt rating of A is higher than the debt rating of B.

Proof:

For any day t, let N_t be the (binomially distributed, with parameters α and t) total number of private information events through day t. For a fixed value of N_t=k, X_t is normally distributed with mean X_0 and variance $t\beta^2\sigma_\gamma^2 + t\sigma_\eta^2 + k\sigma_\iota^2$. Accordingly,

$$P[X_t<0] = \sum_{k=0}^{t} P[X_t<0 \mid N_t=k]P[N_t=k]$$

$$= \sum_{k=0}^{t} \Phi[(-X_0)(t\beta^2\sigma_\gamma^2 + t\sigma_\eta^2 + k\sigma_\iota^2)^{-0.5}]\, P[N_t=k] \quad (A1)$$

where Φ is the standard normal CDF. Since $X_0>0$, the quantity $\Phi[(-X_0)(t\beta^2\sigma_\gamma^2 + t\sigma_\eta^2 + k\sigma_\iota^2)^{-0.5}]$ is increasing in k By Lemma 2, the sum A1 is increasing in α, which establishes that $P[X_t<0]$ is increasing in α for all t. By assumption 2, this implies firm A (with the lower value for α) will have the higher debt rating. ///

Proposition 2: A lower σ_ι implies a higher debt rating.

For any two firms A and B, if $\sigma_\iota^A < \sigma_\iota^B$ and the remaining parameters are equal ($X_0^A = X_0^B = X_0$, $\beta^A = \beta^A = \beta$, $\sigma_\eta^A = \sigma_\eta^B = \sigma_\eta$, and $\alpha^A=\alpha^B=\alpha$) then the debt rating of A is higher than the debt rating of B.

Proof:

From the proof of Proposition 1:

$$P[X_t<0] = \sum_{k=0}^{t} \Phi[(-X_0)(t\beta^2\sigma_\gamma^2 + t\sigma_\eta^2 + k\sigma_\iota^2)^{-0.5}]\, P[N_t=k]$$

Since $X_0>0$, for each value of k, the quantity $\Phi[(-X_0)(t\beta^2\sigma_\gamma^2 + t\sigma_\eta^2 + k\sigma_\iota^2)^{-0.5}]$ is increasing in σ_i. Firms A and B have the same value of α, so they have the same value of $P[N_t=k]$ for all k. This implies that $P[X_t<0]$ is increasing in σ_ι, so firm A (with the lower value of σ_ι) will have the higher debt rating. ///

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Table 1: Sample Summary Statistics – January 1998

The table covers 2831 of the largest 3000 firms as of the end of May 1997; the remaining 169 exited the sample due to merger and acquisition activity. Market Capitalization and Share Price are as of December 31, 1997. Beta and Monthly volatility are measured from January 1995 through December 1997 (60 months). Turnover is measured from January 1997 through December 1997 (12 months). The book value for book-to-market is from the most recent quarterly report published prior to December 31, 1997.

	730 NYSE firms with rated debt [our sample]	862 NYSE firms with no rated debt	170 Nasdaq and Amex Firms with rated debt	1069 Nasdaq and Amex Firms with no rated debt
Panel A: Mean (Median) Characteristics				
Beta	0.89	0.82	1.14	1.23
	(0.86)	(0.78)	(0.98)	(1.09)
Market Capitalization in $Millions	7,664	2,880	2,023	1,116
	(2,481)	(799)	(777)	(427)
Share Price	42.28	33.66	28.77	29.20
	(37.16)	(29.41)	(27.13)	(25.13)
Share Turnover: Fraction per Month	0.08	0.09	0.12	0.14
	(0.07)	(0.08)	(0.12)	(0.13)
Volatility: Std Dev of Monthly Returns	0.08	0.07	0.17	0.18
	(0.06)	(0.06)	(0.12)	(0.13)
Book-to-Market Ratio	0.43	0.40	0.40	0.34
	(0.39)	(0.37)	(0.34)	(0.29)
Panel B: Industry classifications (Numbers in the first column are two-digit SIC codes)				
Durables: 50, 52, 55, 57	3.2%	3.1%	3.0%	2.8%
Nondurables: 51, 53, 54, 56, 58, 59	7.3	6.6	7.7	5.7
Utilities: 48, 49	15.8	6.6	25.4	3.5
Energy: 12, 13, 29	8.2	2.8	2.4	1.2
Construction: 15, 16, 17	1.7	0.9	0.6	0.3
Business equipment: 35, 36, 38	7.5	14.9	11.8	23.3
Manufacturing: 01-10, 14, 20-28, 30-34, 37, 39	25.2	29.5	14.8	18.5
Transportation: 40-47	2.9	1.2	4.1	2.6
Financial: 60-69	20.7	22.0	21.9	18.6
Business services: 70-99	7.5	12.4	8.3	23.5

Table 2: Definitions and Frequencies of Numerical Debt Ratings

The rating for each debt issue of each firm is converted to a numerical value according to the table below. For each rating agency, these values are averaged across the issues weighting by the amount outstanding. If more than one rating agency covers a particular firm, the composite numerical rating is the average across the rating agencies, weighting by the total face value covered by each agency. To produce the final three columns, the composite ratings were rounded to the nearest whole number. During the three time periods reflected in the table, no firms in our sample were rated below Ca2 (CC).

	Rating Agency Categories		Frequencies of composite ratings for NYSE firms with rated debt		
Numerical Rating	Moody's	S&P and Fitch	January 1995 (588 obs.)	January 1998 (730 obs.)	October 2000 (717 obs.)
36	Aaa1	AAA+	0.0%	0.0%	0.0%
35	Aaa2	AAA	1.5	1.1	1.3
34	Aaa3	AAA-	0.3	0.4	0.3
33	Aa1	AA+	0.9	0.4	0.3
32	Aa2	AA	4.4	3.2	2.2
31	Aa3	AA-	5.6	4.5	4.0
30	A1	A+	8.0	8.8	8.9
29	A2	A	12.2	12.3	9.6
28	A3	A-	10.9	10.0	10.6
27	Baa1	BBB+	9.7	12.1	12.8
26	Baa2	BBB	9.2	11.2	11.3
25	Baa3	BBB-	8.0	9.2	9.1
24	Ba1	BB+	3.7	4.4	4.3
23	Ba2	BB	3.2	2.9	4.7
22	Ba3	BB-	5.4	4.4	4.5
21	B1	B+	6.0	7.0	6.4
20	B2	B	6.5	5.6	6.6
19	B3	B-	3.7	2.2	1.8
18	Caa1	CCC+	0.2	0.4	1.3
17	Caa2	CCC	0.3	0.0	0.0
16	Caa3	CCC-	0.2	0.0	0.0
15	Ca1	CC+	0.2	0.0	0.0
14	Ca2	CC	0.2	0.0	0.0

Table 3: Comparisons Among the Three Rating Agencies

Statistics are computed using the 730 NYSE firms with rated debt as of January 1998.

	Standard and Poor's	Moody's	Fitch
Number of Rated Firms	713	711	149
Number NOT rated by EITHER of the others	17	14	0
Comparisons with Other Rating Agencies			
Comparison agency	Moody's	Fitch	Standard and Poor's
Number rated by both	694	144	143
Differences in ratings: (agency rating - comparison agency rating)			
Mean	0.24	-0.52	0.44
Standard Deviation	0.97	.92	0.91
Minimum	-3.00	-3.00	-2.88
Maximum	6.00	2.00	3.00
Differences in face amount covered: (ln(agency amount) - ln(comparison agency amount))			
Mean	0.004	0.198	-0.205
Standard Deviation	0.236	0.581	0.578

Table 4
Debt Rating Changes For Firms With Multiple Rating Agencies And Multiple Issues Outstanding

Panel A examines the 15,880 quarterly observations in our sample where an NYSE firm has debt ratings from both Standard and Poor's and Moody's. Rating agency changes are defined by the firm's debt issue with the earliest change in the quarter, and when multiple debt issues from the same firm have rating changes on the same day we use the debt issue with the earliest issue date. For the same 15,880 observations shown in Panel A, Panel B shows the number of cases where there are multiple issues and examines the behavior of the firm's other debt issues (apart from the one used to define the change) when there is a rating change during the quarter.

Panel A: Comparison of rating changes for Moody's and Standard and Poor's

Moody's rating action	Standard and Poor's rating action during the quarter			
during the quarter	Downgrades	No Change	Upgrades	Total
Downgrades	222	282	9	513
No Change	327	14252	329	14908
Upgrades	9	309	141	459
Total	558	14843	479	15880

Panel B: Rating agency rating changes for firms with multiple issues

	Standard and Poor's		Moody's	
	Downgrades	Upgrades	Downgrades	Upgrades
All rating changes				
Number of observations	558	479	513	459
Percent of total (of 15,880)	3.5%	3.0%	3.2%	2.9%
Changes with multiple debt issues				
Number of observations	397	338	375	345
Total number of debt issues	2374	2895	1977	2600
Other debt issues apart from the one used to define the rating change	1977	2557	1602	2255
Rating changes for other debt issues				
Same direction on the same day	1738	1959	1300	1578
Same direction within 10 days	4	8	16	20
Same direction during the quarter	16	0	15	20
No change during quarter	215	587	243	630
Opposite direction during quarter	4	3	28	7

Table 5: Regressions of Debt Ratings on Adverse Selection Measures

The estimates are from panel data regressions of mean debt ratings on adverse selection measures, debt-to-asset ratio, and yearly and industry dummies using quarterly observations for all large NYSE firms with rated debt for the 1995-2000 sample period. Quoted and effective spreads are scaled by price. Price impact is estimated using Hasbrouck's (1991) VAR model. To make this price-impact measure (which captures the effects of an unanticipated trade rather than a per share cost) comparable to the other measures, we multiply it by the standard deviation of residual trade size and scale by price. The adverse selection component is estimated using Huang and Stoll's (1997) specification of the Glosten and Harris (1988) model and is scaled by price. The EKOP (Easley, Kiefer, O'Hara, and Paperman (1996)) probability of informed trading is stated as a fraction of trades. The logged debt-to-asset ratio is scaled by subtracting the cross-sectional median and then dividing by the difference between the 75th percentile and the median.

	Quoted Spread		Effective Spread		Hasbrouck Price Impact		Glosten and Harris Adv Sel Component		EKOP Probability of Informed Trading	
Explanatory Variables	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
ln(Adv Selection Measure)	-0.706	0.000	-0.650	0.000	-0.153	0.000	-0.228	0.000	-0.174	0.000
ln(Debt/Assets)	-0.046	0.032	-0.050	0.020	-0.126	0.000	-0.123	0.000	-0.149	0.000
Dummy Variables										
1995	21.486	0.000	21.520	0.000	23.615	0.000	23.110	0.000	24.632	0.000
1996	21.444	0.000	21.490	0.000	23.630	0.000	23.139	0.000	24.643	0.000
1997	21.353	0.000	21.436	0.000	23.712	0.000	23.231	0.000	24.707	0.000
1998	21.397	0.000	21.465	0.000	23.805	0.000	23.345	0.000	24.762	0.000
1999	21.422	0.000	21.471	0.000	23.791	0.000	23.325	0.000	24.746	0.000
2000	21.383	0.000	21.437	0.000	23.753	0.000	23.282	0.000	24.689	0.000
Durables	-0.124	0.817	-0.111	0.841	0.279	0.695	0.295	0.678	0.332	0.658
Nondurables	0.253	0.460	0.219	0.532	0.220	0.567	0.279	0.450	-0.199	0.516
Utilities	1.420	0.000	1.432	0.000	1.374	0.002	1.391	0.002	1.653	0.000
Energy	-0.523	0.280	-0.546	0.255	-0.658	0.169	-0.638	0.175	-0.820	0.181
Construction	-2.232	0.000	-2.280	0.000	-2.377	0.000	-2.303	0.000	-2.381	0.000
Business Equipment	-0.686	0.027	-0.753	0.019	-0.834	0.010	-0.764	0.012	-0.872	0.002
Transportation	0.063	0.827	-0.008	0.977	-0.112	0.646	-0.062	0.803	-0.237	0.371
Financial	0.651	0.001	0.633	0.001	0.655	0.002	0.715	0.001	0.788	0.023
Business Services	-0.327	0.239	-0.360	0.201	-0.312	0.361	-0.230	0.509	-0.730	0.222

Table 6: Regressions of Debt Ratings on Decomposed Adverse Selection Variables

The estimates are from panel data regressions of mean debt ratings on the components of the decomposed adverse selection measures, debt-to-asset ratio, and yearly and industry dummies using quarterly observations for all large NYSE firms with rated debt for the 1995-2000 sample period. For the quoted and effective spread and the Hasbrouck and Glosten and Harris measures, the logged value of the modified adverse selection component is equal to the logged value of the same measure used in Table 5 minus the log of the average absolute trade imbalance per day (in trades) and minus the log of the equity-to-asset ratio. The regression in the final column splits the Easley, Kiefer, O'Hara and Paperman PI measure into two component parts using the individual parameter estimates. The logged debt-to-asset ratio is scaled by subtracting the cross-sectional median and then dividing by the difference between the 75^{th} percentile and the median.

	Quoted Spread		Effective Spread		Hasbrouck Price Impact		Glosten and Harris Adv Sel Component		EKOP Probability of Informed Trading	
Explanatory Variables	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
ln(Modified Adv. Sel.)	-0.539	0.000	-0.499	0.000	-0.104	0.000	-0.184	0.000		
ln(Avg Abs Trade Imbal/Day)	0.633	0.000	0.626	0.000	0.168	0.000	0.200	0.000		
ln(Equity/Assets)	1.033	0.000	0.997	0.000	0.809	0.000	0.878	0.000		
ln(α)									-0.206	0.000
ln(μ/(α∗μ+2ε))									-0.408	0.000
ln(Debt/Assets)	0.030	0.344	0.030	0.347	0.001	0.982	0.001	0.984	-0.147	0.000
Dummy Variables										
1995	22.960	0.000	22.870	0.000	24.917	0.000	24.491	0.000	24.420	0.000
1996	22.906	0.000	22.821	0.000	24.902	0.000	24.493	0.000	24.429	0.000
1997	22.821	0.000	22.759	0.000	24.945	0.000	24.551	0.000	24.487	0.000
1998	22.864	0.000	22.786	0.000	25.026	0.000	24.658	0.000	24.520	0.000
1999	22.900	0.000	22.801	0.000	25.054	0.000	24.690	0.000	24.510	0.000
2000	22.891	0.000	22.791	0.000	25.064	0.000	24.705	0.000	24.454	0.000
Durables	-2.248	0.000	-2.255	0.000	-2.414	0.000	-2.405	0.000	0.320	0.668
Nondurables	-0.089	0.868	-0.106	0.843	-0.025	0.965	-0.011	0.985	-0.186	0.552
Utilities	1.193	0.001	1.212	0.001	1.203	0.002	1.192	0.002	1.637	0.000
Energy	-1.597	0.000	-1.605	0.000	-1.670	0.000	-1.663	0.000	-0.806	0.189
Construction	-2.694	0.000	-2.697	0.000	-2.775	0.000	-2.759	0.000	-2.338	0.000
Business Equipment	-1.424	0.000	-1.438	0.000	-1.440	0.001	-1.434	0.001	-0.872	0.002
Transportation	-1.363	0.030	-1.360	0.030	-1.230	0.060	-1.225	0.059	-0.169	0.541
Financial	0.541	0.195	0.547	0.192	0.657	0.173	0.646	0.181	0.815	0.017
Business Services	-1.531	0.017	-1.525	0.019	-1.327	0.086	-1.303	0.094	-0.724	0.221

Table 7: Regressions of Debt Ratings on All Variables

Results of panel data regressions using quarterly observations for all large NYSE firms with rated debt for the 1995-2000 sample period. Yearly intercepts and industry dummy variables are not reported to conserve space. Modified adverse selection measures are those used in Table 6. All continuous explanatory variables in the "other" section of the table are scaled by subtracting the cross-sectional median and then dividing by the difference between the 75th percentile and the median.

	Quoted Spread		Effective Spread		Hasbrouck Price Impact		Glosten and Harris Adv Sel Component		EKOP Probability of Informed Trading	
Explanatory Variables	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Components of the Adverse Selection Measures										
ln(Modified Adv. Sel.)	-0.276	0.000	-0.225	0.003	-0.036	0.078	-0.058	0.124		
ln(Avg Abs Trade Imbal/Day)	0.229	0.010	0.193	0.034	-0.022	0.582	-0.014	0.757		
ln(Equity/Assets)	0.559	0.000	0.510	0.000	0.333	0.001	0.354	0.001		
ln(α)									-0.070	0.005
ln(μ/(α*μ+2ε))									-0.166	0.000
Other Explanatory Variables										
ln(Debt/Assets)	0.086	0.008	0.087	0.007	0.093	0.003	0.092	0.003	0.048	0.088
ln(Stock Price)	-0.010	0.761	0.001	0.987	0.053	0.111	0.053	0.112	0.102	0.012
ln(Market Capitalization)	0.688	0.000	0.690	0.000	0.714	0.000	0.710	0.000	0.726	0.000
ln(Volatility)	-0.284	0.000	-0.285	0.000	-0.278	0.000	-0.277	0.000	-0.291	0.000
Book-to-Market	0.016	0.330	0.016	0.328	0.015	0.339	0.015	0.335	0.009	0.742
Dividend Yield	-0.007	0.875	-0.006	0.892	-0.007	0.877	-0.008	0.863	-0.017	0.700
Past 6-Month Return	-0.063	0.000	-0.063	0.000	-0.063	0.000	-0.063	0.000	-0.065	0.000
Beta	0.036	0.085	0.035	0.091	0.032	0.129	0.032	0.130	0.032	0.143
Interest Coverage	0.016	0.030	0.016	0.031	0.016	0.035	0.016	0.035	0.018	0.042
Profit Margin	-0.004	0.496	-0.004	0.493	-0.005	0.492	-0.004	0.496	-0.003	0.663
Return on Assets	0.020	0.118	0.020	0.116	0.022	0.078	0.022	0.076	0.017	0.217
ln(Cash Flow) if Positive	0.015	0.036	0.015	0.038	0.015	0.037	0.015	0.037	0.020	0.020
Negative CF Dummy	0.003	0.857	0.005	0.807	0.005	0.808	0.004	0.819	0.012	0.569
ln(Cash Flow) if Negative	-0.016	0.054	-0.016	0.056	-0.016	0.060	-0.015	0.064	-0.023	0.012

Table 8: Ordered Probit Regressions Predicting Future Debt Ratings Changes

Parameter estimates from ordered probit regressions of the likelihood of subsequent debt ratings changes. The dependent variable assumes a value of -1 if a ratings downgrade occurs in the subsequent quarter, a value of 0 if no ratings change occurs in the subsequent quarter, and a value of +1 if a ratings upgrade occurs in the subsequent quarter. A positive coefficient indicates an increase in the probability of a downgrade and a decrease in the probability of an upgrade. Threshold parameters, not shown in the table, are consistent with the sample frequencies (5.0% are downgrades, and 5.3% are upgrades). "Change in ln(D/A)" represents the change in the normalized logged debt-to-asset ratio from the previous quarter to the current quarter. The adverse selection measures are the same as those used in Table 5. "Change in ln(Adv Selection)" is the change in the logged adverse selection measure from the previous quarter to the current quarter.

	Quoted Spread	Effective Spread	Hasbrouck Price Impact	Glosten and Harris Adv Sel Component	EKOP Probability of Informed Trading
Panel A: Parameter Estimates (p-values shown in parentheses)					
Change in ln(D/A)	0.076	0.077	0.100	0.098	0.091
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change in ln(Adv Selection)	0.722	0.715	0.074	0.112	0.052
	(0.000)	(0.000)	(0.001)	(0.005)	(0.174)
Panel B: Effect of a One-Standard Deviation Increase in the Logged Adverse Selection Measures					
Increase in Percentage Change in Adv Selection (= 1 Std Dev)	0.191	0.197	0.570	0.334	0.400
Corresponding Change in the Probability of a Downgrade	0.015	0.015	0.005	0.004	0.002
Corresponding Change in the Probability of an Upgrade	-0.012	-0.012	-0.005	-0.004	-0.002
Panel C: Effect of a 0.20 Increase in the Logged Adverse Selection Measures					
Change in the Prob of a Downgrade	0.015	0.015	0.002	0.003	0.001
Change in the Prob of an Upgrade	-0.012	-0.012	-0.002	-0.003	-0.001