The Informational Content and Accuracy of Implied Asset Volatility as a Measure of Total Firm Risk

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Abstract

Although estimates of asset volatility have been used in a variety of empirical situations, very little is known about their empirical properties. We use a set of 19,020 industrial and 2,014 financial firm-quarter observations to investigate the value of asset volatility estimates as forecasting and risk-assessing variables. First, we construct four alternative asset volatility measures (including one of our own design) for the set of industrial firms. Second, we test the information content of these measures by using them to predict defaults, credit rating changes, and realized asset return characteristics. Third, we apply the insights from these tests in the context of bank regulation to examine whether market prices on bank debt and equity can be used to identify financially weak institutions requiring special supervision. Our preliminary findings indicate that asset volatility estimates successfully forecast defaults and credit-rating downgrades, and that the innovative asset volatility estimate proposed in this study does so better than the more traditional estimates.

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The main contribution of Black and Scholes (1973) is considered to be the derivation of the first closed-form valuation formula for exchange-traded options. However, potentially even more important is their realization that the formula can be used in the valuation of firm equity and debt. Their basic insight is that limited liability makes the payoff to a firm's equityholders equivalent to the payoff of a call option written on the firm's assets with an exercise price equal to the face value of the firm's debt. Likewise, risky corporate debt can be valued as a riskless bond with an embedded put (default) option. However, to value both equity and debt using contingent-claim models, we need an estimate of the underlying assets' return volatility. Unlike equity volatility, asset volatility is impossible to measure directly from market prices. Researchers have employed a variety of empirical techniques to estimate a firm's underlying asset volatility. These estimates depend on functional forms and distributional assumptions that are well grounded in theory but seem unlikely to hold in practice. Although estimated asset volatilities have been used in a variety of empirical situations, we know very little about their empirical properties.

This dissertation will construct alternative estimates of asset volatility for a large set of U.S. firms and test their values as forecasting and risk-valuation variables. It begins with general tests for industrial (non-financial) firms, some of which are reported in the present study. A second component of the dissertation will apply the general insights from this research to the specific case of assessing the condition of large financial firms. The value of market prices to assess bank risk has become an important issue among banks and their government supervisors. Banks also provide a valuable opportunity to expand our tests of asset volatility estimates: their extensive supervisory reports provide homogeneous and detailed financial information that can be used to help infer the properties of estimated asset volatilities. This part of the research remains to be implemented, and hence is not described further in the present paper.

The dissertation will include three distinct parts. First, we will construct an innovative asset volatility estimate for a set of 19,020 U.S. industrial-firm observations. Second, we will test the information content of this and other asset volatility estimates by using them to predict defaults, credit rating changes, and asset return features. The result should be specific information on the value of alternative methods for estimating a firm's asset volatility. Third, we apply these lessons in the context of bank regulation and the ability of supervisors to use market prices on bank debt and equity to identify potentially weak institutions that require special supervisory treatment.

This study proposes a contingent-claim-pricing methodology for combining information from debt and equity markets into an estimate of asset volatility. Researchers have employed either debt or equity prices alone to obtain such estimates. This typically requires the use of simplifying assumptions. The most common of these are that balance sheet data is an unbiased estimate of market data, and that equity volatility is a reliable proxy for asset volatility. These assumptions become unnecessary if we use contemporaneous equity and debt prices to estimate asset volatility. The estimates thus obtained have a number of desirable properties. First, they avoid the pitfalls associated with using accounting data as a proxy for the market value of assets. Second, they are inherently forward-looking since they do not rely on historical volatility as a proxy for equity volatility. Third, these estimates of asset volatility might be more accurate than estimates generated from debt or equity prices alone by combining information from different sources and thus reducing the noise in the estimates. However, it is an empirical question whether these estimates are more informative than estimates produced by more restrictive methodologies.

We compute four estimates of asset volatility – asset volatility implied by contemporaneous equity and debt prices (*EDIAV*), asset volatility implied by equity prices alone (*EIAV*), asset volatility implied by debt prices alone (*DIAV*), asset volatility obtained by de-levering equity-return volatility using book leverage (*BIAV*). The preliminary results indicate that implied asset volatility estimates can differ dramatically across methodologies. The low correlations of these estimates indicate that if they are to be used as a measure of total firm risk, then risk rankings will be significantly dependent on the method used to calculate the asset volatility. The correlations are even lower when asset volatilities are combined with leverage to produce a measure of each firm's distance to default (*DD*). These differences justify a closer look at the relative forecasting and risk-valuation ability of the implied volatility and corresponding *DD* estimates.

The first set of tests examines if any of the four *DD* estimates successfully distinguish between firms that default in the three years following the quarter for which *DD* is calculated, and those that do not. We use delisting dates and bankruptcy filing dates as proxies for the occurrence of default. We find that a decrease in any of the four *DD* estimates increases the probability that a firm will subsequently default. We replicate the tests for the subsample of non-investment grade firms in an attempt to achieve a more balanced sample. We find that only the *DD* estimates based on *EDIAV* and *DIAV* help forecast firm default conditional on the firm being non-investment grade. Judging by the fit statistics of the four models in both sets of tests, we conclude that the *DD* calculated from *EDIAV* contains the most information about the occurrence of default.

Second, we investigate the ability of *DD* to explain subsequent changes in a firm's credit rating. Previous studies indicate that credit ratings changes can reliably be used as proxies for changes in default probability. Of the four *DD* measures only those based on *EDIAV* and *DIAV* are statistically significant in explaining subsequent upgrades. However, all four *DD* estimates successfully predict credit rating downgrades – a decrease in *DD* increases the probability that a firm will be downgraded. The *DD* calculated from *EDIAV* seems to be the most accurate predictor as judged by the model's fit statistics.

The other set of tests investigates the relationship between the above four asset volatility estimates and realized asset volatility. First, we construct a time series of estimated realized asset values and calculate the quarterly variance. This allows us to determine which of the four implied volatility measures better predicts realized asset volatility. Second, we investigate whether high implied asset volatility results in extreme asset returns. These two tests still remain to be performed.

The remainder of the paper is structured as follows. Section I reviews the literature on contingent-claim models for valuing a firm’s equity and debt, and summarizes the main applications of these models. The existing methodologies of estimating asset value and volatility are presented in Section II along with the tests that will be conducted to assess their relative informational content and accuracy. Section III reviews the data sources and sample construction. Preliminary empirical results for the set of industrial firms are presented in Section IV. Section V concludes this study and points out paths for future research.

I. The State of the Literature

A. Contingent Claim Valuation Models

Black and Scholes (1973) are the first to recognize that their approach to valuing exchange-traded options can be also used in the valuation of the equity of a firm. With limited liability the payoff to equityholders is equivalent to the payoff of a call option written on the firm’s assets with an exercise price equal to the face value of the firm’s debt. Consider a non-dividend paying firm with homogeneous zero-coupon debt that matures at time T. Assume that the market value of the firm’s assets follows a continuous lognormal diffusion process with constant variance. Then the current equity value of the firm is:

$$E = VN(d_1) - De^{-R_f\tau}N(d_2) \tag{3}$$

where

$$d_1 = \frac{\ln(V/D) + (R_f + 0.5\sigma_V^2)\tau}{\sigma_V\sqrt{\tau}}$$

$$d_2 = d_1 - \sigma_V\sqrt{\tau}$$

E is the current market value of the firm’s equity,
V is the current market value of the firm’s assets,
D is the face value of the firm’s debt,
σ_V is the instantaneous standard deviation of asset return at time,
τ is the time remaining to maturity,
R_f is the risk-free rate over τ,
$N(x)$ is the cumulative standard normal distribution of *x*.

Merton (1974) uses the same insight to derive the value of a firm’s risky debt. He demonstrates that under limited liability, the payoff to debtholders is equivalent to the payoff to holders of a portfolio comprised of riskless debt with the same characteristics as the risky debt, and a short put option written on the firm’s asset with an exercise price equal to the face value of debt. However, he assumes that the firm issues a single homogenous class of debt. In reality, the characteristics of debt are highly variable, which makes Merton’s (1974) realization intuitively useful but not immediately applicable to risky debt valuation.

The single-class debt assumption is relaxed by Black and Cox (1976) who analyze the debt valuation effect of having multiple classes of debtholders. Consider a firm financed by equity and two types of debt differentiated by their priority. Although the probability of default is the same for senior and subordinated debtholders, their expected losses differ and that is reflected in the valuation of their claims. Assume that all of the firm's debt matures on the same date. If at maturity the value of the firm is less than D_1, the face value of senior debt, then senior debtholders receive the value of the firm while subordinated debtholders along with equityholders receive nothing. If at maturity the value of the firm is greater than D_1 but less than the face value of all debt, $D_1 + D_2$, then senior debtholders get paid in full, subordinated debtholders receive the residual firm value, and equityholders receive nothing. Note that the payoff to equityholders is the same whether there is one or two classes of debtholders – if the value of the firm at maturity is higher than the face value of all debt they receive the residual after debt payments are made, and if the value of the firm at maturity is lower than the face value of all debt they receive nothing. Similarly, the breakdown of debt into two priority classes does not affect the payoff to senior debtholders. It is only subordinated debtholders that find the existence of a debt class of higher priority relevant for the pricing of their claims.

Following Black and Cox (1976), the value of a firm's subordinated debt is:

$$X_2 = V\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - D_1 e^{-R_f \tau} N(\tilde{d}_2) + (D_1 + D_2) e^{-R_f \tau} N(\hat{d}_2) \qquad (4')$$

where

$$\tilde{d}_1 = \frac{\ln(V/D_1) + (R_f + 0.5\sigma_V^2)\tau}{\sigma_V \sqrt{\tau}}$$

$$\tilde{d}_2 = \tilde{d}_1 - \sigma_V \sqrt{\tau}$$

$$\hat{d}_1 = \frac{\ln(V/(D_1 + D_2)) + (R_f + 0.5\sigma_V^2)\tau}{\sigma_V \sqrt{\tau}}$$

$$\hat{d}_2 = \hat{d}_1 - \sigma_V \sqrt{\tau}$$

D_1 is the face value of the firm's senior debt,

D_2 is the face value of the firm's subordinated debt,

X_2 is the current value of subordinated debt.

This relationship can be expressed as the spread between the yield on subordinated debt R_2, and the risk-free rate, R_f, of the same maturity:

$$R_2 - R_f = -\ln\left\{\frac{V}{D_2} e^{R_f \tau}\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - \frac{D_1}{D_2} N(\tilde{d}_2) + \frac{D_1 + D_2}{D_2} N(\hat{d}_2)\right\} / \tau \qquad (4)$$

and is the form in which the Black-Cox model most frequently appears in the literature.

B. Applications of Contingent Claim Valuation

The above contingent-claim approach to pricing firm debt has found many applications in the literature on credit risk analysis. Bohn (2000) surveys some of the main theoretical models of risky debt valuation that built on Merton (1974) and Black and Cox (1976).

The empirical validity of these models has been rarely and poorly tested due to the unavailability and low quality of bond data. Jones, Mason, and Rosenfeld (1983) and Frank and Torous (1989) find that contingent-claim models yield theoretical credit spreads much lower than actual credit spreads. In the same year, Sarig and Warga (1989) estimate the term structure of credit spreads and show it to be consistent with contingent-claim model predictions. A more recent study by Wei and Guo (1997) tests the models of Merton (1974) and Longstaff and Schwartz (1995) and finds the Merton model to be empirically superior. It is important to note that in calculating theoretical credit spreads, all of the above studies have used an estimate of the variance of firm assets. One approach of obtaining such an estimate is by constructing a historical time series of firm asset values and calculating the variance. Asset value is typically the sum of market value of equity and book value of debt, or alternatively the sum of market value of equity, market value of traded debt and the estimated market value of nontraded debt. The second approach to estimating the variance of asset returns is by de-levering the historical variance of equity returns as in a simple version of the boundary condition in Merton (1974):

$$\sigma_V = \sigma_E \frac{E}{V} \tag{5'}$$

where σ_E is the historical standard deviation of equity returns and V is the sum of market value of equity and book value of debt. We term this the book-value implied asset volatility, *BIAV*. It is important to note that any test of the contingent-claim models to debt valuation is a test of the joint hypothesis that the model *and* the estimate of σ_V are both correct. Nevertheless, the relative accuracy of different σ_V estimates has not been explored in any of the above studies.

Contingent-claim valuation of equity has been used extensively in the literature on bank deposit insurance where the equity-call model is 'reversed' to generate estimates of the market value of assets from observed stock prices. This approach, along with the observation in Merton (1977) that deposit insurance can be modeled as a put option, allows the calculation of fair deposit insurance premia. This insight is used by Marcus and Shaked (1984), Ronn and Verma (1986), Pennacchi (1987), Dale *et al*. (1991), and King and O'Brien (1991) in the analysis of deposit insurance premia. The approach of these researchers is to solve a system of equations comprised of (3) and Merton's boundary condition:

$$\sigma_V = \sigma_E \frac{E}{VN(d_1)} \tag{5}$$

for the market value and volatility of assets. Their proxy for σ_E is the historical standard deviation of equity returns. We will refer to the volatility estimate produced by this approach as the equity-implied asset volatility, *EIAV*, and the asset value obtained along with it, *V_EIAV*. In addition to calculating the market value of assets for banks and bank holding companies, this methodology has also been used to calculate the market value of assets for savings and loan associations by Burnett *et al*. (1991), and insurance companies and investment banks by Santomero and Chung (1992). Despite its wide use, the accuracy of the estimates it produces has rarely been questioned. We are aware of only one study that investigates whether the market value estimates obtained through this methodology are correct. Diba *et al*. (1995) calculate the asset value for failed banks and find that they greatly exceed the negative net worth estimates of the FDIC. They conclude that the equity-call model produces poor estimates of market values. The accuracy of the asset volatility estimates, however, has not been previously examined.

While the literature on deposit insurance employs the contingent-claim equity pricing model, the literature on market discipline of bank and bank holding companies makes use of the contingent-claim debt pricing model. Starting with Avery, Belton, and Goldberg (1988), yield spreads on bank subordinated notes and debentures have been examined for information about the bank's risk profile. However, Gorton and Santomero (1990) recognize that subordinated yield spreads are a non-linear function of risk and insist that researchers focus on the variance of bank assets instead. They use the methodology of Black and Cox (1976) to estimate σ_V from subordinated debt prices under the assumption that book value is a good proxy for the market value of assets. The authors find that this improvement in methodology does not alter the findings documented by yield-spread studies. Their insight has since been used in Hassan (1993) and Hassan *et al*. (1993) who apply contingent-claim valuation techniques to calculate implied asset volatilities, and in Flannery and Sorescu (1996) who use it to obtain theoretical default risk spreads. We refer to the asset volatility estimate calculated from subordinated debt prices as the debt-implied asset volatility, *DIAV*, and the market value of assets obtained along with it as *V_DIAV*.

The methodology closest in spirit to the one proposed in this study is employed by Schellhorn and Spellman (1996). The authors examine a small sample of four banks over 1987-1988 and calculate two estimates of implied asset volatility for each bank. The first is *EIAV* and is based on the methodology of Ronn and Verma (1986) mentioned earlier. The second solves (3) and (4) simultaneously for both the market value of assets and the standard deviation of asset returns. We refer to this volatility estimate as the equity-and-debt implied asset volatility, *EDIAV*, and the corresponding asset value estimate as *V_EDIAV*. The authors conclude that the two σ_V estimates can differ substantially over the studied period and that the estimates obtained from contemporaneous equity and debt prices are on average 40% higher than those obtained using historical information. The difference between the two estimates increases even more when the banks are perceived to be insolvent. This suggests that if asset volatility is to be used as a proxy for the total risk of a firm, then using historical equity variance can substantially underestimate firm risk.

We expand on Schellhorn and Spellman (1996) in three ways. First, we use a larger and more diverse sample. We obtain data on both industrial and financial firms for the period 1986-1999. Second, we compare a broader range of asset value and volatility estimates. We judge the innovative *EDIAV* and corresponding *V_EDIAV* against estimates calculated using three more traditional methodologies – *BIAV, EIAV, DIAV*, and the corresponding asset value estimates. Third, we set up 'horse-race' tests to determine the relative informational content and accuracy of the four asset volatility estimates.

II. The Informational Content of Implied Asset Volatility

This section starts with a summary of the three methodologies traditionally used to estimate the market value and volatility of assets. It then proposes a new one that relies on contemporaneous equity and debt prices to obtain V and σ_V. Finally, it describes the tests that will be employed to compare the relative ability of the different estimates to capture information about the risk-taking activities of a firm.

A. Methodologies for Calculating Implied Asset Value and Volatility

The book-value-implied asset volatility (*BIAV*) is the most popular estimate of asset volatility found in the finance literature. This is likely due to the straightforwardness of its computation since it employs a simplified version of the boundary condition (5)

$$\sigma_V = \sigma_E \frac{E}{V}$$

where all variables are as previously defined. This methodology assumes that the instantaneous standard deviation of equity returns at the end of quarter t is the standard deviation of equity returns over the quarter. It uses the sum of the market value of equity and book value of debt as a proxy for the market value of assets.

The equity-implied asset volatility (*EIAV*) is calculated by solving the system:

$$E = VN(d_1) - De^{-R_f \tau} N(d_2)$$

$$\sigma_V = \sigma_E \frac{E}{VN(d_1)}$$

for σ_V and V. This is done using the Newton iterative method for systems of nonlinear equations. For the starting value of V we input the sum of the market value of assets and book value of debt, and for the starting value of σ_V we input *BIAV*. Adhering to previous studies we assume that the instantaneous standard deviation of equity at the end of quarter t is the standard deviation of equity return over the quarter.

The debt-implied asset volatility (*DIAV*) is calculated by solving the system of nonlinear equations

$$R_2 - R_f = -\ln\left\{ \frac{V}{D_2} e^{R_f \tau} \left[N(\tilde{d}_1) - N(\hat{d}_1) \right] - \frac{D_1}{D_2} N(\tilde{d}_2) + \frac{D_1 + D_2}{D_2} N(\hat{d}_2) \right\} / \tau$$

$$\sigma_V = \sigma_E \frac{E}{VN(d_1)}$$

for σ_V and V using the Newton iterative method. Once again, for the starting value of V we input the sum of the market value of assets and book value of debt, but for the starting value of σ_V we input the theoretically more accurate *EIAV*. As in the calculation of the equity-implied asset volatilities, we assume that the historical standard deviation of equity over quarter t is a good approximation for the instantaneous standard deviation of equity at the end of the quarter.

The equity-and-debt implied asset volatility (*EDIAV*) is the innovative estimate of asset volatility that is in the center of this study. It is obtained by solving the system of nonlinear equations

$$E = VN(d_1) - De^{-R_f\tau} N(d_2)$$

$$R_2 - R_f = -\ln\left\{\frac{V}{D_2} e^{R_f\tau}\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - \frac{D_1}{D_2} N(\tilde{d}_2) + \frac{D_1 + D_2}{D_2} N(\hat{d}_2)\right\} / \tau$$

for σ_V and V using the Newton iterative method. We use the same starting values for V and σ_V as in the calculation of *DIAV*, and later ensure that the solutions are not sensitive to the input values used. Note that unlike the previous three methodologies, this one needs no historical information about the standard deviation of equity.

The last three methodologies are based on contingent-claim valuation and as a result require that the standard assumptions of Black and Scholes (1976) and Black and Cox (1979) be met. Bliss (2000) points out that this unlikely to be the case. However, it is an empirical question whether deviations from these assumptions make the estimates of asset value and volatility obtained under them less meaningful. In addition to the standard assumptions, applying contingent-claim valuation techniques require that we know the time left to equityholders exercising their option, and the default point of each firm. In obtaining estimates for these we initially adhere to previous studies but later examine the sensitivity of our results to alternative assumptions. It is the goal of this study to determine whether the simplifying assumptions typically made in calculating asset values and volatilities reduce the informational content and accuracy of these estimates.

Starting with Marcus and Shaked (1984) and Ronn and Verma (1986) the time to exercising the equity call option is typically assumed to be one year. Banking researchers claim that the one-year expiration interval is justified because of the annual frequency of regulatory audits. If after an audit the market value of assets is found to be less than the value of total liabilities, regulators can choose to resolve the bank. To start with, we adopt the reasoning of Marcus and Shaked (1984) and Ronn and Verma (1986) and argue that a one-year interval is also appropriate for industrial-firm asset valuation. Industrial firms are required to file accounting reports that are typically certified by outside auditors at least once a year. It can be maintained that if following an audit the value of assets is found to be less than the value of debt, equityholders can choose to default and exercise their call option. An alternative resolution-time assumption is employed by Gorton and Santomero (1990) who set the time to expiration equal to the average maturity of subordinated debt and find that the DIAV estimates calculated under this assumption are significantly higher than the ones calculated under the one-year-to-maturity assumption. However, they offer no evidence as to which maturity assumption produces the better estimate of asset volatility, which is a question we intend to address in the current study. We start by assuming that the time to resolution equals one year and later explore the effects of alternative assumptions.

Although we often assume that firms default as soon as their asset value reaches the value of their liabilities, this is true only if the firm’s debt is due immediately. In reality, firms issue debt of various maturities and as a result their true default point is somewhere between the value of their short-term and long-term liabilities. Unfortunately, while previous studies recognize this (Crosbie and Bohn (2002)), they offer little guidance on choosing each firm's default point. The banking literature adheres to the assumptions made by Ronn and Verma (1986) who set the default point at 97% of the value of total debt. They originally experiment with default points in the range of 95-98% of debt and determine that rank orderings of asset values are significantly affected by the choice of default point. They do not examine the relative accuracy of the estimates obtained under alternative default-point assumptions which is an issue addressed in this study.

B. Tests for Evaluating Implied Asset Volatility

Two types of tests are performed to judge the relative informational content and accuracy of the above volatility measures, *BIAV*, *EIAV*, *DIAV*, and *EDIAV*. The first set of tests focuses on the relationship between implied asset volatility and default probability. It investigates whether a default measure based on the asset volatility estimates is statistically related to credit rating changes and default occurrences. The second set of tests focuses on the relationship between implied asset volatility and realized asset volatility. It examines whether implied asset volatility is correlated with an estimate of realized asset volatility, and whether high implied asset volatility increases the probability of observing extreme asset returns.

B.1. Default and Default Probability Tests

Three elements determine the probability that a firm will default – the market value of its assets, the portion of liabilities due, and the probability distribution of the firm's asset returns. The difference between the first two determines the default point of the firm and as explained earlier it is at first set at 97% of total debt. The last element captures the business, industry, and market risk of the firm and is in fact the estimate of implied asset volatility calculated earlier in the paper. If the asset volatility estimate offers a correct assessment of the firm's risk exposure, then along with the firm's asset and liability values it should be able to forecast default probability accurately. Crosbie and Bohn (2002) combine asset volatility with the value of assets and liabilities into a single measure of default risk and refer to it as the distance-to-default (DD). This measure compares a firm's net worth to the size of one standard deviation move in the asset value and in the present study is calculated as[1]:

$$DD = \frac{(Market\ Value\ of\ \ Assets) - 0.97(Face\ Value\ of\ \ Liabilities)}{(Market\ Value\ of\ \ Assets)(Implied\ \ Asset\ Volatility)}$$

Intuitively, a *DD* value of X tells us that a firm is X standard deviations away from default. Thus, a low *DD* indicates that a firm is close to its default point and has a high probability of default. The opposite is true for firms characterized by high *DD* values.

[1] The DD measure imposes a certain relationship between default probability on one side and asset volatility and leverage on the other. We intend to examine whether relaxing this relationship makes a difference. Instead of using DD, we will replicate the default tests using the sum of log(E), log(V) and log(σ_V).

To compare the relative default-forecasting accuracy of *DD* computed from the four asset volatility estimates, we design two tests. The first one is based on the occurrence of default and the second relies on changes in credit ratings.

B.1.a. Tests Based on the Occurrence of Default

The relative default-forecasting accuracy of the distance-to-default (*DD*) measures can be best examined through their ability to successfully distinguish between firms that default and those that do not. The analysis relates a firm's default status over a three-year period to its *DD* prior to the beginning of that three-year period. Thus, the data are divided into five subperiods: 1986-88, 1989-91, 1992-94, 1995-97, and 1998-2000. The December 1985 estimate of the *DD* measure is used to explain whether or not the firm defaults in 1986, 1987, or 1988. A three-year period is chosen to balance the need for a short window to capture the *DD*-default relationship with the need for a long window to obtain sufficient number of defaults in each subperiod.

We estimate a Logit model in which the dependent variable $DFLT_t$ equals 1 if the firm defaults in the three-year period following quarter *t*, and zero otherwise. The main independent variables are the DD_t in quarter *t* calculated from the four implied asset volatility estimates. That is,

$$\Pr(DFLT_t = 1) = \frac{\exp(\alpha_o + \alpha_1 DD_t + \alpha_2 Controls_t)}{1 + \exp(\alpha_o + \alpha_1 DD_t + \alpha_2 Controls_t)}$$

$$\Pr(DFLT_t = 0) = 1 - \Pr(DFLT_t = 1)$$

The set of control variables includes period indicator variables to absorb the effect of macroeconomic changes on instances of default. It also includes industry indicator variables. Although for the purposes of calculating implied asset volatilities and distance-to-default measures we assume that the default point for all firms is the same – market value of assets equals to 97% of book value of liabilities – this does not have to be so. The default point must be considered in the context of the industry in which a firm operates, since the maturity structure of debt significantly varies across industries. The industry indicator variables are designed to capture these default-point differences. We control for the possibility that small firms are more likely to be delisted due to non-liquidation reasons by including an indicator variable equal to 1 if a firm is in the bottom equity-value decile of the sample.[2]

Although the occurrence-of-default tests are the most direct tests of the *DD* predictive power, they are difficult to conduct because default is an extremely rare event. In fact, Crosbie and Bohn (2002) report that a typical firm has a default probability of around 2% in any year. Given the fact that firms in our sample have publicly traded debt and equity, it is likely that they are not newly established firms and as a result have even lower average probability of default. Thus, the changes-in-credit-rating tests that follow can be potentially more insightful.

[2] A more accurate approach will be to include an indicator variable if the firm is in the bottom equity-value decile relative to the universe of CRSP-tracked firms and an indicator variable if the share price is close to the exchange's lower bound. This remains to be done.

B.1.b. Tests Based on Changes in Credit Ratings

Credit rating agencies, such as Moody's and Standard & Poor's, assess the uncertainty surrounding a firm's ability to service its debt and assign ratings designed to capture the results of these assessments. Credit ratings are revisited and revised often to ensure that they reflect the most recent information on the probability that a firm will default. Although the accuracy of credit ratings is difficult to judge, Altman (1989) shows that bond mortality rates are significantly different across credit ratings and that higher ratings imply higher bond mortality rates over a horizon of up to ten years.

Based on these findings we interpret credit rating changes as proxies for changes in a firm's default probability and examine the relationship between them and the preceding changes in *DD*. If implied asset volatility is a reliable estimate of firm risk, then a change in the corresponding *DD* measure will be highly correlated with a change in the firm's credit rating. The stronger this relationship, the more accurate the asset volatility estimate. We allow for a change in firm default probability to be reflected in its debt and equity valuation up to four quarters before it is reflected in a credit rating change. That is, we use up to four lags of *DD* in the models below. We also allow for the possibility that credit rating downgrades convey more information than credit rating upgrades. Hand *et al*. (1992) and Goh and Ederington (1993) investigate the informational content of credit ratings and conclude that downgrades contain negative information while upgrades contain little or no information as indicated by bond and stock price reactions. Thus, to test our conjecture we estimate two Logit models – one for downgrades versus no changes, and another for upgrades versus no changes. That is, we estimate

$$\Pr(UPGR_t = 1) = \frac{\exp(\beta_o + \sum_{k=1}^{4} b_k DD_{t-k} + \beta_2 Controls_t)}{1 + \exp(\beta_o + \sum_{k=1}^{4} b_k DD_{t-k} + \beta_2 Controls_t)}$$

$$\Pr(UPGR_t = 0) = 1 - \Pr(UPGR_t = 1)$$

where $UPGR_t = 1$ if a firm's credit rating has been upgraded in quarter *t* from its rating in quarter *t-1*. $UPGR_t = 0$ if the rating has remained the same. Similarly, we estimate

$$\Pr(DNGR_t = 1) = \frac{\exp(\gamma_o + \sum_{k=1}^{4} c_k DD_{t-k} + \gamma_2 Controls_t)}{1 + \exp(\gamma_o + \sum_{k=1}^{4} c_k DD_{t-k} + \gamma_2 Controls_t)}$$

$$\Pr(DNGR_t = 0) = 1 - \Pr(DNGR_t = 1)$$

where $DNGR_t = 1$ if a firm's credit rating has been downgraded in quarter *t* from its rating in quarter *t-1*. If the rating has not been changed then $DNGR_t = 0$. The set of controls includes industry indicator variables and a measure of firm size. It is possible that credit rating agencies pay different attention to the financial health of small versus large firms. We control for such differences by including the natural logarithm of the market value of assets corresponding to each volatility estimate in the logit estimations above. The industry indicator variables are designed to control for default-point variations among industry groupings.

B.2. Realized Asset Volatility Tests

Any measure of implied asset volatility should be highly correlated with realized asset volatility if it is to be useful. Since asset value can only be estimated on a quarterly basis, it is not feasible to calculate a meaningful estimate of realized asset volatility and compare it to lagged implied volatility. Instead we use two tests designed to capture the existence and strength of the relationship between the two.

B.2.a. Tests Based on Estimates of Realized Asset Return Volatility

This test is similar in spirit to tests used to examine the ability of *equity-return* volatility implied by equity option prices to predict realized volatility. These studies (e.g. Canina and Figlewski (1993), Day and Lewis (1992), Jorion (1995), Lamoureux and Lastrapes (1993), Poteshman (2000), and Chernov (2001)) yield different results depending on the time period, observation frequency, and data source used. However, their overall conclusion is that implied equity-return volatility is a biased and inefficient estimate of realized volatility. It will be interesting to compare these findings on the informational content of implied *equity* volatility with our findings on the informational content of implied *asset* volatility.

Our difficulty in comparing implied to realized volatility stems from the fact that unlike the market value of equity which is easily and frequently observed, the market value of total assets can not be directly obtained and requires estimation. We construct a hypothetical time series of the market value of assets as the sum of the market value of equity, the last available market value of traded debt, and the book value of nontraded debt. We use this series to calculate the weekly return on assets. The standard deviation of the asset returns over any quarter is an estimate of the realized asset return volatility, *RAV*. We test whether realized asset-return volatility in quarter t is statistically related to the four estimates of implied asset volatility in quarter $t\text{-}1$. That is, we estimate via ordinary least squares

$$RAV_t = \delta_0 + \delta_1 IAV_{t-1} + \delta_2 Controls_{t-1} + \varepsilon_t$$

where IAV_{t-1} is one of the four implied asset volatility estimates at the end of quarter $t\text{-}1$. We hypothesize that the coefficient on IAV_{t-1} is statistically indistinguishable from 1. We test the relative strength of the relationship by examining the R^2 of the four models. The set of controls includes quarter indicator variables designed to capture the effect of macroeconomic changes on asset returns, and industry indicator variables designed to capture industry profitability differentials.

B.2.b. Tests Based on Extreme Realizations of Asset Returns

We base this test on the statistical fact that a high level of volatility is more likely to produce extreme changes in asset value. That is, implied asset volatility should contain information about the distance of the realized return on assets from the mean of the asset-return distribution. We calculate the difference between realized and expected asset returns and refer to it as excess return-on-assets, *XROA*. Our test examines the relationship between the magnitude of *XROA* and the four implied asset volatility estimates as of the end of the previous quarter.

Since the mean of the ROA distribution is not known, we use two measures to proxy for it. We obtain quarterly equity returns for all firms traded on the NYSE, AMEX, and NASDAQ. We de-lever them using each firm's contemporaneous market value of equity and book value of debt in order to obtain an estimate of quarterly asset returns. These asset returns are the expected returns conditional on the realization of the priced risk factors. We average them by industry categories following the 48-industry breakdown in Fama and French (1997). This gives us our first proxy for expected asset returns by industry. For each firm in our sample the variable of interest, *XROA*, is the difference between the firm's quarterly asset return and the realized asset return for the industry in which the firm operates.

Our second proxy is a firm-specific estimate of expected return based on the Fama and Fench (1993) five-factor model. We start with the time series of weekly asset returns constructed earlier. For each firm we regress its asset returns over a year on the weekly realizations of the five factors to obtain factor loadings for that year. For each quarter we use the loadings based on the last four quarters along with the factor realizations for the last week of the quarter to calculate the quarter end expected asset return. This is us our second proxy for *XROA*.

In performing our test, we allow for the possibility that implied asset volatility has different predictive power for positive and negative *XROA*. There are two possible reasons why this might be the case. First, the methodology used to obtain implied asset volatility might produce different estimates depending on whether a firm is doing poorly or well. The implied volatility estimate is computed by a Black-Scholes-type model which considers a firm's equity value as a call option on its assets with an exercise price equal to the face value of its liabilities. If the firm is doing well then the value of its assets is likely much higher than the value of its liabilities. This is equivalent to a call option being deep in-the-money. If the firm is doing poorly and is highly levered then its equity is an at-the-money call. Research on implied equity volatilities indicates that all else equal, the volatility implied by the price of a deep-in-the-money call is significantly higher than that implied by the price of an at-the-money call. This finding holds true for stock options (e.g. MacBeth and Merville (1979), Rubinstein (1994), and Jackwerth and Rubinstein (1996)), currency options (e.g. Shastri and Tandon (1986a), and Bodurtha and Courtadon (1987)), futures options (e.g. Shastri and Tandon (1986b)), and index options (e.g. Chance(1986)). Thus, it is possible that the implied volatility of asset returns is also skewed and that the asset volatility estimates for financially healthy firms contain different information than those for financially distressed ones.

A second possible reason for implied asset volatility to have different predictive power for positive and negative *XROA*, is that managers might reveal favorable private information as soon as they can, while holding on to unfavorable private information.

Studies document that bank regulators' and credit rating agencies' downgrades are regarded as news while upgrades seem to have no informational content. It can be argued that just as regulators and rating agencies force the release of negative information, so do quarterly reports. In other words, managers reveal positive information the instant it becomes known to them and wait to publicize negative information until their quarterly reports are due. This would imply that positive *XROA* and negative *XROA* can contain a notably different amount of new information.

Our test consists of estimating an ordinary-least-squares regression in which the dependant variable is excess asset return at quarter end *t* and the main independent variable is one of the four estimates of asset volatility at quarter end *t-1*. We do so separately for positive and negative *XROA* values, and for ease of exposition, take the absolute value of the negative *XROA*. That is, we estimate via OLS

$$XROA_t^+ = \chi_0 + \chi_1 IAV_{t-1} + \chi_2 Controls + \varepsilon_t^+$$

$$\left| XROA_t^- \right| = \phi_0 + \phi_1 IAV_{t-1} + \phi_2 Controls + \varepsilon_t^-$$

If the asset volatility estimates contain information about realized asset volatilities, we expect that the coefficient on IAV_{t-1} in both regressions be positive. This would imply that high asset volatility is more likely to be followed by extreme asset return.

III. Data Sources

This study combines a number of data sources for the period of 1986-1999. Data on equity prices and characteristics is obtained from the Center for Research in Security Prices (CRSP). Data on bond prices and characteristics is obtained from the Warga-Lehman Brothers Fixed Income Database (WLBFID) and the Warga Fixed Investment Securities Database (FISD). Both sources are used since neither database alone covers the whole study period. Finally, balance sheet and income statement data for industrial firms and bank holding companies comes from the Compustat Database and Y-9 Reports respectively. Combining these four data sources is nontrivial since (1) each database has its own unique identifier with only some of them overlapping across databases, and since (2) some of the identifiers are recycled. Therefore, the merging process that we use requires further explanation.

We start with information from WLBFID and FISD, which use issuer CUSIP as one of their identifiers. We then match the issuer CUSIP against those obtained from CRSP making sure that the date on which the bond data is recorded falls within the date range for which the CUSIP is active in the CRSP database. Merging the WLBFID and FISD data with that from the CRSP database allows us to add one more identifier to our list – PERMNOs. We use them to acquire Compustat data from the Merged CRSP/Compustat database. Finally, the Y-9 reports filed by bank holding companies (BHC) do not report any generally used identifiers. In addition to the BHC name, the reports contain entity numbers assigned by the Federal Reserve. We manually link PERMNOs to entity numbers by first matching by BHC name and then confirming the match by comparing balance sheet data from the Y-9 Report to the data available from the Merged

CRSP/Compustat. If the name is similar and total assets/total liabilities numbers are also comparable, then we consider this a match.

The above matching procedures result in data on at least 560 unique industrial firms and 40 unique financial firms, with the exact number varying by year. These translate into 19,233 firm-quarter observations for industrial firms and 2,128 for financial ones.

A. Bond Prices and Characteristics

The initial sample includes all firms from the WLBFID and FISD whose bonds are traded during the period of 1986-1999. The WLBFID reports monthly information on the major private and government debt issues traded in the United States until March 1997. We identify all U.S. corporate fixed-rate, nonconvertible debentures in the database and collect data on their month-end yield, prepayment options, and amount outstanding. Since the data is substantially incomplete before 1985, we start our sample with December 1985 data. While most prices reflect "live" trader quotes, some are "matrix" prices estimated from price quotes on bonds with similar characteristics. Yields calculated from "matrix" prices are likely to ignore the firm-specific changes we are trying to capture, so we exclude them from our sample.

The FISD contains comprehensive data on public U.S. corporate and agency bond issues with reasonable frequency since 1995. We use the same procedures for retaining observations as we do with the WLBFID in an attempt to make the two databases as comparable as possible – we identify all fixed, non-convertible debentures issued by U.S. corporations. The main difference between the two databases is the source and type of the pricing information. The WLBFID reports bond trader quotes as made available by Lehman Brothers traders. The FISD reports actual transaction prices recorded electronically by Reuters/Telerate and Bridge/EJV who collectively account for 83% of all bond trader screens. In the spirit of making data from the two databases comparable, we calculate each issue's month-end yield using the price closest to the end of the month. A cursory examination of the small number of debt issues that have both WLBFID and FISD data available indicates that yields across the two databases are extremely similar. Nevertheless, when combining the WLBFID with the FISD sample, we choose actual trade prices over quotes only if the trade occurs in the last five days of the month.

In order to compute a credit-risk spread, we also collect the yields on Treasury bonds of different maturities from the Federal Reserve Board's H.15 releases. For each corporate debt issue in our sample we identify a Treasury security with approximately the same maturity as the remaining maturity on the corporate debenture. When there is no precise match, we interpolate to obtain a corresponding Treasury yield. The difference between a corporate yield and a corresponding Treasury yield is a raw spread, which must be adjusted for any noncredit-related factors. Perhaps the most important of these is the value of call options embedded in many corporate yield spreads. Since the value of a call option is always non-negative, the raw spread over Treasuries will always exceed the credit-risk spread unless we adjust for the option's value.

We follow the approach presented in Avery, Belton, and Goldberg (1988) and Flannery and Sorescu (1996) to estimate an option-adjusted credit spread. For each callable corporate bond in our sample, we use the maturity-corresponding Treasury bond to calculate a hypothetical callable Treasury yield. That is, we calculate the required coupon rate on a Treasury bond with the same maturity and call-option parameters as the corporate bond but the same market price as the non-callable Treasury bond. The difference between the yield on the hypothetical callable and the actual non-callable Treasury bond is the value of the option to prepay. We subtract these option values from the raw spreads calculated earlier to obtain option-adjusted credit spreads:

$$CreditSpread_{it} = CorporateYTM_{it} - TreasuryYTM_{it} - CallOption_{it}$$

In a small number of cases these credit spreads turn out to be negative. Since the theoretical motivation used in this study does not allow for negative credit spread values, we exclude them from our sample.

The required yield on the hypothetical Treasury is computed following the method of Giliberto and Ling (1992). They use a binomial lattice based on a single factor model of the term structure to value the prepayment options of residential mortgages. Their methodology uses the whole term structure of interest rates to estimate the drift and volatility of the short-term interest rate process. These two parameters are then used to determine the interest rates at every node of the lattice, which are in turn used to calculate the value of the mortgage prepayment option. Following Flannery and Sorescu (1996) this methodology is adjusted to calculate the call option value of the Treasury bonds instead.

To obtain a firm yield spread, *SPREAD*, we aggregate yield spreads on bonds issued by the same firm using three approaches. The first approach is to construct a weighted-average yield spread by averaging the spreads on same-firm bonds and weighing them by the bonds' outstanding amount. The other approaches use the findings in Hancock and Kwast (2001) and Covitz *et al*. (2002) that due to higher liquidity larger and more recently issued debentures have more reliable prices. To minimize the liquidity component of yield spreads, for each firm we take the spread on its largest issue (based on amount outstanding) as our second measure of firm yield spread, and the spread on its most recent issue as our third measure.

B. Equity Prices and Characteristics

For all firms that have bond data available, we collect equity information from the daily CRSP Stock Files. We calculate the quarterly equity return volatility σ_E as the standard deviation of annualized daily returns during the quarter. The market value of equity MVE is the last stock price for each quarter multiplied by the number of shares outstanding.

We exclude from our sample all stocks with a share price of less than \$5 and for which σ_E is computed from less than fifty equity-return observations. This attempts to reduce the effect of the bid-ask bounce on the estimate of equity-return volatility, and to provide enough observations to make the quarterly estimate meaningful. These two filters reduce our sample size by less than 10%.

C. Accounting Data

Quarterly accounting data for the industrial firms in our sample is obtained from the CRSP/COMPUSTAT Merged Database using PERMNOs. Data for the financial firms comes from the "Consolidated Financial Statement" (FR Y-9 reports) that bank holding companies are required to file with the Federal Reserve Board. These statements consolidate the parent corporation with all of its bank and nonblank subsidiaries. For each industrial and financial firm we collect information on the book value of total assets V_B , and the book value of total liabilities, D, at the end of each calendar quarter during 1986-1999. For the subset of industrial firms we also obtain industry classification codes and following the 48-industry breakdown in Fama and French (1997) construct industry indicator variables.

Our methodology requires information on the priority structure of total debt in addition to its amount. For bank holding companies this issue is easily resolved. The FR Y-9 reports present information on the value of subordinated notes and debentures so we use this as an estimate of D_2. For industrial firms there is no information on the amount of senior versus subordinated debt, so we use the following approach for obtaining an estimate of the priority breakdown. Using the two bond databases described earlier, we aggregate the amount outstanding of each firm's bonds at each quarter end during 1986-1999. We use this as one estimate of the firm's face value of subordinated debt. This simplification is based on the well-known fact that firms tend to take out bank loans before they turn to the public debt markets, and the findings of Longhofer and Santos (2003) that most bank debt is senior. We use the amount outstanding of only the bonds whose yield spreads are used to calculate *SPREAD* as a second estimate of the face value of subordinated debt.

D. Default Data

Two financial distress data sources are used to proxy for the event of default – the firm's delisting date from the exchange that it trades on and the firm's bankruptcy filing date. We obtain delisting dates from CRSP and retain those that are associated with bankruptcy, liquidation, and other financial difficulties (delisting codes greater than 400). We collect bankruptcy-filing dates from FISD. Since an extremely small portion of our sample firms default and since there is a large overlap between the CRSP delisting dates and FISD bankruptcy-filing dates, we combine the two data sources.[3] We construct an indicator variable *DFLT* that equals one for quarter t if a firm is either delisted or files for bankruptcy during the three years following that quarter. It equals zero otherwise.

IV. Empirical Findings for Industrial Firms

[3] Estimating two separate logit models, one for delistings and one for bankruptcy filings, yields identical results.

We use the methodologies described earlier to compute four estimates of implied asset volatility for the industrial firms in our sample. For a small set of firm-quarter observations, the Newton iterative procedure had difficulties converging. We experimented with different starting values and different methods for solving a system of nonlinear equations (the Jacobi method and the Seidel method). We were successful in calculating all four implied volatility estimates for 19,020 out of the 19,233 original observations.

A. Summary Statistics

Table 1 presents summary statistics on the sample of 19,020 firm-quarters. The average market value of assets is in the range of $10,996- $12,640 million and is very similar across methodologies. The highest value is produced by the simple method of summing the market value of equity and the book value of debt. This is not a surprise since this methodology does not account for the riskiness of debt. When the value of the debt put option is subtracted, then the market value of assets is reduced as indicated by the estimates obtained from any of the system-of-equations methodologies. It is interesting to note that the lowest market value of assets is obtained by using subordinated debt prices along with historical equity volatility. This can be the effect of trying to make yield spreads that include a liquidity premium consistent with lower than expected equity volatility.

Unlike the estimates of asset value, the estimates of asset return volatility are significantly different across methodologies. The average implied volatility is the lowest, 16.28%, when calculated by the simple method of de-levering equity volatility using the market value of equity and book value of debt. Once a system-of-equations methodology is used, the average estimates become higher – it is 16.75% for EIAV, 21.08% for DIAV, and 34.58% for EDIAV. This is consistent with the findings of Schellhorn and Spellman (1996) who document that EDIAV is on average 40% higher than EIAV.

We investigate whether these differences vary across quarters. Figure 1 plots median implied asset volatility for each quarter during 1986-1999, and makes three noteworthy points. First, EIAV and DIAV move closely together while EDIAV follows a somewhat different time path. It is interesting to observe that while both EIAV and DIAV dramatically increase in December 1987, EDIAV falls. This is likely due to the reliance of the first two estimates on equity volatilities over a quarter including the crash of 1987. EDIAV on the other hand is not affected by the crash-induced equity volatility and as a result is a more forward-looking assessment of asset volatility. Second, DIAV and EIAV vary notably across quarters and almost triple over the time period studied. EDIAV is relatively stable and over 1986-1999 increases by only a third. Finally, the plot shows that the differences among the three estimates are shrinking over time.

There has been extensive literature on the relationship between implied *equity* volatility and the moneyness of the *call equity* option used to calculate it. It is a well-documented fact that implied volatility from in-the-money options is lower than that from out-of-the-money options written on the same stock. Unfortunately, we do not have available the value of more than one call option on the same firm's assets. Nevertheless, we conduct a cursory examination of whether our estimates of asset volatility are affected by the moneyness of the call option (that is, firm leverage). Figure 2 shows median implied asset volatilities from our four methodologies by leverage quartile. It is apparent that the higher the amount of debt relative to assets, the lower the implied volatility. This could be the result of the simultaneous determination of capital structure and asset volatility, but it is also consistent with the existence of an implied asset volatility smile.

The distance-to-default (*DD*) can possibly avoid problems resulting from the endogenous relationship between implied volatility and leverage since it combines them into a single measure of default probability. Table 1 present summary statistics on *DD* calculated from the four estimates of asset volatility. The average *DD* is 3.42 if calculated from *BIAV*, 3.20 if calculated from *EIAV*, 1.88 if calculated from *DIAV*, and 1.35 if calculated from *EDIAV*. This is consistent with the relationship among the asset volatility estimates for a given leverage quartile presented in Figure 2.

The time series behavior of the median of the four measure of *DD* can be seen in Figure 3. While the *DD* estimates calculated from *BIAV* and *EIAV* are very volatile, the ones calculated from *DIAV* and *EDIAV* are relatively stable. For instance, during 1986-1999 the *DD* calculated from the asset volatility measure proposed in this study (*EDIAV*) has fluctuated only in the range of 1.00-1.50 while the median *DD_EIAV* has fluctuated in the range of 1.25-4.00. Once again, the medians of the four *DD* estimates seem to be converging towards the end of the sample period.

Table 2 and Table 3 examine more closely how correlated the estimates obtained through the four methodologies are. Table 2 presents simple correlations and Table 3 presents rank correlations. Both tables indicate that the estimate of the market value of assets is largely independent of the methodology used to compute it – the simple and rank correlations among all of the four estimates are extremely close to 1.

Three out of the four asset volatility estimates are also highly correlated. *BIAV*, *EIAV*, and *DIAV* have simple and rank correlations in the 90% range. All three measures however have lower simple correlations with *EDIAV* – 70.01% for *BIAV*, 65.80% for *EIAV*, and 83.50% for *DIAV* respectively. The rank correlations are a bit higher for *BIAV* and *EIAV* and almost unchanged for *DIAV*. This indicates that using historical equity volatility produces estimates of asset volatility that are significantly different from those obtained through a methodology that uses contemporaneous equity and debt prices.[4]

The correlations are even lower among the four estimates of *DD*. The *DD* calculated from *EDIAV* has the highest simple and rank correlation with the *DD* calculated from *DIAV* – 57.06% and 74.73% respectively. Its correlation with *BIAV* and *EIAV* is less than 45%. The wide range of correlation values among the asset volatility and among the distance-to-default estimates suggests that different methodologies produce very different estimates. However, whether any of the estimates are superior to the others is an

[4] We conduct non-parametric tests for statistical significance of the differences among asset volatility measures. These are not reported in the current version of the paper.

empirical question that requires a comparison of their informational content and accuracy. We conduct such comparisons in the two subsections that follow.

B. Default Probability Tests

B.1. Tests Based On the Occurrence of Default

We limit our sample to firms that have data available as of the beginning of at least one of the three-year periods defined earlier. This leaves us with 1,180 firm-quarter observations out of which only 18 are for financially distressed firms.[5] Being aware of the econometrics issues that such a 'lop-sided' sample creates, we conduct the occurrence-of-default tests not only on the whole sample but also on the subsample of non-investment grade firms. This relies on the fact that investment grade firms almost never default and allows us to achieve a more balanced dataset – 331 observations out of which 18 for distressed firms.

Table 4 provides summary statistics on the average distance-to-default estimates by financial distress status. Panel A shows that independent of the asset volatility estimate used to calculate it, average *DD* is significantly lower for financially distressed firms. Panel B indicates that if we look at the subsample of non-investment grade firms, the differences in average *DD* persist but become smaller.

Table 5 presents both sets of logit analysis results. Panel A demonstrates that all four *DD* measures are statistically significant in explaining the occurrence of financial distress. Their negative sign indicates that a decrease in the distance to default increases the probability that a firm will default in the following three years. The fit of all four models as indicated by the max re-scaled R-square is very similar and in the range of 35.22%-40.49%. The best fit is provided by the *DD* calculated from *EDIAV*, which contributes 11.57% to the R-square of a base logit model that includes industry, period, and size indicator variables only.

Table 5, Panel B presents the results for the subsample of non-investment grade firms. The coefficients on all four *DD* measures are still negative but their statistical significance differs from that in Panel A. The *DD* measure based on *BIAV* is no longer statistically significant, the one based on *EIAV* is significant at the 10% level, and the one based on *DIAV* at the 5% level. Only the *DD* calculated from *EDIAV* is still strongly significant at the 1% level. The change in statistical significance might be the result of the sample being smaller and more balanced. Alternatively, it might indicates that while methodology choice is not essential for the ability of *DD* to explaining default probability, it is important when predicting default probability conditional on non-investment grade rating. We examine the R-square of the four models and not surprisingly the best fit is obtained when using *EDIAV* closely followed by *DIAV*. The marginal contribution of *EDIAV* to the R-square of a base logit model is 5.92%.

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[5] Rather than having observations for 52 quarters as in our original sample of 19,020 firm-quarters, we now have observations for 4 quarters. This explains the large reduction in sample size from 19,020 firm-quarters to 1,198

In summary, whether analyzing the whole sample or the subsample of non-investment grade firms, the *DD* calculated from *EDIAV* is better than the ones calculated from *BIAV*, *EIAV*, or *DIAV* at distinguishing between firms that default and those that do not. The second best measure is the one obtained form *EIAV* when analyzing the whole sample and *DIAV* when analyzing the non-investment grade subsample.

B.2. Tests Based on Credit Rating Changes

Table 6 breaks down the original sample of 19,020 observations by Moody's average credit rating and offers average *DD* statistics by rating category. A cursory examination suggests that credit rating rankings are generally consistent with average *DD* – as ratings deteriorate, *DD* falls. This relationship is much more pronounced for non-investment grade firms and seems to be independent of the implied asset volatility that *DD* is based on.

Table 7 investigates whether changes in *DD* are consistent with changes in Moody's credit rating during the quarter that follows. The average *DD_EDIAV* and *DD_DIAV* changes seem consistent with the subsequent credit upgrades and downgrades. Moody's appear to downgrade a firm after its *DD* has fallen. This fall is larger if when downgraded the firm moves from investment into non-investment grade. Similarly, when a firm's credit rating is adjusted upwards then its *DD* has just increased with the increase being larger for firms upgraded into investment grade. The average *DD* calculated from *EIAV* or *BIAV* do not follow this pattern. In fact, for the firms whose credit rating changes from non-investment into investment grade, the beginning-of-the-quarter *DD* is lower than that of the previous quarter. This counter-intuitive association between average *DD* and credit rating changes holds true for the firms downgraded from investment grade into non-investment grade when *DD* is based on *BIAV*.

Table 8 presents the logit analysis results for credit rating upgrades. Only the first lag of *DD_EDIAV* and the first two lags of *DD_DIAV* are statistically significant. Since the probabilities are accumulated over the lower event values, the negative signs on these *DD* estimates indicate that a decrease in *DD* reduces the probability of observing an upgrade. The *DD* calculated from *EIAV* and *BIAV* seem to have no informational value since none of their four lags are statistically significant. Interestingly enough, the marginal explanatory power of all of the *DD* estimates results in a worse fit than the fit obtained from a base logistic regression of rating changes on firm size and lagged rating changes. That is, looking at any *DD* estimate in addition to firm size and lagged rating changes worsens our ability to forecast whether a firm's rating will be upgraded or remain unchanged. This finding is consistent with studies, which document that the markets regard upward changes in credit ratings as no news.

The logit results for downgrades versus no-changes are presented in Table 9. In contrast to the lack of explanatory power in the upgrade logit estimations, here all four lags of all four estimates of *DD* are statistically significant. This suggests that the *DD* estimates capture increases in default probability up to a year before these increases are reflected in a credit rating change. We compare the fit of the four models to that of a base model, which includes only firm size and lagged rating change as independent variables. We discover that the *DD* calculated from *EDIAV* provides the highest marginal contribution to the R-square. The marginal contribution of the other three *DD* estimates is very similar and only slightly smaller that that of *DD_EDIAV*.

To sum up, all four *DD* estimates are able to detect credit rating downgrades up to a year before they occur. Out of them the estimate based on *EDIAV* seems to be better at explaining subsequent downgrades than are the estimates based on *EIAV*, *DIAV*, and *BIAV*. Although two of the estimates, *DD_EDIAV* and *DD_DIAV*, are statistically significant in explaining credit rating upgrades, all of them impair our ability to distinguish between upgrades and no-changes as indicated by their marginal contribution to the R-square of a base regression.

C. Realized Asset Volatility Tests

This set of tests still remains to be done.

V. Conclusion and Future Research

This study proposes an innovative methodology for estimating asset value and volatility. In contrast to previously used methodologies, the one put forward in this paper does not rely on historical equity volatility. Instead it combines information from both equity and debt prices to solve a system of equations derived from contingent-claim valuation models. We term this the equity-and-debt implied asset volatility, *EDIAV*.

We evaluate the informational content and accuracy of *EDIAV* by comparing it to three more traditional estimates of asset volatility – asset volatility implied by equity prices alone (*EIAV*), asset volatility implied by debt prices alone (*DIAV*), asset volatility obtained by de-levering equity-return volatility using book leverage (*BIAV*). We calculate the four asset volatility measures for a sample of 19,020 industrial and 2,014 financial quarterly firm observations for the period 1986-1999. We document that these measures are extremely sensitive to the methodology used to compute them. The methodology proposed in this study produces volatility estimates that are much larger and more stable over the sample period.

Our preliminary tests on the sample of industrial firms indicate that implied asset volatility estimates successfully forecast defaults and credit-rating downgrades. Consistent with previous studies on the informational content of credit ratings, we find that the estimates do not improve our ability to distinguish between firms that are subsequently upgraded and those whose rating remains unchanged. The fit statistics in all of the tests indicate that the asset volatility estimate we propose, *EDIAV*, is better than the other three at forecasting default occurrences and credit rating changes. We intend to investigate whether tests of the relationship between implied and realized asset volatility will confirm these findings

The results reported in this study have important implications for financial theory and practice. Researchers in many areas of finance – credit risk assessment, risky bond valuation, and deposit insurance among others – have employed a variety of methods to obtain estimates of asset volatility. This study shows that different methods produce significantly different estimates and that some of them are more informative and accurate than others. Since the choice of methodology for estimating asset volatilities appears to be a non-trivial one, it is extremely reassuring that the tests performed in this study consistently point to *EDIAV* as being superior to more traditional measures in evaluating and forecasting total firm risk.

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Table 1
Summary Statistics

Variable	Min	Max	Median	Mean	StdDev
V_BIAV	43.8	429,459.3	4,415.5	12,640.3	26,984.9
V_EIAV	37.4	418,709.5	4,339.5	12,406.5	26,397.2
V_DIAV	42.2	402,397.8	3,547.8	10,995.8	24,419.4
V_EDIAV	41.6	418,033.4	4,337.4	12,388.3	26,366.9
BIAV	0.0044	1.2046	0.1457	0.1628	0.1029
EIAV	0.0045	1.4494	0.1489	0.1675	0.1095
DIAV	0.0022	1.0868	0.1848	0.2108	0.1289
EDIAV	0.0140	1.2129	0.3286	0.3458	0.1663
DD_BIAV	0.5203	16.9634	3.2231	3.4290	1.4125
DD_EIAV	-0.5231	12.3486	3.0450	3.2057	1.3287
DD_DIAV	-0.6529	7.6749	1.5241	1.8859	1.1504
DD_EDIAV	0.5247	2.0089	1.3760	1.3546	0.2631

Summary statistics are for the sample of 19,020 quarterly observations during 1986-1999. BIAV is the book-value-implied asset volatility, EIAV is the equity-implied asset volatility, DIAV is the debt-implied asset volatility, and EDIAV is the equity-an-debt-implied asset volatility. V_BIAV, V_EIAV, V_DIAV, and V_EDIAV are the corresponding estimates of the market value of assets. DD_BIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the corresponding distance-to-default measures.

Table 2
Simple Correlations

Panel A: Market Value of Assets

Methodology	BIAV	EIAV	DIAV	EDIAV
BIAV	1.0000			
EIAV	1.0000	1.0000		
DIAV	0.9942	0.9936	1.0000	
EDIAV	0.9977	0.9978	0.9918	1.0000

Panel B: Std Dev of Asset Returns

Methodology	BIAV	EIAV	DIAV	EDIAV
BIAV	1.0000			
EIAV	0.9910	1.0000		
DIAV	0.9234	0.9012	1.0000	
EDIAV	0.7001	0.6580	0.8350	1.0000

Panel C: Distance to Default

Methodology	BIAV	EIAV	DIAV	EDIAV
BIAV	1.0000			
EIAV	0.9626	1.0000		
DIAV	0.5451	0.6436	1.0000	
EDIAV	0.3476	0.4002	0.5706	1.0000

Simple correlations are for the sample of 19,020 quarterly observations during 1986-1999. BIAV is the book-value-implied asset volatility, EIAV is the equity-implied asset volatility, DIAV is the debt-implied asset volatility, and EDIAV is the equity-an-debt-implied asset volatility. The market value of assets and distance to default correspond to the implied asset volatilities as indicated.

Table 3
Rank Correlations

Panel A: Market Value of Assets

Methodology	BIAV	EIAV	DIAV	EDIAV
BIAV	1.0000			
EIAV	1.0000	1.0000		
DIAV	0.9938	0.9935	1.0000	
EDIAV	0.9999	0.9999	0.9937	1.0000

Panel B: Std Dev of Asset Returns

Methodology	BIAV	EIAV	DIAV	EDIAV
BIAV	1.0000			
EIAV	0.9976	1.0000		
DIAV	0.9669	0.9639	1.0000	
EDIAV	0.7854	0.7677	0.8302	1.0000

Panel C: Distance to Default

Methodology	BIAV	EIAV	DIAV	EDIAV
BIAV	1.0000			
EIAV	0.9682	1.0000		
DIAV	0.4936	0.5791	1.0000	
EDIAV	0.4146	0.4315	0.7473	1.0000

Rank correlations are for the sample of 19,020 quarterly observations during 1986-1999. BIAV is the book-value-implied asset volatility, EIAV is the equity-implied asset volatility, DIAV is the debt-implied asset volatility, and EDIAV is the equity-an-debt-implied asset volatility. The market value of assets and distance to default correspond to the implied asset volatilities as indicated.

Table 4

Panel A: All Observations

Default Status	Number of Observations	Average DD Calculated from: EDIAV	EIAV	DIAV	BIAV	Average Yield Spread
All	1,180	1.3424	3.3681	1.9447	3.6406	0.0196
Non-defaulting	1,162	1.3496	3.3871	1.9649	3.6549	0.0192
Defaulting	18	0.8818	2.1437	0.6449	2.7188	0.0458

Panel B: Noninvestment-Grade Observations

Default Status	Number of Observations	Average DD Calculated from: EDIAV	EIAV	DIAV	BIAV	Average Yield Spread
All	331	1.0755	2.3821	0.9679	2.6493	0.0384
Non-defaulting	313	1.0874	2.4032	0.9866	2.6530	0.0379
Defaulting	18	0.8557	1.9926	0.6228	2.5795	0.0477

Average Statistics by Default Status

Summary statistics are on the pooled sample of observations for the fourth quarter of 1988, 1991, 1994, and 1997. A firm is considered ‘Defaulted’ if it is delisted due to liquidation or files for bankruptcy in the three years following the fourth quarter of 1988, 1991, 1994, and 1997. BIAV is the book-value-implied asset volatility, EIAV is the equity-implied asset volatility, DIAV is the debt-implied asset volatility, and EDIAV is the equity-an-debt-implied asset volatility. DD is the distance to default measure calculated from the corresponding asset values and volatilities. Yield Spread is the yield spread on the firm’s most recently issued bonds.

Table 5
Logit Analysis of Defaults

Panel A: All Observations

Independent Variable	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)
Intercept=0	1.9372	0.7209	-1.2279	-0.1198	-2.8973 ***
	(1.2492)	(1.0943)	(0.7591)	(1.0759)	(0.6839)
DD_EDIAV	-4.4822 ***				
	(1.0764)				
DD_EIAV		-1.2272 ***			
		(0.3238)			
DD_DIAV			-1.8149 ***		
			(0.5503)		
DD_BIAV				-0.7796 ***	
				(0.2579)	
SMALL	0.0337	0.2261	0.4218	0.3652	1.0585 *
	(0.6576)	(0.6273)	(0.6125)	(0.6222)	(0.5779)
R-Square	0.4049	0.3965	0.3887	0.3522	0.2892
Marginal Contribution of DD to R-Square	0.1157	0.1073	0.0995	0.0630	

Panel B: Noninvestment-Grade Observations

Independent Variable	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)
Intercept=0	1.1969	0.1496	-0.6092	-0.7314	-1.7159 **
	(1.3058)	(1.2034)	(0.8493)	(1.1916)	(0.7444)
DD_EDIAV	-3.0212 ***				
	(1.1667)				
DD_EIAV		-0.7403 *			
		(0.3949)			
DD_DIAV			-1.8005 **		
			(0.7238)		
DD_BIAV				-0.3181	
				(0.3079)	
SMALL	-0.3903	-0.2059	-0.1324	-0.1783	-0.0050
	(0.6605)	(0.6436)	(0.6419)	(0.6575)	(0.6293)
R-Square	0.4110	0.3856	0.4073	0.3609	0.3518
Marginal Contribution of DD to R-Square	0.0592	0.0338	0.0554	0.0091	

These are the results from a logistic regression on the sample of all 1,180 observations (Panel A) and the subsample of 331 non-investment-grade observations (Panel B). The dependent variable equals 1 if the firm is delisted due to liquidation or files for bankruptcy in the three years following the fourth quarter of 1988, 1991, 1994, and 1997; it equals 0 otherwise. DD_BIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the book-value-implied, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. R-Square is the maximum re-scaled R-square, which is an indicator of fit for logit models. The marginal contribution of each DD to R-Square is the difference between the R-square of the model including that DD and the R-square of a base model excluding it. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and * respectively.

Table 6

Average Statistics by Moody's Credit Rating

		Average DD Calculated from					
	Moody's Credit Rating	**EDIAV**	**EIAV**	**DIAV**	**BIAV**	**Average Yield Spread**	**Number of Observations**
	Missing	1.25	2.72	1.46	2.96	0.0299	828
Investment Grade	Aaa	1.40	3.79	2.62	3.99	0.0079	365
	Aa1	1.43	4.08	2.63	4.20	0.0104	219
	Aa2 or Aa	1.44	4.09	2.70	4.26	0.0096	773
	Aa3	1.47	3.65	2.59	3.78	0.0095	795
	A1	1.45	3.75	2.46	4.00	0.0106	1710
	A2 or A	1.48	3.65	2.33	3.91	0.0111	2014
	A3	1.46	3.64	2.21	3.89	0.0122	1757
	Baa1	1.46	3.48	2.02	3.76	0.0133	1325
	Baa2 or Baa	1.43	3.34	1.91	3.54	0.0140	1338
	Baa3	1.40	3.32	1.78	3.58	0.0167	1086
Noninvestment Grade	Ba1	1.30	2.88	1.37	3.08	0.0241	513
	Ba2 or Ba	1.23	2.51	1.25	2.72	0.0294	504
	Ba3	1.15	2.42	1.09	2.62	0.0344	976
	B1	1.07	2.16	0.97	2.38	0.0442	1649
	B2 or B	1.01	2.09	0.91	2.31	0.0440	789
	B3	1.01	1.95	0.93	2.15	0.0486	376
	Caa1	0.87	1.69	0.74	1.92	0.0465	46
	Caa2 or Caa	0.86	1.86	0.76	2.05	0.0601	41
	Caa3	1.02	1.18	1.03	1.22	0.0556	2

Summary statistics are on the sample of 19,020 firm-quarters for the period 1986-1999. BIAV is the book-value-implied asset volatility, EIAV is the equity-implied asset volatility, DIAV is the debt-implied asset volatility, and EDIAV is the equity-an-debt-implied asset volatility. DD is the distance to default measure calculated from the corresponding asset values and volatilities. Yield Spread is the yield spread on the firm's most recently issued bonds.

Table 7
Average Statistics by Credit Rating Change

Moody's Rating Change	Average Change in DD Calculated from: EDIAV	EIAV	DIAV	BIAV	Average Change in Yield Spread	Number of Observations
Missing	0.0003	0.0906	-0.0152	0.0986	0.0003	706
0	-0.0521	-0.0197	-0.1363	0.0099	0.0057	88
1	-0.0060	-0.0733	-0.0290	-0.0716	0.0013	846
2	0.0005	0.0021	0.0088	0.0030	-0.0001	14,541
3	0.0145	0.0152	0.0655	0.0113	-0.0015	840
4	0.0663	-0.0419	0.3113	-0.0769	-0.0043	85

Summary statistics are on the sample of 19,020 firm-quarters for the period 1986-1999. Moody's rating change equals 0 if the firm is downgraded from investment to non-investment grade; equals 1 if the firm is downgraded without crossing the non-investment grade threshold; equals 2 if the credit rating remains the same; equals 3 if it is upgraded without crossing the investment grade threshold; and equals 4 if it is upgraded from non-investment to investment grade. BIAV is the book-value-implied asset volatility, EIAV is the equity-implied asset volatility, DIAV is the debt-implied asset volatility, and EDIAV is the equity-an-debt-implied asset volatility. DD is the distance to default measure calculated from the corresponding asset values and volatilities. Yield Spread is the yield spread on the firm's most recently issued bonds. Changes are calculated on a quarterly basis.

Table 8
Logit Analysis of Credit Rating Upgrades

Independent Variable	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)
Intercept=3	4.8279 ***	4.7412 ***	4.5999 ***	4.7397 ***	5.2073 ***
	(0.4357)	(0.4337)	(0.4356)	(0.4336)	(0.3817)
Intercept=4	7.3118 ***	7.2221 ***	7.0731 ***	7.2207 ***	7.7634 ***
	(0.4524)	(0.4504)	(0.4522)	(0.4503)	(0.3995)
SIZE_lag	-0.0931 ***	-0.0872 ***	-0.0808 **	-0.0867 ***	-0.0992 ***
	(0.0326)	(0.0325)	(0.0326)	(0.0325)	(0.0289)
dRTG_lag	-0.6912 ***	-0.6953 ***	-0.6562 ***	-0.6966 ***	-0.8939 ***
	(0.0931)	(0.0931)	(0.0940)	(0.0931)	(0.0826)
dDD_EDIAV_lag1	-1.6834 ***				
	(0.3832)				
dDD_EDIAV_lag2	-0.4296				
	(0.3877)				
dDD_EDIAV_lag3	-0.1488				
	(0.3955)				
dDD_EDIAV_lag4	-0.0516				
	(0.3840)				
dDD_EIAV_lag1		-0.0318			
		(0.0426)			
dDD_EIAV_lag2		-0.0564			
		(0.0481)			
dDD_EIAV_lag3		0.0143			
		(0.0480)			
dDD_EIAV_lag4		0.0383			
		(0.0433)			
dDD_DIAV_lag1			-0.1594 ***		
			(0.0473)		
dDD_DIAV_lag2			-0.1232 **		
			(0.0531)		
dDD_DIAV_lag3			-0.0363		
			(0.0550)		
dDD_DIAV_lag4			-0.0165		
			(0.0505)		
dDD_BIAV_lag1				-0.0157	
				(0.0400)	
dDD_BIAV_lag2				-0.0333	
				(0.0452)	
dDD_BIAV_lag3				0.0325	
				(0.0451)	
dDD_BIAV_lag4				0.0457	
				(0.0407)	
R-Square	0.0540	0.0506	0.0507	0.0506	0.0576
Contribution of DD to R-Square	-0.0036	-0.0069	-0.0068	-0.0070	

Moody's rating change equals 2 if the credit rating remains the same; equals 3 if it is upgraded without crossing the investment grade threshold; and equals 4 if it is upgraded from non-investment to investment grade. The model estimates the probability of no rating change. dDD_BIAV, dDD_EIAV, dDD_DIAV, and dDD_EDIAV are quarterly changes in the distance-to-default measures calculated from the book-value-implied, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. SIZE is the log of the market value of assets. dRTG is the change in credit rating. Lags of variables are so indicated. Indicator variables are not presented for ease of exposition. R-Square is the maximum re-scaled R-square, which is an indicator of fit for logit models. The contribution of each DD to R-Square is the difference between the R-square of the model including that DD and the R-square of a base model excluding it. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and * respectively.

Table 9

Logit Analysis of Credit Rating Downgrades

Independent Variable	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)	Estimate (Std Error)
Intercept=1	-6.6990 ***	-6.6760 ***	-6.6425 ***	-6.6717 ***	-6.7530 ***
	0.4870	0.4874	0.4879	9.4875	0.4333
Intercept=2	-4.1244 ***	-4.1034 ***	-4.0725 ***	-4.0995 ***	-4.3227 ***
	0.4715	0.4719	0.4724	0.4720	0.4202
SIZE_lag	0.1386 ***	0.1381 ***	0.1339 ***	0.1379 ***	0.1740 ***
	0.0322	0.0322	0.0323	0.0323	0.0291
dRTG_lag	-0.0838	-0.1011	-0.0826	-0.1062	-0.1042
	0.0997	0.1003	0.0999	0.1002	0.0933
dDD_EDIAV_lag1	-1.3080 ***				
	0.3719				
dDD_EDIAV_lag2	-1.2500 ***				
	0.3791				
dDD_EDIAV_lag3	-1.2376 ***				
	0.3895				
dDD_EDIAV_lag4	-1.6292 ***				
	0.3721				
dDD_EIAV_lag1		-0.1634 ***			
		0.0403			
dDD_EIAV_lag2		-0.2190 ***			
		0.0452			
dDD_EIAV_lag3		-0.1419 ***			
		0.0456			
dDD_EIAV_lag4		-0.0820 **			
		0.0415			
dDD_DIAV_lag1			-0.1286 ***		
			0.0452		
dDD_DIAV_lag2			-0.1648 ***		
			0.0485		
dDD_DIAV_lag3			-0.1905 ***		
			0.0485		
dDD_DIAV_lag4			-0.1499 ***		
			0.0443		
dDD_BIAV_lag1				-0.1423 ***	
				0.0383	
dDD_BIAV_lag2				-0.1933 ***	
				0.0429	
dDD_BIAV_lag3				-0.1235 ***	
				0.0432	
dDD_BIAV_lag4				-0.0705 *	
				0.0392	
R-Square	0.0419	0.0399	0.0393	0.0391	0.0329
Marginal Contribution of DD to R-Square	0.0090	0.0070	0.0063	0.0061	0.0000

Moody's rating change equals 0 if the firm is downgraded from investment to non-investment grade; equals 1 if the firm is downgraded without crossing the non-investment grade threshold; and equals 2 if the credit rating remains the same. The model estimates the probability of credit rating downgrade. dDD_BIAV, dDD_EIAV, dDD_DIAV, and dDD_EDIAV are quarterly changes in the distance-to-default measures calculated from the book-value-implied, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. SIZE is the log of the market value of assets. dRTG is the change in credit rating. Lags of variables are so indicated. Industry indicator variables are not presented here for ease of exposition. R-Square is the maximum re-scaled R-square, which is an indicator of fit for logit models. The contribution of each DD to R-Square is the difference between the R-square of the model including that DD and the R-square of a base model excluding it. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and * respectively.

Figure 1
Median Implied Asset Volatility

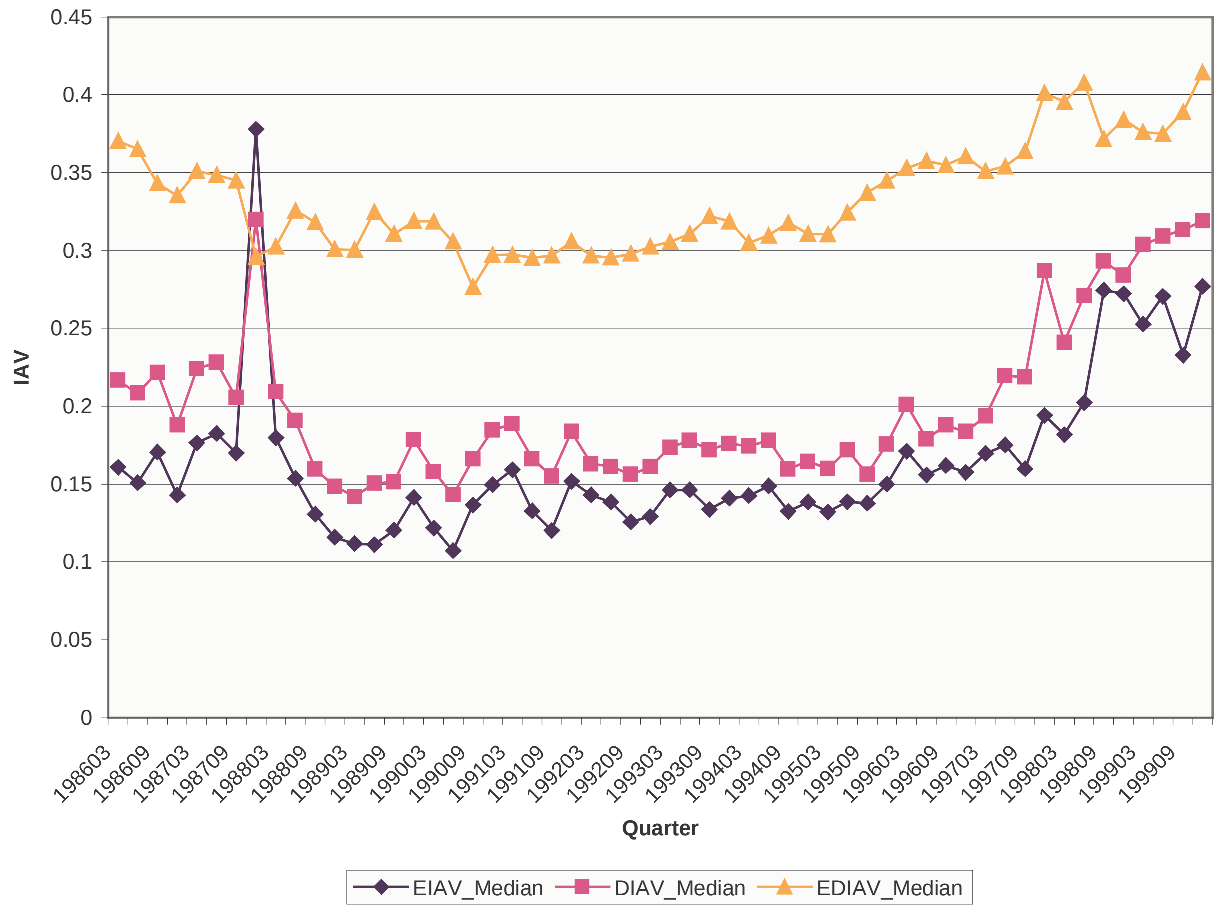

Figure 2
Median Implied Asset Volatility by Moneyness Quartile

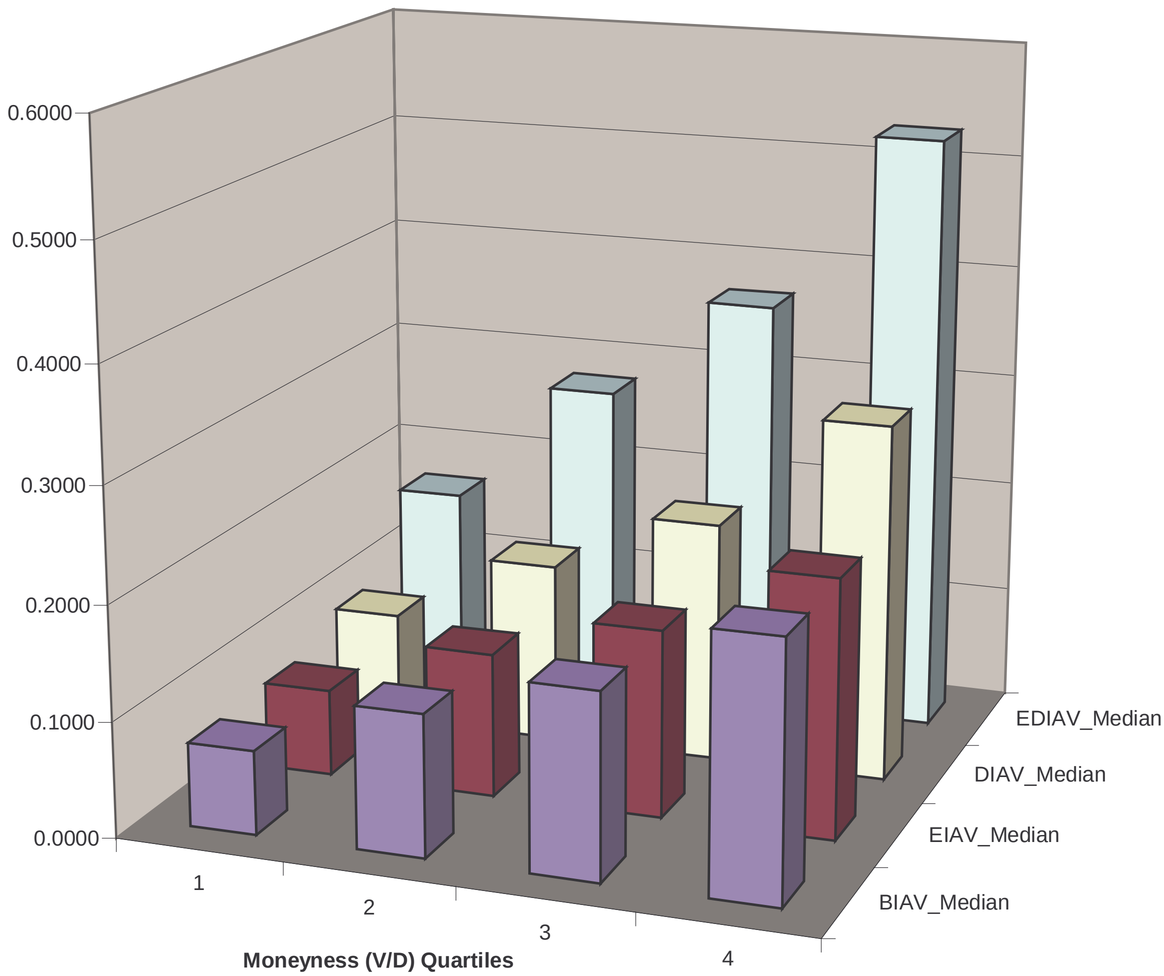

Figure 3
Median Values of Distance-to-Default Measures