Credit Ratings and Stock Liquidity

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We analyze contemporaneous and predictive relations between credit 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 credit ratings are poorer. We also show that future rating changes can be predicted using current levels of adverse selection. Collectively, our results validate widely used microstructure measures of adverse selection and offer new insights into the value of credit ratings and the specific nature of the information they contain.

The level of uncertainty about the value of a firm's assets has a direct impact on the risk of the firm's debt and equity. Naturally, both academics and practitioners have developed many measures of uncertainty to assess the risk of these financial securities. For example, extensive research examines the ability of credit ratings to capture uncertainty about the value of a firm's debt. Furthermore, measures of equity-market adverse selection risk from the market microstructure literature reflect the uncertainty about equity value that is revealed through trades. In general, increased uncertainty about total firm value means increased uncertainty about the value of both debt and equity; yet the literature on credit ratings and the literature on equity-market adverse selection have developed completely independently of one another.

In this article, we link these two distinct lines of research by examining the relation between credit ratings and market microstructure measures of equity adverse selection. We begin by developing a simple model that guides our empirical analysis. The model decomposes the uncertainty about future asset value into shocks that will be observed by all market participants simultaneously, and shocks that are initially observed by one or more "insiders." While both types of asset-value uncertainty are

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relevant for credit ratings, it is the latter type that causes a linkage between a firm's credit rating and the level of adverse selection in the trading of the firm's equity. Holding capital structure, asset tangibility, and the risk of publicly observed shocks constant, the model predicts that firms with greater risk of private shocks, and therefore higher levels of equity-market adverse selection, will have lower credit ratings. Our model also suggests ways to modify the standard adverse selection measures to better isolate the uncertainty parameters related to credit ratings.

We test for contemporaneous and predictive relations between credit ratings and adverse selection, using both the standard measures from the literature and the modified versions of these measures suggested by our model. We demonstrate in panel data regressions that credit ratings are in fact poorer when adverse selection—as captured by quoted and effective spreads, Glosten and Harris' (1988) adverse selection component of the spread, Hasbrouck's (1991) information-based price impact measure, and Easley et al.'s (1996) probability of informed trading—is higher. When we modify these standard measures, we find that the portion that reflects the amount of private information is significantly negatively related to credit ratings, as predicted by the model.

For the modified measures calculated using either quoted and effective spreads or the Easley et al. procedure, the statistical significance of the relation between adverse selection and credit ratings holds even after controlling for total asset volatility, as well as for other factors related to credit ratings and liquidity. This is consistent with 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 credit ratings and returns on debt and equity after controlling for other factors.[2]

Anecdotal and empirical evidence suggests that rating agencies are sometimes slow to respond to new information.[3] We extend this work by analyzing the ability of changes in the adverse selection measures to predict future rating changes. Our estimation of an ordered probit model reveals that future rating changes can be predicted using recent changes in the levels of adverse selection and the ratio of equity to assets. This provides additional evidence that the agencies are sometimes slow to react and also suggests that adverse selection measures may be a useful tool for assessing credit risk on a more timely basis.

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

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

[3] See, for example, Chan and Jegadeesh (2001), Hand, Holthausen, and Leftwich (1992), Hite and Warga (1997), Johnson (2003) and Weinstein (1977).

Collectively, our results provide independent validation of 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. Our results also offer new insights into the value of credit ratings, their relationship to firm-value uncertainty, and the speed with which they reflect changes in uncertainty.

1. A Model of Credit Ratings and Adverse Selection

We present a simple model of firm value that predicts a negative association between credit ratings and equity adverse selection costs. In many respects, our model is similar to the model developed by Longstaff and Schwartz (1995) to value risky debt. As in Longstaff and Schwartz, our model takes the firm's debt level as given, assumes that the asset-value process does not depend on the debt level, assumes that default occurs when the asset value falls below a fixed dollar amount (in our case, the face value of the debt), and assumes that in the event of default, the debt holders receive a fraction of the face value.[4] Unlike Longstaff and Schwartz, we assume three separate sources of asset-value uncertainty. Two of the shocks to asset value are publicly observed, one related to market-wide information and the other related to public announcements about the firm. The third type of shock is privately 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. The equity-market adverse selection measures respond to the third type of shock. Of course, all three types of shocks are important to debt holders; they will not care whether they arrive publicly or privately. Because a larger risk of *private* events corresponds to a larger risk of *total* events, greater adverse selection risk implies higher asset-value uncertainty. In summary, the privately observed shock causes the link between credit ratings and equity adverse selection.

1.1 Assumptions

Formally, let t denote time in days, and let A_t denote the total market value of the firm's assets on day t. We assume that the natural logarithm of the value of the assets evolves each day as follows:

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

where γ_t is the economy-wide ("systematic") shock on day t, β is the firm's sensitivity to that economy-wide shock, η_t is a publicly observed

[4] We are using our model to draw conclusions about default probabilities and expected payments in default, but unlike Longstaff and Schwartz we are not trying to assign a value to the bond, so we do not make any assumption about the risk-free interest rate process.

unsystematic shock, I_t is a Bernoulli random variable that equals 1 if a private information event occurs on day t, and τ_t is the conditional value of the private information event. The probability that such an event occurs on any given day is denoted as α, which is analogous to the α parameter used by Easley et al. (1996) to capture the frequency of private information events. In their model, unlike ours, the private information event is the sole source of uncertainty. Furthermore, they model changes in asset value using a Bernoulli distribution, whereas we assume that τ_t, as well as γ_t and η_t, is normally distributed with mean zero and standard deviations σ_τ, σ_γ, and σ_η, respectively. We also assume that γ_t, η_t, τ_t, and I_t are jointly and serially independent.

The face value of the firm's debt, which is assumed to remain constant in the future, is denoted as D. 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 X_t has the same transition equation as $\ln(A_t)$. Our model assumes that default occurs if the total value of the assets falls below the face value of the debt, or equivalently $X_t < 0$. In the event of default, the debt holders receive only a fraction of the face value, ρD, due to dead weight losses in bankruptcy. The recovery rate, ρ, does not play a crucial role in our model. We include it because credit rating agencies assert that their ratings are sensitive to both the probability of default and the anticipated recovery rate in the event of default.[5]

Although we assume that credit ratings are related to the probability of insolvency at some time in the future and to the expected recovery rate, we do not take any stand on the particular form of this relation. Instead, we assume that credit ratings satisfy two kinds of stochastic dominance: if recovery rates are the same, then a higher probability of default at every future date means a lower rating, and if default probabilities are the same, then a lower recovery rate means a lower rating. These assumptions are stated more formally as follows.

For any two firms A and B:

(i) If $P\left[X_t^{\mathrm{A}} < 0\right] < P\left[X_t^{\mathrm{B}} < 0\right]$ for every $t > 0$ and $\rho^{\mathrm{A}} = \rho^{\mathrm{B}}$, then A has a higher credit rating than B;

(ii) If $\rho^{\mathrm{A}} > \rho^{\mathrm{B}}$ and $P\left[X_t^{\mathrm{A}} < 0\right] = P\left[X_t^{\mathrm{B}} < 0\right]$ for every $t > 0$, then A has a higher credit rating than B.

1.2 Predictions

With the assumptions above, we can show that higher credit ratings are associated with lower levels of adverse selection, as reflected by the probability of a private information event (α) and the magnitude of that event (σ_τ).

[5] See, for example, Standard and Poor's Corporate Rating Criteria (2002).

Proposition 1: A Lower α Implies a Higher Credit Rating
For any two firms A and B, if $\alpha^{\mathrm{A}} < \alpha^{\mathrm{B}}$ *and the remaining parameters are equal* ($X_0^{\mathrm{A}} = X_0^{\mathrm{B}} = X_0$, $\beta^{\mathrm{A}} = \beta^{\mathrm{B}} = \beta$, $\sigma_\eta^{\mathrm{A}} = \sigma_\eta^{\mathrm{B}} = \sigma_\eta$, $\rho^{\mathrm{A}} = \rho^{\mathrm{B}} = \rho$, and $\sigma_\tau^{\mathrm{A}} = \sigma_\tau^{\mathrm{B}} = \sigma_\tau$) *then the credit rating of A is higher than the credit rating of B.*

Proof: See appendix.

Proposition 2: A Lower σ_τ Implies a Higher Credit Rating
For any two firms A and B, if $\sigma_\tau^{\mathrm{A}} < \sigma_\tau^{\mathrm{B}}$ *and the remaining parameters are equal* ($X_0^{\mathrm{A}} = X_0^{\mathrm{B}} = X_0$, $\beta^{\mathrm{A}} = \beta^{\mathrm{B}} = \beta$, $\sigma_\eta^{\mathrm{A}} = \sigma_\eta^{\mathrm{B}} = \sigma_\eta$, $\rho^{\mathrm{A}} = \rho^{\mathrm{B}} = \rho$, and $\alpha^{\mathrm{A}} = \alpha^{\mathrm{B}} = \alpha$) *then the credit rating of A is higher than the credit rating of B.*

Proof: See appendix.

The propositions are quite intuitive. Additional uncertainty of any type is likely to reduce credit ratings. In our empirical analysis, we test the relation between adverse selection and credit ratings using common adverse selection measures that capture α and σ_τ (as discussed in the next section). One obvious question is whether the magnitude of the private information events will be large enough to be an important determinant of credit ratings. Hasbrouck (1988) shows that approximately 34% of total stock price changes can 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.

1.3 Potential limitations of the model

A potentially restrictive assumption in our model is the *ex ante* symmetry (normality) of the private information shocks. To illustrate, we construct a simple example based on a modification of our model where the information events can assume one of just two possible values as in Easley et al. (1996). To focus on the salient characteristics of the example, we assume there is no uncertainty associated with public information events (i.e., β and σ_η are zero). We also assume investors are risk-neutral and the risk-free rate is zero.

Our example considers two firms, A and B, with the same face value of debt ($100), and the same probability of an information event, equal to 0.5. We assume that the two firms have the same mix of informed and uninformed traders, and if an information event occurs, we assume that the informed traders learn the true end-of-day value of the firm.

Figure 1 shows the starting values and the potential end-of-day values for both firms. If an event occurs, A's total firm value as of the end of the day will be either $150 with probability 0.9 or $200 with probability 0.1,

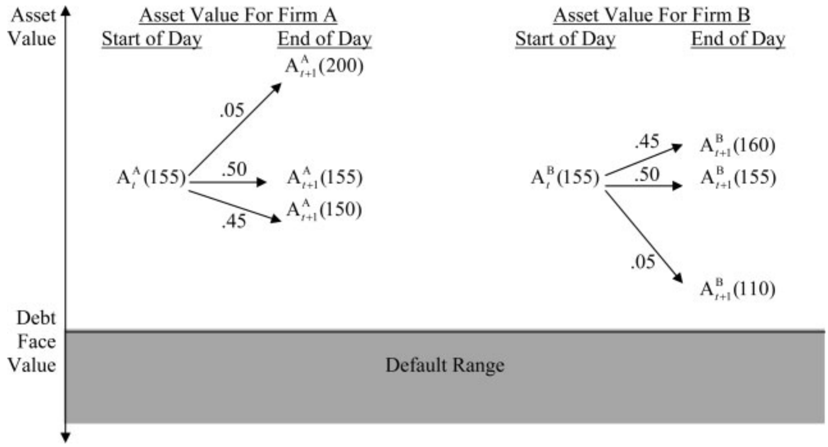

Figure 1
An example with asymmetric information events.

so A's *ex ante* total firm value is $0.9\times150 + 0.1\times200 = \$155$. Likewise, if an event occurs, B's total firm value at the end of the day will be \$110 with probability 0.1 or \$160 with probability 0.9, so B's ex ante total firm value is also \$155. If no event occurs for a firm (with probability 0.5), all market participants will maintain the same beliefs about the possible values, so the end-of-day value will be unchanged.

By construction, firms A and B have the same *ex ante* firm value and the same amount of outstanding debt, so they have the same leverage ratio. Also by construction, they have the same degree of equity information asymmetry, in the sense that the variance of the end-of-day price is the same and the informed traders' expected profit is the same. It is very unlikely that A and B would have the same credit ratings, however, because firm A's value will be comfortably above the face value of the debt in both the high and low states, whereas B has a 0.1 probability of coming near default. The example shows that when the *ex ante* distribution of private information events is asymmetric, there may not be a simple correspondence between the variance of private information events and credit ratings.

Another potentially restrictive assumption in our model is that a drop in the value of assets always means a drop in the value of the equity and an increase in the probability of default. This strict relation may not hold for two reasons. First, the volatility of the assets may change along with the total value of the assets. For example, the arrival of a new investment opportunity might increase the value of A_t, yet at the same time increase the variability of total asset value by just enough to leave the probability of default unchanged.[6] In this case, the *ex ante* risk that such a project may or may not arrive could result in equity adverse selection (assuming that arrival would be privately observed); yet the risk of this project's arrival would be nearly irrelevant to the debt holders.

In a world with transaction costs, there is another potential distinction between the value of the equity and the total value of the assets. Large order imbalances can cause temporary deviations from long-run "fair value." Since these effects are temporary, the associated equity uncertainty should be of little concern to the debt holders.

The factors discussed above could produce a weaker empirical relation between adverse selection and credit ratings than would be predicted by our model. It is also possible that factors outside of the model could *explain* a potential association between credit ratings and equity adverse selection measures. As in models by Merton (1974) and Longstaff and Schwartz (1995), our model assumes that the firm's total asset value evolves independently of the firm's capital structure. This assumption will be violated if the credit rating has a direct effect on the operating decisions made by the firm. In some cases, if a firm's credit rating falls below a certain level, it will activate covenants that restrict new investment or cause other suboptimal asset decisions [Pulvino (1998)]. If this situation also tends to result in additional private information events, for example if some traders are better able to predict renegotiation of covenants with debt holders, then lower credit ratings could directly cause higher equity adverse selection. Of course, there is also reason to suspect that interactions between capital structure and operating decisions could result in a *positive* relation between ratings and adverse selection costs. Higher rated, and therefore less financially constrained, firms may be considering substantial investment projects, and the large changes in equity value associated with some of these projects may be privately observed events.

2. Adverse Selection Measures

Adverse selection measures seek to quantify market makers' risk of facing traders with better information. This risk is more severe when information events are more likely (when α is higher) or when information events are potentially more extreme (when σ_T is higher). In other words, there should be a relation between credit ratings and adverse selection because they are both related to fundamental asset-value uncertainty.

Several adverse selection measures have been proposed in the literature, and each takes a slightly different approach to capturing this risk. Dennis

[6] Since A_t is the market value of future cash flows, the arrival of the project would increase A_t by the NPV of the project times one minus the *ex ante* probability that the project would arrive.

and Weston (2001) find that many measures behave in a largely consistent manner, but not all are 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.

We also recognize that the standard adverse selection measures were not designed to isolate the parameters α and σ_T from our model. To the extent that they also capture other features of the firm, like trading intensity or capital structure, there could be an empirical relation between credit ratings and these standard measures that is driven by factors outside of our model. For example, if the stock has high liquidity, then it may be easier to issue new equity to avoid financial distress, which would in turn make the outstanding debt less risky. Accordingly, after describing the general approach used to calculate each standard measure, we discuss linkages between the measures and our model, and then propose ways to modify the standard measures to better isolate the impact of α and σ_T. Specific details for estimating the various measures are covered in Section 3, after we describe our data and sample selection procedure.

2.1 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 some traders may possess better information, they set bid-ask spreads that allow them to offset their losses 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 for buy orders is calculated as twice the difference between the transaction price and the midpoint of the quoted bid-ask spread, divided by the quote midpoint. For sell orders, the transaction price is subtracted from the spread midpoint.

2.2 Adverse selection component of the spread

Although quoted and effective spreads are natural measures of adverse selection risk, they may reflect other costs as well. Thus, a 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. Models by George, Kaul, and Nimalendran (1991), Glosten and Harris (1988), Huang and Stoll (1997), Roll (1984), and Stoll (1989) 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:[7]

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

where P is the transaction price, Q is a buy/sell indicator variable, 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 $\lambda S/2$, which we simply refer to as the adverse selection component. We divide by the share price at the start of the quarter to convert it to a relative measure.

2.3 Information-based price impact

Hasbrouck (1991) develops an approach that is conceptually similar to the adverse selection component of the spread, but stems from a somewhat different estimation method. He uses 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 his 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:

$$Z_t = a_Z + \sum_{i=1}^{5} b_i \Delta P_{t-i} + \sum_{i=1}^{5} c_i Z_{t-i} + \omega_t \tag{2}$$

$$\Delta P_t = a_P + d\Delta Q_t + \lambda \omega_t + e_t \tag{3}$$

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 (ω) from the first equation reflect the unexpected portion of each trade, so the λ in the second equation captures the information-based price impact.

[7] 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).

We normalize λ in two ways. First, we multiply it by the standard deviation of the residuals (ω) 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 above. We also divide by the share price at the start of the calendar quarter to convert it to a relative measure.

2.4 Probability of informed trading

The final approach, developed by Easley et al. (1996), yields a measure of the probability that a trader possesses private information. Their model exploits the fact that information events result in persistent order imbalances. In their model, equity can assume one of two possible values—high or low. Information events, which arrive with probability α each day, reveal the true value of equity to informed traders. When a positive (negative) event occurs, informed buyers (sellers) arrive steadily throughout the day at a rate μ. The market maker updates prices in response to the order imbalance, but can never be completely sure of the existence or direction of an information event because of the presence of noise traders, who arrive on each side of the market at rate ε. This lack of certainty means that the market maker does not fully adjust quotes to reflect either the low or high value, so the informed traders continue to trade throughout the day.

In this model, the probability of informed trading is equal to:

$$\mathrm{PIN} = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}$$

The parameters are estimated by maximizing the following likelihood function:

$$L(B, S \mid \alpha, \varepsilon, \delta, \mu) = \prod_{i=1}^{I} \left\{ \begin{array}{l} (1-\alpha)\left[e^{-\varepsilon T}\frac{(\varepsilon T)^{B_i}}{B_i!}e^{-\varepsilon T}\frac{(\varepsilon T)^{S_i}}{S_i!}\right] \\ +\alpha\delta\left[e^{-\varepsilon T}\frac{(\varepsilon T)^{B_i}}{B_i!}e^{-(\mu+\varepsilon)T}\frac{[(\mu+\varepsilon)T]^{S_i}}{S_i!}\right] \\ +\alpha(1-\delta)\left[e^{-(\mu+\varepsilon)T}\frac{[(\mu+\varepsilon)T]^{B_i}}{B_i!}e^{-\varepsilon T}\frac{(\varepsilon T)^{S_i}}{S_i!}\right] \end{array} \right\} \tag{4}$$

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. As in Easley et al. (1996), we estimate the parameters using daily counts of buys and sells (i.e., $T = 1$), and constrain μ and ε to be positive and α and δ to be between 0 and 1.

2.5 Linkage between the measures and the model

In this subsection, we describe the link between the privately observed component of uncertainty, captured by α and σ_τ, and the standard adverse selection measures described above. Although we believe our model provides a useful framework for comparing the microstructure measures and linking them to the uncertainty that drives credit ratings, we recognize that no model can do this in a completely rigorous fashion because the measures have different underlying assumptions. For example, the spread-based measures implicitly assume a constant degree of information asymmetry, whereas in the Easley et al. (1996) model, the information asymmetry declines throughout the day. In addition, the Hasbrouck measure assumes multiple trade sizes and allows predictable time-variation in noise-trader behavior, whereas the other two measures are based on unit trade sizes and stationarity in noise-trader behavior. Consequently, much of the analysis in this section is based on economic arguments as opposed to formal proofs.

The α parameter in our model relates closely to Easley et al.'s (1996) model in which information events arrive on α of the days. Unlike Easley et al. (1996), our model assumes that information events are drawn from a normal distribution rather than having just two possible outcomes. We make this assumption partly because we feel it is somewhat more realistic, and partly because it allows us to rigorously establish a link between the uncertainty parameters and credit ratings. Although assuming many outcomes has advantages, it makes the trading game more complicated. Consider the case when the signal is positive but small. The informed traders will buy initially, but the market maker's reaction to the order imbalance may cause prices to overshoot the privately observed value, which may in turn cause the informed traders to sell. Despite this complication, firms with more frequent information events should still have more days with significant order imbalances. Accordingly, we interpret the α from their estimation procedure as a proxy for the α in our model.

Our initial empirical tests use the PIN measure, because it has become standard in the microstructure literature. In our later tests, we separate the PIN measure into the parameter of interest, α, and the remainder, $\mu/(\alpha\mu+2\varepsilon)$, which may capture the effects of liquidity as well as information.

The spread-based measures reflect both the probability of an information event, α, and the value impact of the event, σ_T. We focus specifically on the relation between our model and the Glosten and Harris (1998) adverse selection component, and then argue that the other spread-based measures behave similarly. 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 the private signal is incorporated into the share price through trading:

(i) Each trade moves the public's assessment of the log asset value by an amount ϕQ_j, where Q_j is the buy/sell indicator for the trade
(ii) 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 (i)] 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 et al. (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 (ii), 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:

$$I_t \tau_t = \phi \sum_{j=1}^{N} Q_j \tag{5}$$

where $N =$ the number of trades during the day.[8]

Recall that in our model, information events are normally distributed and occur on α of the days. Also 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 τ_t are independent, $E[|I_t \tau_t|] = \alpha\sigma_\tau\sqrt{2/\pi}$. Using Equation (5), this implies $\phi = \alpha\sigma_\tau\sqrt{2/\pi}/N^I$, where $N^I = E\left[\left|\sum_{j=1}^{N} Q_j\right|\right]$ is the average daily absolute trade imbalance (measured in number of trades).

Further, note that for small percentage changes, the change in the log value is approximately equal to the percentage change, so ϕ is approximately equal to the percentage change in asset value ($\Delta A/A$) per trade. Assuming that the value of the debt is roughly constant, the change in the equity value is approximately equal to 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 $\Delta A/E = (\Delta A/A)(A/E) \approx \phi(A/E)$, where (A/E) is the ratio of asset value

[8] Note that these two quantities will not be exactly equal because τ_t is a continuous random variable and the trade imbalance is discrete.

to equity value. Combined with the above results, this means the Glosten and Harris measure is proportional to $\alpha\sigma_T(A/E)/N^I$. In summary, an increase in either α or σ_T will both increase the Glosten and Harris measure and decrease the firm's credit 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_T. Likewise, the quoted and effective spreads contain the adverse selection component, so they should respond positively to an increase in either α or σ_T, as well.

The above discussion suggests that we modify the standard spread-based adverse selection measures by multiplying 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 $\alpha\sigma_T$ and purged of the effects of trading frequency and capital structure. In our empirical tests, we first examine the relation between credit ratings and the standard adverse selection measures, and then run separate tests using the modified measures, along with trading frequency and capital structure.

3. Data and Methods

3.1 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.[9] For the subsequent quarters beginning July 1, October 1, January 1, and April 1, we select from these 3000 stocks 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.[10]

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 (S&P). In addition, we obtain estimates of asset volatility from Moody's/KMV.[11] For each measure, we use

[9] 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.

[10] 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 1990s and that the problem persists through the end of their sample in mid-1995.

[11] We are grateful to Moody's/KMV for providing these data.

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 1% of the firm-quarter observations in our sample. In addition, asset volatilities and some of the COMPUSTAT data items are missing for some of the observations. In our regression tests, we replace missing asset volatilities with predicted values (as described in detail in Section 4). We replace missing values of other variables (except the adverse selection measures) with sample medians.[12]

Table 1 summarizes data (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.[13]

3.2 Credit ratings

Credit ratings are taken from the Fixed Income Securities Database, which was obtained from LJS Global Information Services.[14] We include only U.S.-dollar denominated debt 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 illustrated in Table 2, credit ratings for the firms in our sample tend to cluster between A+ and BBB– (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 S&P

[12] Firms with missing COMPUSTAT are included in the "manufacturing" industry category.

[13] 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.

[14] This database is now distributed by Mergent, Inc.

Table 1
Sample summary statistics—January 1998

	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	7664	2880	2023	1116
	(2481)	(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: standard deviation 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

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 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.

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 S&P 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.

Table 2
Definitions and frequencies of numerical credit ratings

	Rating agency categories		Frequencies of composite ratings for NYSE firms with rated debt		
Numerical rating	Moody's	S&P and Fitch	January 1995 (588 observations)	January 1998 (730 observations)	October 2000 (717 observations)
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

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 debt 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).

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.

3.3 News stories

We construct a variable that captures the risk of publicly announced firm-specific shocks to asset value (the parameter σ_η in our model) using news releases from Business Wire. For each firm quarter, we search Lexis-Nexis by ticker symbol and count the number of stories appearing in Business Wire for the period. For a few firms, Lexis-Nexis does not accept searches by ticker symbol; in these cases, we search by company name instead. Our search yields 125,153 news stories, or an average of 7.3 stories per firm per quarter.

There is a strong correlation between the number of news releases and firm size. Naturally, an event that results in a 2% change in the value of a large firm is more "newsworthy" than an event that results in a 2% change

Table 3
Comparisons among rating agencies

	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

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

in the value of a small firm. To control for this effect, we regress the natural logarithm of the number of stories (plus one, so logs can be taken even when no news releases appeared) on the natural logarithm of total assets. We also include quarterly dummy variables in the regression to control for the upward trend in the number of news stories over the sample period. The residuals from this regression constitute our news story variable.

3.4 Intraday data and estimation of adverse selection measures

For each quarter, 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. Firm quarters with fewer than 25 trades are omitted because the number of degrees of freedom in the estimation procedure seems unreasonably low. We use all trades on all exchanges that occur during regular trading hours (9:30 A.M. to 4:00 P.M.), but we use NYSE quotes rather than constructing the National Best Bid and Offer (NBBO) across all competing market centers because quote data from some of the regional exchanges can be somewhat unreliable. Furthermore, Blume and Goldstein (1997) show that the NYSE is at the inside of the NBBO approximately 97% of the time. Trade direction is determined using the Lee and Ready algorithm (1991), which compares trade prices to the midpoint of the quote as of five seconds prior to the trade report and uses the tick test to classify midpoint trades. As

Table 4
Credit rating changes

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

Moody's rating action during the quarter	Standard and Poor's rating action 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

Panel A examines the 15,880 quarterly observations in our sample where an NYSE firm has credit 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.

recommended by Odders-White (2000), we repeat our tests after eliminating midpoint transactions. Since NYSE trades are often reported in two or more pieces, we follow Easley et al. (1996) (and others) by combining any trades on the same exchange that occur within five seconds of one another at the same price.

Relative quoted spreads for each firm quarter are computed as time-weighted averages over the period, and relative effective spreads are simple averages across all trades. The adverse selection component of the spread [Equation (1)] and the information-based price impact measure [Equations (2) and (3)] are estimated using ordinary least squares. Negative estimates of the Glosten and Harris adverse selection component and the Hasbrouck price impact measure are dropped, as are values in excess of the effective spread. This eliminates 0.05% of the adverse selection component estimates and 1% of the price impact estimates. All four spread-based measures are scaled by price as described above.

The probability of informed trading is estimated via maximum likelihood [see Equation (4)]. Starting values are selected non-randomly based on the distribution of prior estimates to increase the likelihood of convergence. The estimation procedure failed to converge for a small fraction of the stocks in our sample.[15] All tests exclude such cases, as well as cases in which the estimation procedure converged to a boundary.

Table 5 contains summary statistics on the estimated adverse selection measures, along with correlation coefficients between the measures. Statistics are computed using all firm-quarter observations in the sample with good estimates for the chosen measure and are generally consistent with the existing literature. Panel A presents means, medians, and standard deviations for each measure. As in Huang and Stoll (1997), the adverse selection component makes up roughly 11% of the effective spread. Likewise, our estimates of the probability of informed trading are similar to those for the most active stocks in Easley et al. (1996). Panel B contains the correlation coefficients. Owing to differences in scaling, most of our estimates are not directly comparable to those in Dennis and Weston (2001). The one exception is the correlation between the probability of informed trading and the quoted spread, and our estimate of this correlation coefficient is very similar to theirs.

4. Tests of the Relation between Credit Ratings and Adverse Selection Measures

We examine the relation between adverse selection risk and credit 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, Rating is the weighted average of the numerical ratings across all issues and rating agencies as of the first day of each quarter (as in Table 2), 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 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:

[15] 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.

Table 5
Adverse selection measures

	(Relative) Quoted spread	(Relative) Effective spread	Glosten and Harris adverse selection component	Hasbrouck price impact	EKOP probability of informed trading
Panel A: Summary statistics					
Mean	0.0065	0.0045	0.0005	0.0002	0.1412
Median	0.0049	0.0033	0.0004	0.0001	0.1324
Standard deviation	0.0065	0.0051	0.0004	0.0002	0.0605
N	17161	17161	17153	16981	14253
Panel B: Pearson correlation coefficients					
(Relative) Quoted spread	1.0000	0.9841	0.5246	0.5474	0.3501
(Relative) Effective spread	0.9841	1.0000	0.4412	0.4795	0.3168
Glosten and Harris adverse selection component	0.5246	0.4412	1.0000	0.7965	0.3288
Hasbrouck price impact	0.5474	0.4795	0.7965	1.0000	0.3060
EKOP probability of informed	0.3501	0.3168	0.3288	0.3060	1.0000

Quoted spreads are computed as time-weighted averages for each firm quarter. Effective spreads are simple averages across all trades for each firm quarter. Both are scaled 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. Price impact is estimated using Brennan and Subrahmanyam's (1996) adaptation of Hasbrouck's (1991) VAR model. To make the price-impact measure (which captures the effects of an unanticipated trade rather than a per share cost) comparable to the others, we multiply it by the standard deviation of residual trade size and scale by price. The EKOP [Easley et al. (1996)] probability of informed trading is stated as a fraction of trades. Statistics presented in the table are computed using all firm-quarter observations in the sample with good estimates for the selected measure. All correlation coefficients are statistically significant at the 0.01% level.

$$\varepsilon_{it} = u_i + v_{it} \tag{7}$$

where the u_i terms are independent across firms and the v_{it} terms are independent across all 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 credit 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 modify the variables in a natural way.

For example, in the previous section, we argued that the Glosten and Harris measure is proportional to $\alpha\sigma_\tau(A/E)/N^I$. The fact that $\ln(\alpha\sigma_\tau(A/E)/N^I) = \ln(\alpha\sigma_\tau) - \ln(E/A) - \ln(N^I)$ 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 (logged) 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 from the probit regressions.

Most of the control variables in our regressions are point-in-time values that reflect the publicly available information at the time the credit rating was recorded. Ideally, we would also like point-in-time values for the adverse selection measures, but these must be estimated over some time period (in our analysis we have chosen a calendar quarter). The estimation of these quantities raises a possible errors-in-variables problem that is particularly worrisome if the measurement error is correlated with the credit ratings. To illustrate, consider a public announcement that not only changes the credit rating, but also substantially changes how people perceive the firm (such as value versus growth and low risk versus speculative). Such an announcement may cause some mutual funds to sell the stock, not because it is no longer a good investment, but because it no longer fits their investment style. This type of non-information-based trading may be recognized as such by the specialists, so there may be many trades that have very little price impact. This leads to estimation error in the adverse selection measures that is related to the change in credit ratings.

We address this issue by matching credit ratings at the start of each quarter with adverse selection measures calculated over that quarter. This timing ensures that credit ratings are uncorrelated with the error in the adverse selection estimates, as required. As a robustness check, we also estimate all of our panel data regressions using the time-weighted average rating over the quarter as the dependent variable and the results are similar.

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. We also include variables to control for the publicly observed sources of uncertainty—asset beta, which captures systematic risk, and the unexpected news variable, which reflects the risk of firm-specific public information. Asset beta is computed by multiplying the equity beta (estimated from a monthly market model regression over the most recent 60 months) by the ratio of equity to total assets. The unexpected news stories variable is computed as described in subsection 3.3.

Because our model is simple, it does not capture all of the features that we believe will be important to credit ratings. Industry dummy variables, which reflect the fact that credit ratings may not be comparable across industries due to differences in asset tangibility and marketability, control for differences in recovery rates (ρ). Intercept terms are allowed to vary by year to eliminate any estimated relation that might result if both credit ratings and adverse selection levels change systematically through time. To make the coefficients on the continuous control variables more readily interpretable, we subtract the cross-sectional median and divide the result by the difference between the 75th percentile and the median for each variable. 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.

Table 6 summarizes the results from our first set of regressions of credit ratings on the adverse selection variables. Recall that a higher quality credit rating corresponds to a higher numerical score. Consequently, if poorer credit ratings are associated with higher adverse selection risk as we expect, then the coefficients on the adverse selection measures will be negative and significant.

The first column contains the results for the quoted spread. Consistent with our model's prediction, credit ratings worsen as the quoted spread increases. The same holds in the regressions including the effective spread, the adverse selection component, and the information-based price impact measure (columns 2 through 4), and the coefficients are statistically significant in all cases. This demonstrates that the association between spreads and credit 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.[16] The final column of Table 6 provides 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. When we run the regressions after eliminating mid-point transactions, the results (not reported) are similar to those presented here for all five adverse selection measures.

In all regressions, the coefficient on debt-to-assets is negative and statistically significant, meaning that firms with higher fractions of debt have lower credit ratings. Asset beta is positive in all cases and marginally significant for all but the quoted and effective spread regressions. Although the positive coefficients on asset beta are inconsistent with the predictions of our model, this variable may be picking up variation in asset tangibility within industries, and, therefore, acting as another proxy

[16] We also ran panel data regressions using logged *dollar* (rather than relative) adverse selection measures with price included as a control variable. The results are similar, but the coefficient on the Hasbrouck price impact measure loses statistical significance.

Table 6
Regressions of credit ratings on adverse selection measures

	Quoted spread		Effective spread		Glosten and Harris adverse selection component		Hasbrouck price impact		EKOP probability of informed trading	
Explanatory variables	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
ln(adverse selection measure)	–0.634	0.000	–0.580	0.000	–0.182	0.000	–0.079	0.002	–0.150	0.000
ln(debt/assets)	–0.087	0.002	–0.092	0.001	–0.171	0.000	–0.180	0.000	–0.210	0.000
Asset beta	0.034	0.157	0.035	0.149	0.051	0.049	0.051	0.053	0.046	0.097
News stories	–0.024	0.125	–0.023	0.140	–0.024	0.125	–0.022	0.153	–0.031	0.064
Dummy variables										
1995	21.816	0.000	21.868	0.000	23.478	0.000	24.179	0.000	24.630	0.000
1996	21.774	0.000	21.837	0.000	23.497	0.000	24.195	0.000	24.632	0.000
1997	21.697	0.000	21.793	0.000	23.583	0.000	24.271	0.000	24.691	0.000
1998	21.743	0.000	21.827	0.000	23.687	0.000	24.357	0.000	24.744	0.000
1999	21.779	0.000	21.845	0.000	23.689	0.000	24.363	0.000	24.761	0.000
2000	21.757	0.000	21.829	0.000	23.672	0.000	24.344	0.000	24.738	0.000
Durables	–0.023	0.967	–0.008	0.989	0.376	0.611	0.492	0.518	0.436	0.572
Nondurables	–0.260	0.188	–0.303	0.121	–0.388	0.082	–0.337	0.078	–0.503	0.029
Utilities	1.351	0.001	1.361	0.001	1.305	0.003	1.333	0.003	1.628	0.000
Energy	0.087	0.812	0.069	0.852	0.052	0.894	0.086	0.830	–0.343	0.291
Construction	–2.626	0.000	–2.671	0.000	–2.749	0.000	–2.768	0.000	–2.740	0.000
Business equipment	–0.704	0.027	–0.770	0.019	–0.832	0.008	–0.674	0.021	–0.874	0.002
Transportation	0.031	0.909	–0.036	0.891	–0.121	0.607	–0.111	0.619	–0.245	0.341
Financial	0.685	0.000	0.668	0.000	0.722	0.001	0.777	0.001	0.856	0.014
Business services	–0.386	0.167	–0.417	0.142	–0.461	0.257	–0.429	0.321	–0.846	0.146

The estimates are from panel data regressions of mean credit 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 Brennan and Subrahmanyam's (1996) adaptation of 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 et al. (1996)] probability of informed trading is stated as a fraction of trades. All continuous control variables are scaled by subtracting the cross-sectional median and then dividing by the difference between the 75th percentile and the median.

for the recovery rate, ρ. The asset beta coefficient remains positive in a panel data regression of credit ratings on debt-to-assets and asset beta alone (with no industry dummies, news, or adverse selection measures), which offers support for this interpretation. The coefficients on the industry dummy variables suggest that they also reflect differences in recovery rates, as expected. For example, utilities tend to have higher credit ratings and firms in the construction industry tend to have lower credit ratings. While the coefficients on the news stories variable are all negative, only the coefficient in the Easley et al. (EKOP) regression is statistically significant.

While Table 6 shows that the standard adverse selection measures are related to credit ratings in ways that are consistent with our model, these standard measures impound factors beyond the parameters in the model, like trading frequency and capital structure. In Table 7, we attempt to isolate the effects of the uncertainty described in the model by modifying the logged adverse selection measures along the lines of the discussion in subsection 2.5. 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.[17] We 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 measures in these four regressions should be related to $\alpha\sigma_T$. In the fifth regression, we replace ln(PIN) with $\ln(\alpha)$ and $\ln(\mu/(\alpha\mu + 2\varepsilon))$.

Table 7 shows that the modified adverse selection measures are related to credit ratings as predicted by the model, and the results are all statistically significant. This confirms our original interpretation of the results by demonstrating that, even after controlling for net order flow, the modified versions of the adverse selection measures are negatively related to credit ratings. Likelihood ratio tests reject the model in Table 6 in favor of the model in Table 7 at the 1% level in all cases. The results for the four spread-based measures also show that credit 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 7 demonstrates that, as expected, credit 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 reflects the intensity of informed trading when an event occurs, is also related to the uncertainty captured by credit ratings.

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

Table 7
Regressions of credit ratings on modified adverse selection variables

	Quoted spread		Effective spread		Glosten and Harris adverse selection component		Hasbrouck price impact		EKOP probability of informed trading	
Explanatory variables	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
ln(modified adverse selection)	–0.363	0.000	–0.330	0.000	–0.102	0.011	–0.045	0.033		
ln(average absolute trade imbalance per day)	0.440	0.000	0.429	0.000	0.129	0.011	0.100	0.030		
ln(equity/assets)	1.216	0.000	1.192	0.000	1.173	0.000	1.093	0.000		
ln(α)									–0.182	0.000
ln($\mu/(\alpha \times \mu+2\varepsilon)$)									–0.348	0.000
ln(debt/assets)	0.023	0.508	0.023	0.503	0.009	0.792	0.002	0.951	–0.208	0.000
Asset beta	–0.005	0.856	–0.005	0.850	–0.007	0.791	–0.008	0.761	0.044	0.112
News stories	–0.036	0.017	–0.037	0.015	–0.037	0.013	–0.036	0.017	–0.026	0.128
Dummy variables										
1995	24.163	0.000	24.144	0.000	25.437	0.000	25.755	0.000	24.450	0.000
1996	24.102	0.000	24.087	0.000	25.409	0.000	25.724	0.000	24.449	0.000
1997	24.044	0.000	24.045	0.000	25.442	0.000	25.747	0.000	24.502	0.000
1998	24.074	0.000	24.065	0.000	25.508	0.000	25.798	0.000	24.536	0.000
1999	24.133	0.000	24.109	0.000	25.569	0.000	25.856	0.000	24.557	0.000
2000	24.152	0.000	24.128	0.000	25.610	0.000	25.889	0.000	24.534	0.000
Durables	–2.330	0.000	–2.338	0.000	–2.439	0.000	–2.450	0.000	0.428	0.578
Nondurables	–1.007	0.012	–1.013	0.012	–1.026	0.012	–1.036	0.012	–0.491	0.036
Utilities	1.121	0.005	1.134	0.005	1.116	0.007	1.126	0.006	1.608	0.000
Energy	–0.451	0.469	–0.462	0.457	–0.416	0.520	–0.385	0.550	–0.355	0.283
Construction	–3.050	0.000	–3.052	0.000	–3.102	0.000	–3.119	0.000	–2.703	0.000
Business equipment	–1.357	0.001	–1.368	0.001	–1.373	0.001	–1.376	0.001	–0.882	0.002
Transportation	–1.255	0.051	–1.251	0.051	–1.152	0.082	–1.086	0.111	–0.185	0.487
Financial	0.699	0.120	0.704	0.120	0.801	0.105	0.785	0.112	0.879	0.011
Business services	–1.295	0.060	–1.283	0.064	–1.106	0.155	–1.098	0.158	–0.838	0.146

The estimates are from panel data regressions of mean credit ratings on the elements of the modified 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 corresponding measure used in Table 6 plus the log of the average absolute trade imbalance per day (in trades) and plus the log of the equity-to-asset ratio. The regression in the final column splits the Easley et al. PIN measure into two parts using the individual parameter estimates. All continuous control variables are scaled by subtracting the cross-sectional median and then dividing by the difference between the 75th percentile and the median.

Regarding the other variables in the model, the results seem 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 credit ratings than does the log of the debt-to-asset ratio, at least in regressions that include the modified adverse selection measures. The news variable is negative and significant in the four regressions using the spread-based measures, which is consistent with the idea that higher risk of publicly announced firm-specific news leads to lower credit ratings. Asset beta is insignificant in all regressions.

The results thus demonstrate that credit 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 credit ratings.[18] The natural question is whether adverse selection measures contain incremental information beyond these other factors. We address this question by adding a comprehensive set of control variables to our panel data regressions from Table 7.

The first of these variables is an alternative measure of asset-value uncertainty provided by Moody's/KMV (MKMV). This implied asset-volatility measure is calculated using the market values of debt and equity and the maturity structure of the debt obligations. MKMV uses these volatilities as inputs when calculating their Expected Default Frequency™ (EDF™) credit measure. We were unable to obtain asset volatilities for roughly 15% of the firm quarters in our sample. For those firms without data, we use predicted values created using coefficients from a regression of MKMV asset volatility on equity volatility and debt-to-asset ratio.[19]

Choices of additional variables are guided by both the prior literature and S&P's description of its credit rating criteria. In "Corporate Ratings Criteria," S&P 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.

When determining a firm's credit 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 S&P 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

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

[19] The R^2 of the regression is 0.74. The panel data regression results are similar to those in Table 8 if we omit the firms with missing asset volatilities from the regressions.

competitive issues" (Standard and Poor's, 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" (Standard and Poor's, 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 based on the sign and then take absolute values. We also add a dummy variable that allows the intercepts to differ across the cases with positive and negative cash flow. 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 credit ratings. Accordingly, we include the ratio of the book value of equity to the market value of equity to capture growth potential, and we include 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. We also include share price both because distressed firms tend to have lower stock prices and because liquidity research has shown that relative spread measures are related to share price [see, e.g., Breen, Hodrick, and Korajczyk (2002) and Chordia, Roll, and Subrahmanyam (2001)]. Finally, we include time-specific intercepts and, of course, the chosen adverse selection measure, modified as in Table 7.

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 as we did in Tables 6 and 7.[20] The components of the adverse selection measures, which are the parameters of interest, have not been scaled.

The results, which are presented in Table 8, demonstrate that even after controlling for other observable determinants of credit ratings and liquidity, lower quality credit ratings are still significantly associated with higher adverse selection risk captured by quoted spreads, effective spreads, and the probability of informed trading. The magnitudes of the

[20] 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).

Table 8
Regressions of credit ratings on all variables

Explanatory variables	Quoted spread		Effective spread		Glosten and Harris adverse selection component		Hasbrouck price impact		EKOP probability of informed trading	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Components of the adverse selection measures										
ln(modified adverse selection)	–0.224	0.003	–0.184	0.015	–0.030	0.422	–0.020	0.287		
ln(average absolute trade imbalance per day)	0.170	0.049	0.142	0.111	–0.038	0.368	–0.044	0.249		
ln(equity/assets)	0.815	0.000	0.778	0.000	0.642	0.000	0.625	0.000		
ln(α)									–0.073	0.004
ln($\mu/(\alpha \times \mu+2\varepsilon)$)									–0.161	0.000
Other explanatory variables										
ln(debt/assets)	0.067	0.074	0.069	0.070	0.073	0.049	0.066	0.063	0.023	0.577
Asset beta	–0.006	0.790	–0.007	0.781	–0.009	0.704	–0.010	0.672	0.001	0.976
News stories	–0.032	0.026	–0.032	0.025	–0.031	0.031	–0.028	0.050	–0.023	0.156
ln(asset volatility)	–0.079	0.051	–0.082	0.044	–0.081	0.050	–0.079	0.055	–0.048	0.255
ln(stock price)	0.015	0.658	0.023	0.495	0.066	0.044	0.063	0.056	0.124	0.002
ln(market capitalization)	0.642	0.000	0.645	0.000	0.662	0.000	0.662	0.000	0.774	0.000
Book-to-market	0.015	0.472	0.015	0.473	0.014	0.478	0.023	0.179	0.004	0.883
Dividend yield	0.033	0.152	0.034	0.146	0.033	0.150	0.026	0.223	0.024	0.273
Past six-month return	–0.077	0.000	–0.077	0.000	–0.077	0.000	–0.075	0.000	–0.078	0.000
Interest coverage	0.014	0.011	0.014	0.012	0.014	0.014	0.014	0.012	0.013	0.025
Profit margin	–0.002	0.771	–0.002	0.767	–0.002	0.774	0.001	0.922	0.000	0.979
Return on assets	0.019	0.125	0.019	0.119	0.021	0.086	0.017	0.129	0.022	0.073
ln(cash flow) if positive	0.013	0.096	0.012	0.100	0.013	0.094	0.011	0.119	0.019	0.034
Negative CF dummy	0.000	0.992	0.001	0.959	0.001	0.975	0.003	0.887	0.006	0.762
ln(|cash flow|) if negative	0.016	0.026	0.016	0.026	0.016	0.029	0.016	0.024	0.019	0.016

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 7. 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.

adverse selection coefficients are smaller in Table 8 than in Table 7, which is consistent with previous findings that credit ratings are predictable by other factors. There is also a negative, but insignificant, relation between credit ratings and the Glosten and Harris and Hasbrouck measures.[21] The lower statistical significance for these two variables may stem from the fact that the estimates of these measures contain more noise than quoted and effective spreads.

The strongest *statistical* results in Table 8 are for the quoted spread and the EKOP α, followed by the effective spread. We examine *economic* significance by calculating the predicted change in credit ratings associated with an increase in each of the standard spread-based measures of 0.01% of the stock price, starting from the sample mean. For example, Table 5 shows that the sample mean of the Glosten and Harris component of the spread is 0.05% of the stock price, so increasing the measure by 0.01% of the stock price would bring it to 0.06% of the stock price. Converting to logs, this is a change of $\ln(0.06/0.05) = 0.182$. Assuming that the equity-to-asset ratio and order imbalance are not changed, this would also imply a 0.182 increase in the log of the modified adverse selection measure. Using the coefficient estimate from Table 8, this change would result in a $-0.030 \times 0.182 = -0.005$ change in the predicted credit rating.

We compute the impact of an identical increase in the Hasbrouck measure and quoted and effective spreads analogously and compare the results across the four measures. The results (not reported) reveal that the economic impact on credit ratings is similar for all spread-based measures, ranging from –0.003 for the quoted spread to –0.008 for the Hasbrouck measure. (A value of –1 would represent a downgrade of one category, e.g., from AA to AA–.) The fact that the economic significance of the Hasbrouck and Glosten and Harris measures exceeds that of the quoted and effective spreads supports our conjecture that the lack of statistical significance in the regressions is related to noise in these estimates.

While the probability of informed trading is statistically significant, it is still interesting to assess its economic significance relative to the spread-based measures. If we assume that the 0.182 change in the logged Glosten and Harris measure represents a change only in α (and not σ_T), then the coefficient in Table 8 implies a $-0.073 \times 0.182 = -0.013$ change in the predicted credit rating. Although this is larger than the impact of the other measures, changes in the spread-based measures could stem from changes in σ_T as well as α.

[21] When we estimate the regressions without midpoint transactions, the results for all five measures are similar to those in Table 8.

As expected, credit ratings are negatively related to total asset volatility, and the relation is statistically significant for the four spread-based measures. Capital structure remains important for credit ratings, and the news variable is negative and significant in the regressions using the spread-based measures. Several other control variables are also statistically significant, and likelihood ratio tests confirm that the specification in Table 8 dominates the more restrictive model in Table 7.[22] Consistent with intuition, credit ratings are positively associated with firm size, stock price, and interest coverage. Firms with larger positive cash flows also tend to have higher ratings. Surprisingly, firms with large *negative* cash flows or poor returns over the past six months have higher ratings as well. The fact that many of the control variables are correlated with one another makes interpretation of some of these results more difficult.

Although our method of assigning numerical values to credit ratings is common in the literature, we recognize that differences in ratings near the investment grade cutoff may be larger in economic terms than differences far from the cutoff. For example, the distinction between a rating of BBB+ (investment grade) and BB+ (non-investment grade) is probably much more important than the distinction between a rating of AAA+ and AA+, but both represent a three-category change using our rating variable.

To address this possibility, we examine an alternative specification of the panel data regressions in Table 8 using a rescaled rating variable. Specifically, we assign all three ratings in the same letter category (e.g., AAA+, AAA, and AAA–) the same numerical score, *except* for the two groups that straddle the investment-grade cutoff (BBB and BB). These groups maintain their original scaling, meaning that a change from BBB+ to BBB represents a one-unit change in the new variable, as does a change from AAA+ to AA+. The coefficients and p-values from the regressions using the rescaled rating variable are similar to those in Table 8.

Our model assumes a symmetric probability distribution for the privately observed shocks, which implies similar price responses to buy and sell orders. If instead this distribution were asymmetric, one might expect credit ratings to be more closely related to the risk of negative shocks, which would be captured by the probability of and price response to sell orders. To test for this possibility, we first estimate separate Glosten and Harris and Hasbrouck price response coefficients for buy and sell orders (see appendix for details). We then modify the panel data regressions shown in Table 7 by adding the natural logarithm of the ratio of the sell-side response to the average response across buy and sell orders. We also modify the EKOP regressions by adding the natural logarithm

[22] We also estimate the model in Table 6 (rather than Table 7) after adding the control variables, and the results are similar to those presented here.

of δ (the estimated probability that a given event is bad news) to the panel data regression using the EKOP α. In all cases (results not reported), the coefficients on these added variables are statistically insignificant, and the magnitude of the coefficients on the original measures remains nearly unchanged.

In summary, our results demonstrate that the adverse selection measures are related to credit ratings even after controlling for several other factors. Although we interpret our adverse selection measures as capturing asymmetric information, we recognize that they may also reflect other types of uncertainty. As mentioned in Section 2, many microstructure models decompose quoted and effective spreads into some combination of three components: order processing, adverse selection, and inventory. The order processing component is purged from the Glosten and Harris and Hasbrouck measures by design, but in theory, these measures could reflect inventory risk if specialists' use quoted prices to actively manage inventory levels. If specialists use quoted prices to control inventory, we would expect changes in quotes to be partially reversed, but Hasbrouck and Sofianos (1993) found little evidence that NYSE specialists' price responses are temporary. Furthermore, active inventory control would imply negative correlation in signed order flow, but Huang and Stoll (1997) demonstrated that orders are positively correlated.

It is difficult to determine whether inventory risk is reflected in the fixed component (i.e., the component unrelated to order flow) of quoted and effective spreads. The fact that specialist firms are diversified across many stocks and can hedge their positions using derivative securities suggests that specialists may not be very sensitive to inventory. Madhavan and Smidt's (1993) result that specialists are patient when adjusting inventory levels provides support for this argument.

5. Prediction of Future Rating Changes

We now examine the ability of adverse selection measures to predict future rating changes. Both anecdotal and empirical evidence suggest that debt ratings are slow to respond.[23] Consequently, one would expect that adverse selection measures could be used to predict rating changes. Specifically, if rating agencies respond with a lag, periods with higher (lower) adverse selection are likely to be followed by ratings downgrades (upgrades) in the future.

[23] Hand, Holthausen, and Leftwich (1992), Hite and Warga (1997), and Weinstein (1977) 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 that 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.

We study the effects of adverse selection on the probability of subsequent rating changes using an ordered probit model. For all firm quarters in which the credit 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 0 otherwise. For each firm-quarter observation, we compare the logged values of the modified adverse selection measures, along with the debt-to-asset ratio, asset beta, and the unexpected news variable, in the *current* quarter to those from the *previous* quarter. We estimate ordered probit regressions of the indicator of ratings change in the coming quarter on the changes in each of these variables from the prior quarter.

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 S&P 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 past quarter to measure the changes in the independent variables and one future quarter to define the rating change variable. 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 9 contains the estimated parameters. The estimation procedure models the probability of a ratings downgrade. The positive coefficients reported in the first line of Table 9 indicate that firms with increased adverse selection risk, as measured by the (modified) quoted or effective spread, are significantly more likely to have their debt downgraded in a subsequent quarter, and firms with narrower spreads are more likely to have subsequent upgrades. The results for the modified Glosten and Harris and Hasbrouck measures have the predicted sign, but the coefficients are not statistically significant. Likewise, the coefficient on α in the final column is positive but insignificant. Although not reported, when we estimate the model after eliminating midpoint trades, the Hasbrouck measure and α become statistically significant. The remaining rows of Panel A show that changes in capital structure affect the likelihood of downgrades, as do changes in liquidity in the quoted and effective spread regressions. Changes in the other variables are not statistically significant.

The results suggest that the rating agencies do not immediately reflect the information contained in the adverse selection measures in their

Table 9
Ordered probit regressions predicting future credit rating changes

	Quoted spread		Effective spread		Glosten and Harris adverse selection component		Hasbrouck price impact		EKOP probability of informed trading	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Panel A: Parameter estimates										
Change in ln(adverse selection)	0.616	0.000	0.628	0.000	0.037	0.400	0.031	0.123		
Change in ln(absolute trade imbalance per day)	–0.624	0.000	–0.665	0.000	–0.033	0.490	–0.025	0.522		
Change in ln(E/A)	–1.337	0.000	–1.351	0.000	–0.952	0.000	–0.959	0.000		
Change in ln(α)									0.059	0.125
Change in ln($\mu/(\alpha \times \mu+2\varepsilon)$)									0.105	0.100
Change in ln(D/A)	0.011	0.753	0.011	0.764	0.025	0.464	0.028	0.413	0.190	0.000
Change in asset beta	0.021	0.505	0.022	0.477	0.019	0.541	0.021	0.499	0.010	0.780
Change in unexpected news	–0.004	0.782	–0.004	0.786	–0.006	0.701	–0.005	0.759	–0.017	0.355
Panel B: Effect of a one-standard deviation increase in the modified (logged) adverse selection measures										
One standard deviation increase in adverse selection	0.4178		0.4348		0.3956		0.6975		0.6511	
Corresponding change in the probability of a downgrade	0.0317		0.0340		0.0015		0.0022		0.0038	
Corresponding change in the probability of an upgrade	0.0216		–0.0226		–0.0015		–0.0023		– 0.0039	
Panel C: Effect of a 1 basis point increase in adverse selection										
Change in Prob(downgrade)	0.0009		0.0014		0.0007		0.0012		0.0010	
Change in Prob(upgrade)	–0.0010		–0.0014		–0.0007		–0.0013		–0.0011	

Parameter estimates from ordered probit regressions of the likelihood of subsequent credit rating 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). The adverse selection measures are the modified measures used in Tables 7 and 8. "Change in __" represents the change in the variable from the previous quarter to the current quarter. In panel C, the marginal effects for the spread-based measures are computed assuming an increase in the measure equal to 0.01% of the stock price. The marginal effect for the EKOP measure uses the increase in the Glosten and Harris measure and assumes that the increase stems entirely from a change in α.

ratings. Instead, the agencies incorporate this information with a lag, consistent with the anecdotal and academic evidence that agencies are slow to react. As a result, adverse selection measures provide an indication of the probability of future rating changes. Whether the adverse selection measures contain incremental information for predicting rating changes beyond other factors, such as announcements about debt and changes in the market value of the outstanding debt, remains an open question for future research.

Panels B and C of Table 9 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 modified adverse selection measures. The next two lines show the changes in predicted probabilities that result from a one standard deviation increase in adverse selection (i.e., moving from no change in adverse selection to a one standard deviation change). The first line in Panel B indicates that the sample standard deviations of changes in the log of the modified quoted and effective spread measures are 0.4178 and 0.4348 respectively. Note that $e^{0.4178} = 1.52$, so these reflect roughly 50% changes in the measures prior to taking logs. When the modified quoted and effective spread measures increase by these amounts, the second line of Panel B shows that the predicted probabilities of a downgrade in the following quarter increase by 0.0317 and 0.0340, respectively. The unconditional probability of a downgrade is 0.05, so these increases in the modified measures increase the probability of a downgrade by more than 60%. A similar analysis of the third line of Panel B indicates that the same increases in the modified measures decrease the probability of an upgrade in the following quarter by roughly 40%. Although the other adverse selection measures can also be used to predict rating changes, their results are less striking, possibly because these measures contain additional estimation error.

The results in Panel C of Table 9 allow for a more direct comparison of the economic significance of each measure. We adopt the approach we used to evaluate economic significance in Table 8 and compute changes in the predicted probabilities associated with an increase in the standard spread-based measures of 0.01% of the stock price. As above, we compute the impact of a change in α by assuming that the full 0.01% change in the Glosten and Harris measure stems from an increase in α. The results in Panel C reveal that, despite lower statistical significance for the Glosten and Harris, Hasbrouck, and EKOP measures, the economic impact of a change in these variables is similar to that for quoted and effective spreads. As in Table 8, it appears that the stronger statistical results from the measures based on quoted and effective spreads stems from the fact that they are inherently less noisy.

6. Conclusion

This study relates credit ratings to equity measures of adverse selection. We present a model that links these two measures of uncertainty 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 credit ratings and higher adverse selection costs in trading their equity. The model also suggests ways to modify the standard adverse selection measures to better isolate the uncertainty parameters related to credit ratings.

In panel data regressions, we show that credit ratings are in fact poorer when several common measures of adverse selection are larger. This is true for both the standard measures and the modified measures motivated by our model. For quoted and effective spreads and the Easley et al. (1996) measure of the probability of informed trading, this relation is statistically significant even after controlling for other variables commonly associated with credit ratings. Moreover, our ordered probit results show that adverse selection measures can be used to predict future rating changes.

Our results indicate that adverse selection measures contain information that could be useful for assessing asset-value uncertainty and that agencies are sometimes slow to react to new information. The results also 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.

Appendix

Lemma 1: *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.*

Proof:

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

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

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

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

canceling terms leaves

$$\frac{dQ(k,p,n)}{dp} = \frac{n!}{(n-k)!(k-1)!} p^{k-1}(1-p)^{n-k} > 0$$

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 $k = 1, 2, 3, \ldots, n$. As in Lemma 1, let $Q(k,p,n) = P[r \geq k]$.

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

so

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

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

Proof of Proposition 1:
For any day t, let N_t be the total number of private information events through day t. N_t is binomially distributed, with parameters α and t. For a fixed value of $N_t = k$, X_t is normally distributed with mean X_0 and variance $t\beta^2\sigma_\gamma^2 + t\sigma_\eta^2 + k\sigma_\tau^2$. Accordingly,

$$\begin{aligned} P[X_t < 0] &= \sum_{k=0}^{t} P[X_t < 0 | N_t = k] P[N_t = k] \\ &= \sum_{k=0}^{t} \Phi\left[(-X_0)\left(t\beta^2\sigma_\gamma^2 + t\sigma_\eta^2 + k\sigma_\tau^2\right)^{-0.5}\right] P[N_t = k] \end{aligned} \tag{A1}$$

where Φ is the standard normal CDF. Since $X_0 > 0$, the quantity $\phi\left[(-X_0)\left(t\beta^2\sigma_\gamma^2 + t\sigma_\eta^2 + k\sigma_\tau^2\right)^{-0.5}\right]$ is increasing in k. By Lemma 2, the expression in equation (A1) is increasing in α, which establishes that $P[X_t < 0]$ is increasing in α for all t. The fact that $\rho^A = \rho^B$ then implies that firm A (with the lower value for α) will have the higher credit rating (See assumption (i) in Section 1.1).

Proof of Proposition 2:
From the proof of Proposition 1:

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

Since $X_0 > 0$, for each value of k, the quantity $\Phi\left[(-X_0)\left(t\beta^2\sigma_\gamma^2 + t\sigma_\eta^2 + k\sigma_\tau^2\right)^{-0.5}\right]$ 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_τ, so firm A (with the lower value of σ_τ) will have the higher credit rating (See assumption (i) in Section 1.1).

Computing separate buy- and sell-side price impact measures

The sell-side price impact measures used in the robustness check in Section 4 are computed by adapting the original Glosten and Harris and Hasbrouck specifications in Equations (2) through (4) as follows:

Glosten and Harris: $$\Delta P_t = \tfrac{S}{2}\Delta Q_t + \alpha_B \tfrac{S}{2} Q_{t-1}\text{Buy}_{t-1} + \alpha_S \tfrac{S}{2} Q_{t-1}\text{Sell}_{t-1} + e_t \tag{A2}$$

Hasbrouck: $$Z_t = a_Z + \sum_{i=1}^{5} b_i \Delta P_{t-i} + \sum_{i=1}^{5} c_i Z_{t-i} + \omega_t \tag{A3}$$

$$\Delta P_t = a_P + d\Delta Q_t + \lambda_{\mathrm{B}}\tau_t\text{Buy}_t + \lambda_{\mathrm{S}}\tau_t\text{Sell}_t + e_t \tag{A4}$$

where $\text{Buy}_t(\text{Sell}_t)$ equals 1 if transaction t is buyer-initiated (seller-initiated) and zero otherwise.

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