TWO ESSAYS IN FINANCIAL ECONOMICS: FIRM RISK REFLECTED IN SECURITY PRICES

By

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A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

UNIVERSITY OF FLORIDA

2004

I would like to dedicate this dissertation to my parents, Margarita and Marincho Nikolovi; and my brother, Roumen Nikolov.

ACKNOWLEDGMENTS

I would like to thank my supervisory committee members Mark Flannery, Jason Karceski, Nimal Nimalendran, Dave Brown, and Chunrong Ai. All of them have made the completion of this dissertation possible. I am grateful for their willingness to review my doctoral research and to provide me with constructive comments.

I am especially thankful to Mark Flannery, my supervisory committee chair, who has been a major source of academic and personal encouragement. I thank him for his guidance, patience, and friendship through the painful process of writing this dissertation. His contagious enthusiasm for research, and willingness to share his knowledge and experience, stimulated me and kept me going. I also thank Jason Karceski for being an invaluable mentor throughout my graduate studies, gladly helping anytime I requested professional or research advice.

I am grateful to all the people of the Finance Department: the professors who guided me through coursework and supported my research; and the fellow graduate students, too numerous to name but instrumental in my growth as a scholar.

Finally, I want to thank my friends, without whom I would have finished this dissertation much sooner.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Abstract of Dissertation Presented to the Graduate School
of the University of Florida in Partial Fulfillment of the
Requirements for the Degree of Doctor of Philosophy

TWO ESSAYS IN FINANCIAL ECONOMICS: FIRM RISK REFLECTED IN SECURITY PRICES

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August 2004

Chair: Mark J. Flannery
Major Department: Finance, Insurance, and Real Estate

We examine the ability to extract risk information from the market prices of a firm's securities. We use contingent claim models for firm valuation to construct risk measures from equity prices, debt prices, and a combination of both. We provide empirical evidence on the relative accuracy and forecasting ability of these measures for industrial and financial firms.

We compare a number of methodologies for constructing implied asset volatility estimates for industrial firms. We document that while different methodologies produce different estimates, these differences are not crucial in explaining realized asset volatility, Moody's credit ratings, Altman's Z scores, or default occurrences. Within each test, some estimates outperform others, but no estimate is consistently best. We also show that, while the choice of using equity or debt prices to extract firm risk information appears to be inconsequential, the choice of model parameters is quite important. The manner in which we adjust yield spreads to account for embedded call options, and tax differences

between corporate and Treasury securities as well as assumptions about the maturity of debt and debt priority structure have a significant effect on the level and rank ordering of firm risk measures.

Finally, we address the value of market information in the government oversight of U.S. bank holding companies. We construct risk measures obtained from equity prices alone, debt prices alone, and a combination of both. We observe that default risk measures constructed from debt prices generally outperform those constructed from equity prices in both contemporaneous and forecasting models. We further document that models using information from both equity and debt prices improves on the explanatory power of equity-only or debt-only models. Risk measures constructed from both equity and debt prices are more closely related to bank credit ratings, asset-portfolio quality indicators, and overall financial health. In addition, models using both equity and debt price information can better predict material changes in the firm's default probability, and quarter-to-quarter changes in the firm's asset-portfolio quality and overall condition.

CHAPTER 1
INTRODUCTION

The ability to accurately assess firm total asset risk has important applications in many areas of finance – risk management, bank lending practices, and regulation of financial firms, among others. Thus, improving this ability can have important implications for both finance researchers and practitioners. Although considerable research effort has been put toward extracting firm risk information from either equity or debt prices, to the best of our knowledge, no previous study has assessed the relative informational quality of firm risk measures obtained from equity and debt prices; or the impact of alternative model assumptions on the accuracy of these measures.

Financial theory suggests that in a world of complete and frictionless markets, both equity and debt prices fully reflect the available information about a firm's condition. We can value firm equity as a call option written on the market value of the firm's assets (Black and Scholes 1973), and we can value risky debt as a riskless bond with an embedded put (default) option (Merton 1974). Since both the equity-call and debt-put options are written on the same underlying – the firm's total assets – they are functions of the same set of variables: the market value of firm's assets, the volatility of the firm's assets, the face value of debt, short-term interest rates, and the time to firm resolution (debt maturity). A firm's credit risk should then be reflected in both equity and debt prices, if markets were perfect. However, both equity and debt markets are characterized by frictions. Which of these is characterized by fewer frictions, and which market's frictions have lower impact on firm risk measures?

Debt markets are notorious for their lack of transparency and data availability. While some corporate bonds trade on NYSE and Amex, they account for no more than 2% of market volume (Nunn et al. 1986). In addition, data quotes on OTC trades tend to be diffused and based on matrix valuation rather than on actual trades. Warga and Welch (1993) document that there are large disparities between matrix prices and dealer quotes. Hancock and Kwast (2001) compare bond-price data from four sources and find that correlation between bond yields from the different sources are in the 70-80% range. Even if bond data were readily available, extracting firm risk information can be difficult. The typical approach is to use debt prices, and calculate yield spreads as the difference between a corporate yield and the yield on a Treasury security of the same maturity. This spread is assumed to be a measure of credit risk. However, corporate yields will differ from Treasury yields for a number of reasons other than credit risk (Delianedis and Geske 2001, Elton *et al*. 2001, Huang and Huang 2002). These include premiums for tax and liquidity differences between corporate and Treasury securities, as well as compensation for common bond-market factors. Yield spreads reflect not only default probability but also expected losses, which requires an adjustment for recovery rates. Adjustments are also needed for redemption and convertibility options, sinking fund provisions, and other common bond features. Finally, yield spreads reflect differences in duration/convexity, because cash flows of corporate and Treasury bonds are not perfectly matched. Despite all of these shortcomings, yield spreads are commonly used as a proxy for firm risk.

In contrast to debt markets, equity markets are liquid and deep. Equity prices of high frequency and quality can be easily obtained. Nevertheless, these markets are also characterized by imperfections. Stock prices have been documented to overreact or

underreact to news, and have been shown to appear too volatile than a basic dividend model would predict (Cochrane 1991, LeRoy and Porter 1981, Shiller 1981, West 1988). Also, while yield spreads are easily interpreted as a measure of firm risk, there is no analogous measure obtained from equity prices. Although some researchers have used equity abnormal returns as a measure of firm risk, these are not immediately interpreted as such: an increase in abnormal return might be the result of an increase in firm profitability and/or increase in firm risk.

Since both equity and debt markets are characterized by frictions, and since both equity and debt prices impose challenges in extracting information about firm risk, whether one of these two information sources is better than the other is an empirical question. We evaluate the relative informational content and accuracy of firm risk measures obtained from equity or debt prices, and examine whether combining information from both markets can produce more accurate risk measures.

We construct alternative estimates of asset volatility for a large set of U.S. firms, and tests their value as forecasting and risk-valuation variables. Chapter 2 focuses on industrial firms. We start by constructing asset volatility estimates for a set of 1,264 U.S. industrial firms. We then test the information content of these estimates by using them to predict defaults, credit-rating changes, and asset-return features. The result is specific information on the value of alternative methods for estimating a firm's asset volatility. Chapter 3 applies general insights from the industrial-firm analysis 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. We start by constructing three implied asset volatility estimates for a set of 84 U.S. bank holding companies (BHCs) over the period 1986-1999. These asset volatilities are then combined with firm leverage to produce three versions of a single measure of default risk – distance to default (DD). We then investigate the contemporaneous association among the three DD measures and other indicators of bank risk, and their ability to foresee changes in bank risk. Results of this analysis will have important implications for the regulation of large financial firms.

CHAPTER 2
INDUSTRIAL-FIRM RISK REFLECTED IN SECURITY PRICES: PREDICTING CREDIT RISK WITH IMPLIED ASSET VOLATILITY ESTIMATES

The ability to accurately assess firm total asset risk has important applications in many areas of finance – claim pricing, risk management, and bank lending practices among others. Thus, improving this ability can have important implications for both finance researchers and practitioners. Although considerable research effort has been put toward extracting firm risk information from either equity or debt prices, to the best of our knowledge no previous study has assessed the relative informational quality of industrial-firm risk measures obtained from equity and debt prices, and the impact of alternative model assumptions on the accuracy of these measures.

Since both equity and debt markets are characterized by frictions, and since both equity and debt prices impose challenges in extracting information about firm risk, whether one of these two information sources is better than the other is an empirical question. In this chapter, we evaluate the relative informational content and accuracy of firm risk measures obtained from equity or debt prices, and examine whether combining information from both price sources can produce more accurate risk measures. First, using information from equity and/or debt prices, we construct four asset volatility estimates for a set of 1,264 U.S. industrial firms over the period 1975-2001. Second, we test the information content of these asset volatility estimates by using them to predict defaults, credit ratings, Altman's (1968) Z scores, and asset-return features. The result is specific information on the value of alternative methods for estimating a firm's total asset

volatility. Finally, we investigate the effect of alternative-model assumptions on the quality of the firm risk measures.

Four estimates of asset volatility are analyzed in this chapter:

- Asset volatility obtained by de-levering equity-return volatility: simple implied asset volatility (SIAV).
- Asset volatility implied by equity prices alone (EIAV).
- Asset volatility implied by debt prices alone (DIAV).
- Asset volatility implied by contemporaneous equity and debt prices (EDIAV).

Our analysis indicates 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 measures of total firm risk, then risk rankings will depend significantly on the method used to calculate 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) – the number of standard deviations required to push a firm into insolvency. These differences justify a closer look at the relative forecasting and risk-valuation ability of the implied asset volatility and corresponding DD estimates.

Because implied asset volatility is the market's forecast of future volatility, the first set of tests examines the association among the four implied asset volatility (IAV) estimates and the subsequent realized volatility of total asset returns. We document that all of the IAV estimates are biased forecasts of realized volatility. Furthermore, they do not seem to incorporate all of the historical information available at the time they are calculated. Fit statistics indicate that SIAV and EIAV tend to outperform the others when it comes to forecasting realized volatility. Also, of the four IAV estimates, DIAV seems to add the most new information to historical asset volatility in forecasting realized

volatility. This is contrary to the conventional assumption that debt prices are extremely noisy.

The second set of tests examines if any of the four DD estimates successfully distinguishes firms that default from those that do not. We find that a decrease in any of the four DD estimates increases the probability that a firm will then default. We replicate the tests for the subsample of non-investment grade firms, in an attempt to achieve a more balanced sample. For non-investment grade firms, we find that only the DD estimates based on EDIAV and SIAV help forecast default. Judging by the fit statistics of the four models in both sets of tests, we conclude that the DD calculated from SIAV contains the most relevant information about an upcoming default.

Because previous studies indicate that credit ratings can reliably proxy for default probability, our third test investigates the relation between a firm's DD and its Moody's credit rating. Although all four DD measures are statistically significant, the one based on EIAV seems to be the most accurate, as indicated by its marginal contribution to the model's fit. It is outperformed by DD_EDIAV when we limit ourselves to the subset of non-investment grade firms, and by DD_DIAV when we limit ourselves to the subset of investment-grade firms. We also examine the ability of changes in DD to predict credit-rating upgrades and downgrades. Although only some lags of the DD estimates are statistically significant in explaining Moody's upgrades, all of them successfully predict credit downgrades – a decrease in DD increases the probability that a firm will be downgraded. The DD calculated from EIAV seems to be the most accurate predictor, as judged by the model's fit statistics.

Finally, we replicate the credit-rating tests above using another proxy for default probability – Altman's (1968) Z score. We find that variations in DD successfully explain variations in Z but only for low-Z (high default probability) firms. This is consistent with Dichev (1998) who shows that Z is a better measure of default risk when the *ex ante* default probability is high. Of the four DD estimates, those calculated from EIAV and DIAV seem to add the most explanatory power to a base model that includes only control variables. We analyze the relationship between changes in DD and changes in Z separately for negative and positive changes, analogously to our separate analysis of rating downgrades and upgrades. Consistent with our rating-change results, we find that lagged changes in DD have more explanatory power for negative Z-score changes than for positive ones. The fit statistics of these models indicate that DD adds little-to-no new information to lagged Z changes, and that the most new information is added by the DD estimate calculated from EIAV.

In summary, different methodologies produce different estimates of implied asset volatility. These differences are even larger when compounded by leverage differences to produce DD measures. However, the analysis in this chapter suggests that these differences are not crucial in explaining realized asset volatility, Moody's credit ratings, Altman's (1968) Z scores, or default occurrences. Within each test, some IAV and DD measures outperform others, but no estimate is consistently "best." This implies that firm risk can be extracted from equity and debt prices equally accurately, thus suggesting that researchers and practitioners can use high-frequency and high-quality equity prices without losing much important information.

While the choice between equity and debt prices as a source of firm risk information appears to be inconsequential, the choice of contingent-claim-model assumptions does not. The informational content of risk measures is significantly affected by tax and call-option adjustments, as well as time-to-firm-resolution and debt-priority-structure assumptions. This provides an important checklist of robustness tests for those conducting empirical research using contingent-claim pricing models.

2.1. The State of the Literature

2.1.1. Contingent Claim Valuation Models

Black and Scholes (1973) were the first to recognize that their approach to valuing exchange-traded options could also be used to value firm equity. 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

$$E = VN(d_1) - De^{-R_f \tau} N(d_2) \tag{2-1}$$

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 returns,
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 consisting of riskless debt with the same characteristics as the risky debt, and a short put option written on the firm's assets with an exercise price equal to the face value of debt. Re-arranging the formula used by Merton (1974) allows us to express the credit-risk premium as the spread between the yield on risky debt, R, and the yield on risk-free debt with otherwise the same characteristics:

$$R - R_f = -\ln\left\{\frac{V}{D}e^{R_f\tau}N(-d_1) + N(d_2)\right\}/\tau \qquad (2\text{-}2)$$

One of the basic assumptions underlying Merton's (1974) derivation is that the firm issues a single homogenous class of debt. In reality, the characteristics of debt are highly variable, which makes his model intuitively useful, but not precisely 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. Thus, while knowing the precise breakdown of debt into priority classes is crucial for debt valuation, it does not affect the valuation of equity.

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

$$X_2 = V\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - D_1 e^{-R_f\tau} N(\tilde{d}_2) + (D_1 + D_2) e^{-R_f\tau} N(\hat{d}_2) \qquad \text{(2-3')}$$

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.

The Black-Cox model most frequently appears in the literature as the spread between the yield on subordinated debt (R_2) and the risk-free rate (R_f) of the same maturity:

$$R_2 - R_f = -\ln\left\{\frac{V}{D_2} e^{R_f\tau}\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - \frac{D_1}{D_2} N(\tilde{d}_2) + \frac{D_1 + D_2}{D_2} N(\hat{d}_2)\right\} / \tau \qquad \text{(2-3)}$$

2.1.2. Applications of Contingent Claim Valuation

The above contingent-claim approach to pricing firm debt has 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 because of 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. Sarig and Warga (1989) estimate the term structure of credit spreads, and show it to be consistent with contingent-claim model predictions. Wei and Guo (1997) test the models of Merton (1974) and Longstaff and Schwartz (1995), and find the Merton model to be empirically superior. It is important to note that in calculating theoretical credit spreads, all of these studies require an estimate of the variance of firm assets. One way to obtain 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. Another way to estimate 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):

$$\sigma_V = \sigma_E \frac{E}{V} \qquad (2\text{-}4')$$

where σ_E is the historical standard deviation of equity returns, E is the market value of equity, and V is the sum of E and book value of debt. We call this the simple implied asset volatility (SIAV). 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 that consists of Eq. 2-1 and Merton's boundary condition

$$\sigma_V = \sigma_E \frac{E}{VN(d_1)} \tag{2-4}$$

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 is 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 for 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) use a contingent-claim model to calculate the equity values of failed banks and find that these greatly exceed the negative net-worth estimates of the FDIC. They conclude that the equity-call model produces poor estimates of the market value of assets. The accuracy of the asset volatility estimates, however, has not been previously examined.

While the literature on deposit insurance uses 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 nonlinear 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. Their methodology insight has since been used by Hassan (1993) and Hassan *et al*. (1993) who apply contingent-claim valuation techniques to calculate implied asset volatilities; and by 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 is V_DIAV.

The last methodology we analyze is closest in spirit to the one used by Schellhorn and Spellman (1996). They examine four banks over 1987-1988, and calculate two estimates of implied asset volatility for each bank. The first estimate is EIAV and is based on the methodology of Ronn and Verma (1986) described earlier. The second estimate solves Equations 2-1 and 2-3 simultaneously for 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 is V_EDIAV. Schellhorn and Spellman (1996) 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 the work of Schellhorn and Spellman (1996) in three ways. First, we use a larger and more-diverse sample. We obtain data on industrial firms for the period 1975-2001. Second, we compare a broader range of asset value and volatility estimates. We judge the EDIAV and corresponding V_EDIAV against estimates calculated using three more traditional methodologies (SIAV, 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.

2.2. Methodologies for Constructing Risk Measures from Market Prices

This section summarizes the three methodologies traditionally used to estimate the market value and volatility of assets. It then proposes one that relies on contemporaneous equity and debt prices to obtain V and σ_V. Finally, it explains the construction of default-risk measures from implied asset value and volatility estimates.

2.2.1. Methodologies for Calculating Implied Asset Value and Volatility

The simple implied asset volatility (SIAV) is the most popular estimate of asset volatility found in the finance literature. This is likely due to the ease of computation since it uses a simplified version of the boundary condition

$$\sigma_V = \sigma_E \frac{E}{V} \qquad (2\text{-}4')$$

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. This is equivalent to assuming that the firm's debt is risk-free, which implies that we will overestimate its market value by the value of the put option embedded in risky debt. Thus, we expect this methodology to produce a market-value-of-assets estimate higher than those produced by the three simultaneous-equation methodologies that follow.

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

$$E = VN(d_1) - De^{-R_f\tau}N(d_2) \tag{2-1}$$

$$\sigma_V = \sigma_E \frac{E}{VN(d_1)} \tag{2-4}$$

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 use the sum of the market value of assets and book value of debt; and for the starting value of σ_V we use SIAV. 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 returns over the quarter.

The debt-implied asset volatility (DIAV) is calculated by solving the system of nonlinear equations:[1]

$$R_2 - R_f = -\ln\left\{\frac{V}{D_2}e^{R_f\tau}\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - \frac{D_1}{D_2}N(\tilde{d}_2) + \frac{D_1 + D_2}{D_2}N(\hat{d}_2)\right\}/\tau \tag{2-3}$$

$$\sigma_V = \sigma_E \frac{E}{VN(d_1)} \tag{2-4}$$

for σ_V and V using the Newton iterative method. Once again, for the starting value of V, we use the sum of the market value of assets and book value of debt; but for the

[1] We use the subordinated-debt valuation model, because we assume that publicly traded debt is likely to be last in a firm's debt-priority structure. We discuss the reasonableness of this assumption later and explore the sensitivity of our results to alternative assumptions.

starting value of σ_V we use the theoretically more-accurate EIAV. As in the calculation of 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 returns at the end of the quarter.

The equity-and-debt implied asset volatility (EDIAV) is obtained by solving the system of nonlinear equations

$$E = VN(d_1) - De^{-R_f\tau}N(d_2) \tag{2-1}$$

$$R_2 - R_f = -\ln\left\{\frac{V}{D_2}e^{R_f\tau}\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - \frac{D_1}{D_2}N(\tilde{d}_2) + \frac{D_1 + D_2}{D_2}N(\hat{d}_2)\right\}/\tau \tag{2-3}$$

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

2.2.2. Calculating Credit-Risk Measures from Implied Asset Value and Volatility

Three elements determine the probability that a firm will default – the market value of its assets, the portion of liabilities due, and the volatility of asset returns. The first two determine the default point of the firm, which as explained earlier is at first set to 97% of total debt. The last element, asset volatility, captures business, industry, and market risks faced by the firm. If the implied asset volatility estimates calculated in our study are correct assessments of the firm's future risk exposure, then along with the firm's asset and liability values they should reflect default probability accurately. We 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 is calculated as

$$DD = \frac{\ln(V/D) + \left(R_f - 0.5\sigma_V^2\right)\cdot T}{\sigma_V \sqrt{T}}$$

Intuitively, a DD value of X tells us that a firm is X standard deviations of assets away from default. Thus, a low DD indicates that a firm has a high probability of default.

2.2.3. Methodology Assumptions

The methodologies above 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) lists a series of deviations from these assumptions. However, it is an empirical question whether these deviations make the estimates of asset value and volatility less meaningful. In addition to the standard assumptions, applying contingent-claim valuation techniques requires 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. Our study aims to determine which of the simplifying assumptions made in calculating asset values and volatilities affect the informational content and accuracy of the 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 1 year. Banking researchers claim that the 1-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 close the bank. An alternative resolution-time assumption is used 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 1-year-to-maturity assumption. However, they offer no evidence as to which maturity assumption produces the better estimate of asset volatility. In the application of contingent-claim models to the valuation of industrial firms there is much less uniformity in the time-to-expiration assumption. Huang and Huang (2002) use the actual maturity of debt, Delianedis and Geske (2001) use the duration of debt, and Crosbie and Bohn (2002) use an interval of 1 year. Since the empirical properties of implied total asset volatility are not the focus of these studies, they offer little evidence on the sensitivity of their results to alternative time-to-expiration assumptions. To start with, we assume that the time to resolution equals 1 year. We later explore the effects of two alternative assumptions – time to resolution equals to either the weighted average duration or the weighted average maturity of the firm's bond issues.

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. However, they do not examine the relative accuracy of the estimates obtained under alternative default-point assumptions.

2.3. Data Sources

To construct the above estimates of asset value and volatility, we combine a number of data sources for the period of December 1975 - December 2001. 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 comes from the Compustat Database. 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. These matching procedures result in data on at least 1,264 unique industrial firms which give us 28,262 firm-quarter observations for 1975-2001.

2.3.1. Bond Prices and Characteristics

The initial sample includes all firms from the WLBFID and FISD whose bonds are traded during the period of 1975-2001. 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 coupon-paying debentures that are not convertible, putable, secured, or backed my mortgages/assets. We collect data on their month-end yield, prepayment options, and amount outstanding.[2] 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, non-putable, and non-secured debentures issued by U.S. corporations. The main difference between the two databases is the source and type of 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

[2] Data for December 1984 is substantially incomplete and produces no viable observations for the fourth quarter of that year. We use the November data to match it against balance sheet data for the last quarter of 1984.

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 need to subtract from each corporate yield the yield on a debt security that is risk-free but otherwise has the same characteristics as the corporate bond. The most common approach to calculating a credit-risk spread is to difference the yield on a corporate bond with that on a Treasury bond of the same remaining maturity. To do so we collect 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 our first measure of the raw credit-risk spread.

2.3.1.1. Tax adjustment

There is growing evidence that corporate yield spreads calculated as above cannot be entirely attributed to the risk of default. Huang and Huang (2002) and Delianedis and Geske (2001) demonstrate that at best less than half of the difference between corporate and Treasury bonds is due to default risk. Elton *et al*. (2001) suggest that this difference can be explained by the differential taxation of the income from corporate and Treasury bonds. Since interest payments on corporate bonds are taxed at the state and local level while interest payments on government bonds are not, corporate bonds have to offer a higher pre-tax return to yield the same after-tax return. Thus, the difference between the yield on a corporate and the yield on a Treasury bond must include a tax premium. Elton *et al*. (2001) illustrate that this tax premium accounts for a significantly larger portion of

the difference than does a default risk premium. For example, they find that for 10-year A-rated bonds, taxes account for 36.1% of the yield spread over Treasuries compared to the 17.8% accounted for by expected losses. Cooper and Davydenko (2002) derive an explicit formula for the tax adjustment proposed by Elton *et al*. (2001). They calculate that the tax-induced yield spread over Treasuries is:

$$\Delta y^{tax} = \frac{1}{t_M} \ln\left[\frac{1-\tau}{1-\tau \exp\left(-r_{t_M}^{rf} t_M\right)}\right]$$

where t_M is the time to maturity for both the corporate and the Treasury bonds, τ is the applicable tax rate, and $r_{t_M}^{rf}$ is the Treasury yield.[3] We use this formulation along with the estimated relevant tax rate of 4.875% from Elton *et al*. (2001) to calculate a hypothetical Treasury yield if Treasuries were to be taxed on the state and local level.[4] The difference between a corporate yield and a corresponding "taxable" Treasury rate is a measure of the tax-adjusted raw credit-risk spread.

Alternatively, we can difference corporate yields with the yield on the highest rated bonds under the assumption that these almost never default. We obtain Moody's average yield on AAA-rated bonds from the Federal Reserve Board's H.15 releases. It is important to note that differencing a corporate yield with the AAA yield might allow us to extract a more accurate estimate of the credit-risk premium by controlling for liquidity as well as tax differential between corporate and Treasury bonds. However, it is also the

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[3] This formulation of the yield spread due to taxes assumes that capital gains and losses are treated symmetrically and that the capital gain tax is the same as the income tax on coupons.

[4] Corporate bonds are subject to state tax with maximum marginal rates generally between 5% and 10% depending on the state. This yields an average maximum state tax rate in the U.S. of 7.5%. Since in most states, state tax for financial institutions (the main holder of bonds) is paid on income subject to federal taxes, Elton *et al.* (2001) use the maximum federal tax rate of 35% and the maximum state tax rate of 7.5% to obtain an estimate for τ of 4.875%. An alternative estimate is produced by Severn and Stewart (1992) and equals to 5%.

case that the AAA yield has a number of drawbacks – it averages the yields on bonds of different maturity and different convertibility/callability options. Nevertheless, for the non-AAA-rated bonds in our sample we use the difference between their yield and the average AAA yield as an alternative tax adjustment for the raw credit-risk spread. We start by differencing the corporate yields with the hypothetical taxable Treasury yields. However, in the spirit of this study we later investigate whether using the average AAA yields significantly affects the accuracy and informational content of the implied asset volatility estimates.

2.3.1.2. Call-option adjustment

The tax-adjusted yield spreads calculated above might still contain some non-credit related components. 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 spread over Treasuries whether adjusted for taxes or not, will 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 "taxable" 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 adjusted for taxes. 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 tax-adjusted spreads calculated earlier to obtain option-adjusted credit spreads.

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.

In a small number of cases these credit spreads turn out to be negative. A cursory examination of these occurrences indicates that when the term structure of interest rates is relatively flat and interest rate volatility high, our option-adjustment methodology produces higher option values. When combined with an initially low yield (high-rated bonds) these high option values lead to negative credit spreads. Since the theoretical motivation used in this study does not allow for negative credit spreads and since negative credit spreads are heavily concentrated in highly rated bonds, we winsorize our set of credit spreads at zero.

2.3.1.3. Yield spread aggregation

To obtain a firm yield spread, YS, 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. We investigate whether different aggregation approaches produce significantly different IAV estimates.

2.3.2. 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 annualized standard deviation of daily returns during the quarter. The market value of equity 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 fewer than fifty equity-return observations in a quarter. These data filters attempt to reduce the effect of the bid-ask bounce on the estimate of equity-return volatility, while providing enough observations to make the quarterly volatility estimate meaningful.

2.3.3. Accounting Data

Quarterly accounting data is obtained from the CRSP/COMPUSTAT Merged Database using PERMNOs. For each 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 1975-2001. We also obtain industry classification codes to construct 48-industry indicator variables following Fama and French (1997).

Our methodology requires information on the priority structure of total debt in addition to its amount. 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 1975-2001. We use this as one estimate of the firm's face value of subordinated debt and input it into Eq. 2-3. This simplification is based on the fact that firms tend to take out bank loans before they turn to the public debt markets, and is supported by the findings of Longhofer and Santos (2003) that most bank debt is senior. We investigate the sensitivity of our findings to two alternative assumptions about debt priority structure. The first one treats all debt as of a single priority class and as of homogeneous risk. That is, credit spreads calculated earlier are assumed to reflect the default probability on total debt and not only the default probability on bond issues outstanding. We use the credit spread, YS, and total debt as inputs into Eq. 2-2. The second alternative assumption allows for at least two priority and risk classes of debt. If YS is of a bond issue explicitly described as senior, then the spread is assumed to reflect the risk of the firm's most senior debt. Along with the face value of the firm's senior bonds outstanding it is inputted in Eq. 2-2. If YS is instead that of a non-senior bond issue, then it is assumed to reflect the risk of the firm's most junior debt claims. This credit spread and the face value of subordinated bonds are then used as inputs in Eq. 2-3. This second alternative assumption is equivalent to assuming that senior bonds are the company's most senior debt compared to the base assumption that senior bonds might be subordinated to bank loans and private debt. If this generalization is incorrect and a firm has debt senior to the senior bond issues, then YS will overestimate the riskiness of the firm's assets and produce IAV estimates higher than those produced by the base case.

2.3.4. Default Data

We use two proxies 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 for the period 1975-2001 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 for the period 1995-2001. Since an extremely small portion of the firms in our sample default and since there is a large overlap between the CRSP delisting dates and FISD bankruptcy-filing dates, we combine the two data sources.[5] 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.

2.4. Summary Statistics

We use the methodologies described earlier to compute four estimates of implied asset value and volatility. The base input assumptions are: the time to debt resolution equals one year; the default point is at 97% of total debt; the issuer's yield is the yield on the most recently issued bonds; the adjustment for taxes is based on Cooper and Davydenko (2002); and, subordinated debt's face value is the face value of the firm's bonds outstanding. 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 asset value and volatility estimates for 27,723 out of the 28,557 original observations.

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

Table 2-1 presents summary statistics on the sample of 27,723 firm-quarters. The average market value of assets is in the range of $6.3-8.1 billion 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.

Unlike the estimates of asset value, the estimates of asset volatility are significantly different across methodologies. The average implied volatility is the lowest, 16.9%, 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 estimate becomes higher – it is 17.9% for EIAV, 22.9% for DIAV, and 31.9% for EDIAV. The magnitude of the EIAV and DIAV estimates is consistent with that documented in Cooper and Davydenko (2002) and Huang and Huang (2002) both of who rely on historical equity volatility in computing IAV.

We investigate whether the IAV differences vary across quarters. Figure 2-1 plots median implied asset volatility for each quarter during 1975-2001, and makes four noteworthy points. First, the four IAV measures appear to follow a similar time pattern. The one notable exception is the last quarter of 1987 when median EIAV, DIAV, and SIAV dramatically increase, while EDIAV falls. This is likely due to the reliance of the first three estimates on historical equity volatility calculated over the three-month period that includes the October 1987 crash. On the other hand, EDIAV is not affected by the crash-induced historical equity volatility and as a result is a more forward-looking

assessment of asset volatility. In fact, EDIAV increases in the second quarter of 1986 possibly in anticipation of the 1987 events. Third, the plot shows that the median SIAV is consistently the lowest estimate of IAV. This is an important observation given the wide use of the estimate in finance research. Finally, the plot shows that the four IAV estimates have significantly increased and the differences among them decreased since the latter part of 1998.

We also explore whether our estimates of implied asset volatility are affected by firm leverage. At the end of each quarter, we use firm assets-to-debt ratio ranking to assign them to one of four quartiles. Figure 2-2 shows median implied asset volatilities from our four methodologies by assets-to-debt ratio quartile. It is apparent that the higher the amount of debt relative to assets, the lower the implied volatility. A possible explanation for this finding is that firm capital structure and asset volatility are simultaneously determined. Firms financed with relatively less debt might be willing to take on more risk since they have a significant equity cushion to absorb changes in asset value. Conversely, those that have relatively more debt in their capital structure might be more risk averse since small fluctuations of total asset value can push them into default.

The distance-to-default (DD) measure 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 2-1 present summary statistics on DD calculated from the four estimates of asset volatility. The average DD is 5.08 if calculated from SIAV, 4.66 if calculated from EIAV, 2.17 if calculated from DIAV, and 2.23 if calculated from EDIAV.

The time series behavior of the median of the four DD measures can be seen in Figure 2-3. While the DD estimates calculated from SIAV and EIAV are very volatile, the ones calculated from DIAV and EDIAV are relatively stable. For instance, during 1980-1997 the DD calculated from EDIAV has fluctuated only in the range of 1.50-2.50 while the median DD_EIAV has fluctuated in the range of 1.00-6.50. Once again, the medians of the four DD estimates seem to be converging towards the end of the sample period.

Table 2-2 examines more closely the correlation among the four IAV estimates. The table indicates that market value of assets estimates are largely independent of the methodology used to compute them – 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. SIAV, EIAV, and DIAV have simple and rank correlations in the 90% range. Two of the three measures however have lower simple correlations with EDIAV – 67.5% for SIAV and 62.4% for EIAV – with the rank correlations only slightly higher. In contrast, EDIAV is highly correlated with DIAV as indicated by the simple (rank) correlation of 90.5% (88.3%).

The simple and rank correlations among the four estimates of DD indicate a strong association between DD_SIAV and DD_EIAV on one hand, and DD_DIAV and DD_EDIAV on the other. Correlations between the first two are 91.3% (simple) and 92.3% (rank), and those between the second two are 94.7% (simple) and 90.9% (rank). In contrast, the DD calculated from DIAV has the lowest simple and rank correlation with the DD calculated from SIAV – 19.1% and 21.7%. The correlation of DD_EDIAV with

DD_SIAV and DD_EIAV is always less than 50%. Interestingly enough, the differences in DD measures do not simply reflect differences in IAV as indicated by the high correlation of DIAV with EIAV and SIAV, and relatively low correlations of DD_DIAV with DD_EIAV and DD_SIAV.

The wide range of implied asset volatility and distance to default correlations reported in Table 2-2 suggests that different methodologies produce very different estimates. Although all of the simple and rank correlations are statistically different from zero, all of them are also statistically different from one. By using information from different sources the four methodologies discussed in this study produce total risk and default measures not only of different magnitude but also of different ranking. However, whether any of the estimates are superior to the others is an empirical question that requires a comparison of their informational content and accuracy. We conduct such comparisons in the two sections that follow.

2.5. Realized Asset Volatility Tests

We start our comparison of the implied volatility measures by examining the relationship between them and realized asset volatility. We explore whether implied asset volatility is a rational forecast of realized asset 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 (Canina and Figlewski 1993, Chernov 2001, Day and Lewis 1992, Jorion 1995, Lamoureux and Lastrapes 1993, Poteshman 2000) 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 forecast of realized volatility and that it does not use available information efficiently. It will be interesting to relate these findings on the informational content of

implied equity volatility with our findings on the informational content of implied total 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 monthly time series of the market value of assets as the sum of the market value of common equity, the last available book value of preferred equity, and an estimate of the last available market value of debt. We use two alternative estimates for the market value of debt. The first estimate uses the monthly price of each bond issue and the amount outstanding of all bond issues tracked in the two bond databases to calculate an estimate of each issuer's total bond market value. It then substitutes the bonds' market value for their face value in the amount of total debt available from quarterly balance sheet reports. That is, the first estimate is the sum of the market value of each firm's publicly traded debt and the book value of its non-traded debt. The second estimate assumes that the yield on non-traded debt is the same as that on traded debt, and discounts the book value of total debt accordingly.

We use the monthly series of the market value of assets to calculate continuously compounded total asset returns. We define realized asset volatility, RAV_t, as the annualized standard deviation of these monthly returns over the two years following the end of quarter t. Historical asset volatility, HAV_t, is the annualized standard deviation of monthly returns over the year prior to quarter t. $RAV_1$and HAV_1 use our first estimate of the market value of debt, and RAV_2 and HAV_2 use the second.

2.5.1. Correlation between Implied Asset Volatility and Realized Asset Volatility

Table 2-3 presents the simple and rank correlations of the implied asset volatility (IAV) and historical asset volatility (HAV) estimates with realized volatility. The table suggests that IAV is significantly correlated with RAV with simple and rank correlation coefficients in the range of 25.1-31.2% and 42.5-56.7% respectively.[6] Among the four IAV estimates the DIAV has the highest simple correlation with RAV closely followed by SIAV and EIAV. The rank correlation of SIAV with RAV is the highest with the correlation of EIAV and DIAV with RAV coming in a close second and third. That is, none of the four implied volatilities appears to be a consistent winner with respect to its correlation with realized volatility. However, there is a consistent looser – the correlation between EDIAV and RAV is always the lowest. It is interesting to note that the HAV estimate is very highly correlated with RAV. It has the highest simple and rank correlation coefficient among all the volatility forecast measures.

Since a previous section of this study demonstrates that median implied asset volatilities vary with firm leverage, we investigate whether this variation occurs in the correlation between IAV and RAV as well. We calculate simple and rank correlations separately for each asset-to-debt ratio quartile and present these in Table 2-3. We find that as the amount of debt decreases (assets-to-debt ratio increases) simple correlations tend to increase. So do rank correlations of EDIAV and DIAV with RAV. On the other hand, rank correlations of EIAV and SIAV with RAV at first increase but then decrease as asset-to-debt ratio increases.

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[6] The correlations become smaller when the market value of debt is calculated under the assumption that all of a firm's debt is of the same risk class. This implies that such a generalization introduces additional noise in the implied volatility estimates.

2.5.2. Is Implied Asset Volatility a Rational Forecast of Realized Asset Volatility?

Theoretically, the estimates of implied total asset volatility calculated earlier are the market's forecasts of future asset volatility. We can assess the accuracy of these forecasts by examining the relation between them and realized asset volatility. Note that realized volatility can be viewed as its expected value conditional on information available at quarter-end t plus a zero-mean random error that is orthogonal to this information. That is

$RAV_{t,n} = E[RAV \mid I_{t,n}] + \varepsilon_{t,n}$ where $E[\varepsilon \mid I_{t,n}] = 0$.

This formulation leads to the regression test for forecast rationality[7]:

$$RAV_{t,n} = \delta_0 + \delta_1 Volatility\ Forecast_{t,n} + \varepsilon_{t,n} \qquad (2\text{-}5)$$

where Volatility $\text{Forecast}_{t,n}$ is one of the four implied asset volatility (IAV) estimates at the end of quarter t for firm n. If IAV_t is the true expected value of realized asset volatility conditional on information available at t, then regressing realized asset volatilities on their expectations should produce estimates of 0 and 1 for δ_0 and δ_1 respectively. Deviation from these values will be evidence of bias and inefficient use of information in the market's forecasts. Note that the forecast error must be orthogonal to any rationally formed forecast for any information set available at t. Thus, estimating the above regression for each of our IAV_t should produce $\delta_0 = 0$ and $\delta_1 = 1$ regardless of the quality of the information that IAV_t is based on. However, a more inclusive information set will produce a forecast that explains a relatively larger portion of the variation in the realization. That is, an implied asset volatility estimate derived from a more appropriate model will produce a higher R^2.

[7] Theil (1966) is credited with introducing this test for forecast rationality. The test has be successfully used in economics research, see Brown and Maital (1981) for an example.

The above tests might lead us to reject the null hypothesis that implied volatility is an unbiased forecast of realized volatility, if realized volatility is simply difficult to predict. That is, if the market's information set at quarter-end t contained very little useful information, then our results would be driven by estimation errors. To investigate whether realized asset volatility is at all predictable using information available at quarter-end t, we use yet another volatility forecast – historical asset volatility, HAV. We calculate this from a time series of historical asset values under the assumption that past volatility trends will continue in the future. We then estimate the model above with HAV as the Volatility Forecast.

Table 2-4 presents the results from the estimation of Eq. 2-5 for the whole sample of 21,570 firm-quarter observations. All of the intercepts are statistically different from zero which implies that both forward-looking and historical forecasts of asset volatility are positively biased. This bias is the smallest for the DIAV estimate (0.089) and the largest for the HAV estimate (0.137). The volatility forecasts do not appear to use information optimally as indicated by their coefficient estimates – in all of the estimations these are significantly different from one. The relative magnitude of the coefficients suggests that DIAV and SIAV make the best use of available information with coefficients of 0.453 and 0.460. The lowest forecast efficiency is displayed by the EIAV estimate with a coefficient of 0.293. The whole-sample results indicate that there is some variation in the quality of information on which each of the forecasts is based. Out of the four IAVs, the SIAV, EIAV and DIAV seem to be the most informative RAV forecasts as indicated by their R^2 of 9.6, 8.1, and 9.7% respectively. However, the R^2

produced by the HAV is even higher (10.3%) implying that this forecast is based on even better information.

Our conjecture that assets-to-debt ratio might affect the forecasting abilities of IAV is supported by the results from estimating Eq. 2-5 for each of the four assets-to-debt quartiles. The first and fourth quartiles display relatively higher intercepts and lower coefficient estimates compared to the second and third quartiles. This suggests that biases in the IAV forecasts tend to be larger for firms with extremely low or extremely large amount of debt in their capital structures. The explanatory power of the models also varies across assets-to-debt ratio quartiles. The IAV measures produce an R^2 that is extremely low in the first quartile – in the range of 0.7-3.5% – but increases as we move to higher quartiles. Nevertheless, explanatory power is always the highest for the model in which HAV is the independent variable. Its R^2 starts at 8.2 and increases to 15.5%.

It is interesting to note that the fourth assets-to-debt-ratio quartile is characterized by the highest explanatory power which implies that IAV estimates contain better information for low-debt firms. One possible explanation for this surprisingly high R^2 is that the realized volatility of firms in that quartile is simply easier to predict since a larger proportion of their total asset volatility comes from equity volatility. Since equity markets are characterized by higher trading volume and more transparency than debt markets, equity volatility might be easier to estimate and forecast than debt volatility. However, the results in Table 2-4 suggest that information from equity prices alone is not enough to form a good asset volatility forecast. Except for the first quartile DIAV always outperforms EIAV – it has the lower intercept implying lower bias, the higher coefficient implying higher informational efficiency, and the higher R^2 implying better information.

It is disappointing that EDIAV is a considerably worse forecast of RAV than any of the other IAV measures. This can be due to the fact that EDIAV is calculated from a single equity and debt value pair observed at the end of each quarter. This approach might produce measurement errors which can be reduced by using historical equity volatility calculated from equity prices over a whole quarter. As a result any of the IAV measures calculated from historical equity volatility might contain better information than EDIAV.

2.5.3. Is Implied Asset Volatility a Better Forecast Than Historical Asset Volatility?

Having both implied asset volatility and realized asset volatility available allows us to examine their relative informational content by estimating a model that includes both:

$$RAV_{t,n} = \rho_0 + \rho_1 IAV_{t,n} + \rho_2 HAV_{t,n} + \varepsilon_{t,n} \qquad (2\text{-}6)$$

If the information that is used to calculate one of the forecasts is a subset of the information used to calculate the other, then the coefficient on the more informative forecast will be statistically 1 and the coefficient on the redundant forecast will tend to 0. On the other hand, if the two forecasts are based on different subsets of information then both ρ_1 and ρ_2 will be significantly different from 0 with the larger coefficient corresponding to the more informative forecast. The difference between the R^2 of Eq. 2-6 and that of Eq. 2-5 when the Volatility Forecast is HAV will indicate the relative contribution of implied asset volatility to historical data in forecasting future asset volatility.

We estimate Eq. 2-6 for the whole sample of 21,570 firm-quarters and then separately for each of the asset-to-debt-ratio quartiles. The whole-sample results in Table 2-5 indicate that the coefficient estimates on both asset volatility forecasts are significantly different from zero. This implies that rather than being redundant, IAV and HAV are based on largely different information sets. Adding IAV to the regression of

RAV on HAV significantly increases the R^2. This suggests that implied asset volatility contributes a statistically and economically significant amount of information to a forecast based on historical asset values alone. The marginal contribution is the highest for the DIAV estimate. Interestingly enough, the coefficient estimate on HAV remains significant which suggests that markets do not fully impound historical asset-return volatility in their forecasts of future volatility. No matter the methodology used to extract implied asset volatility from equity and/or debt prices, these prices do not appear to reflect all of the information available. Day and Lewis (1992) and Lamoureux and Lastrapes (1993) reach the same conclusion when examining the relative informational content of implied and historical equity volatility. They document that information available at the time that market prices are set can be used to predict realized return variance better than the variance forecast embedded in stock option prices.

The results by assets-to-debt ratio quartiles in Table 2-5 confirm that IAV adds a significant amount of information to HAV. The marginal information contribution does not appear to be systematically related to leverage. However, it is interesting to note that DIAV estimates display the largest marginal increase in R^2 in all but the lowest assets-to-debt ratio quartile. Along with the results in Table 2-4, this suggests that for all but the highly levered firms DIAV is not only based on better information than any of the other IAV estimates but that a larger portion of that information is new and different from the information contained in historical asset-return volatility.

2.6. Default and Default Probability Tests

To compare the relative default-forecasting accuracy of DD computed from the four asset value and volatility estimates, we design three tests. The first one is based on the occurrence of default and the other two on default probability. We use two proxies for

default probability – Altman's (1968) Z score and Moody's credit ratings. The two measures are likely to complement each other well because they are derived using different sets of information. The Z score is calculated from financial ratios that are publicly available, while credit ratings are believed to be based on proprietary models and inside information.

2.6.1. 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. We divide the data into eight subperiods: 1983-85, 1986-88, 1989-91, 1992-94, 1995-97, 1998-2000, and 2001-03. [8,9] The December 1982 estimate of the DD measure is used to explain whether or not the firm defaults in 1983, 1984, or 1985. 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 limit our sample to firms that have data available as of the beginning of at least one of the non-overlapping three-year periods defined earlier. This leaves us with 1,795 firm-quarter observations out of which only 35 are for defaulted firms.[10] Being aware of

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[8] We exclude from our original sample observations prior to 1982 for two reasons. First, the Bankruptcy Reform Act of 1978 revised the administrative and, to some extent, the procedural, legal, and economic aspects of corporate bankruptcy filings in the United States. The Act went into effect on October 1st, 1979. Second, only one of the firms in our sample defaults before 1982.

[9] We chose to split our sample into the above listed three-year periods because this particular split allowed us to retain the maximum number of default occurrences. Either of the other two possible splits (starting in 1982 or 1984) yields identical results.

[10] Rather than having observations for 52 quarters as in our original sample of 23,857 firm-quarters, we now have observations for 4 quarters. This explains the large reduction in sample size from 23,857 firm-quarters to 1,795.

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 allows us to achieve a more balanced dataset – 519 observations out of which 30 for distressed firms – while biasing our results against detecting a relationship between DD and default occurrences.

Table 2-6 provides summary statistics on the average distance-to-default estimates by financial distress status. It shows that independent of the asset volatility estimate used to calculate it, average DD is significantly lower for financially distressed firms. If we look at the subsample of non-investment grade firms, the differences in average DD persist but become smaller and less significant for DD_EIAV and DD_DIAV.

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 four DD_t calculated from the four implied asset volatility estimates. That is,

$$\Pr(DFLT_{t,n} = 1) = g(\alpha_o + \alpha_1 DD_{t,n} + \alpha_2 Controls_{t,n}) \qquad (2\text{-}7)$$

The control variables include period indicator variables intended to absorb the effect of macroeconomic changes on instances of default. It also includes an indicator variable, $SMALL_t$ that equals 1 if during quarter t a firm is in the bottom equity-value decile of all traded firms. Since for the purposes of our study we define default as a bankruptcy filing, or delisting due to bankruptcy or performance, our set of defaulted firms might include firms that are delisted for non-liquidation reasons (e.g., violation of price limits, not enough market makers, and infrequent trading). We believe that this is more likely to be a problem for relatively small firms and thus employ the variable $SMALL_t$ to control for the effects of miscategorizing firms into the set of defaulted ones.

Table 2-7 presents the results from the estimation of Eq. 2-7. The whole-sample results indicate 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 experience financial difficulties in the following three years. The fit of all four models as indicated by the max re-scaled pseudo R-square, $\widetilde{R}^2$, is in the range of 19.01-22.26%. The best fit is provided by the DD calculated from SIAV, which contributes 7.30% to $\widetilde{R}^2$ of a base logit model that includes period and size indicator variables only. The second best performance is displayed by DD_EDIAV with $\widetilde{R}^2$ of 20.88% and marginal contribution of 5.92% to a base model's $\widetilde{R}^2$.

The DD coefficient estimates, produced by fitting a logit model to the subsample of non-investment-grade firms, are still negative but of less statistical significance. The DD measures based on EIAV and DIAV are no longer statistically significant, the one based on EDIAV is significant at the 10% level, and the one based on SIAV at the 5% 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 $\widetilde{R}^2$ of the four models and not surprisingly the best fit is obtained when using SIAV closely followed by EDIAV. The marginal contribution of SIAV and EDIAV to $\widetilde{R}^2$ of a base logit model is 2.91% and 1.83% respectively.

In summary, whether analyzing the whole sample or the subsample of non-investment grade firms, the DD estimates calculated from SIAV and EDIAV are better

than the ones calculated from EIAV or DIAV at distinguishing between firms that default and those that do not. However, we should be cautious in interpreting these results as conclusive since they are based on a sample characterized by an extremely small percentage of defaults.

2.6.2. Tests Based on Credit Ratings

Credit rating agencies, such as Moody's and Standard & Poor, 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 a Moody's credit rating as a proxy for the default probability of a firm and examine the relationship between credit ratings and DD. If implied asset volatility is a reliable estimate of firm risk, then the corresponding DD measure will be highly correlated with the firm's credit rating. The stronger this relationship, the more accurate the asset volatility estimate. We allow for the DD estimates produced by the four IAV methodologies to differ for the subsamples of investment and non-investment grade firms.

Table 2-8 breaks down the original sample of 20,298 observations by Moody's average credit rating and offers median 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 2-9 investigates whether quarterly changes in firm DD over the period of 1975-2001 are consistent with subsequent quarterly changes in Moody's credit rating. The median 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 SIAV do not follow this pattern. In fact, for the firms whose credit rating changes from investment into non-investment grade, the beginning-of-the-quarter DD is higher 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 SIAV.

In order to control for the effect of other variables on firm credit rating, we estimate a multivariate regression model separately for investment and non-investment grade firms. That is, we estimate via OLS: [11]

$$\begin{aligned} RTG_{t,n}^{invest} &= \chi_0^{invest} + \chi_1^{invest} DD_{t,n} + \sum_k \chi_k^{invest} Controls_{k,t,n} + \varepsilon_{t,n}^{invest} \\ RTG_{t,n}^{junk} &= \chi_0^{junk} + \chi_1^{junk} DD_{t,n} + \sum_k \chi_k^{junk} Controls_{k,t,n} + \varepsilon_{t,n}^{junk} \end{aligned} \tag{2-8}$$

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

[11] Credit ratings are categorical variables which would suggest that the above model is better estimated via logit or probit model. We choose to use OLS for two reasons. First, although issue credit ratings are discrete, issuer credit ratings are not since they are the average issue ratings for that issuer. Second, the fact that issuer credit ratings are not discrete leaves us with more than 100 issuer rating categories and that creates convergence problems for an ordered logit model.

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. It might also be the case that the credit ratings of regulated firms contain different information compared to those of non-regulated firms. If government agencies intervene to correct problems as soon as they are detected, then all else equal the default risk of a regulated firm is less than that of a non-regulated one. We allow for this possibility by including an indicator variable REG that equals 1 if a firm operates in a regulated industry during the quarter in question, and equals 0 otherwise. Finally, the set of controls includes industry indicator variables that are designed to control for default-point variations among industry groupings.

The results from estimating Eq. 2-8 via OLS are presented in Table 2-10. They indicate that DD measures calculated from any of the four IAV estimates are an accurate assessment of firm default risk as proxied by Moody's credit rating. The coefficient on DD is always negative and statistically significant which implies that higher distance to default is associated with a higher-number rating (lower credit rating is denoted by a higher number).

In evaluating the relative accuracy of the four DD estimates we focus on the marginal contribution of each measure to the explanatory power of a regression that includes control variables only. The whole-sample results indicate that the increase in R^2 is the highest (7%) when we add DD_EIAV to the set of independent variables. The second highest marginal contribution is provided by DD_SIAV (5.8%) and then by DD_EDIAV (3.6%). Assuming that Moody's credit rating is an accurate proxy of the probability that a firm defaults, then our results indicate that EIAV is the most precise

forecast of future volatility. It is interesting to note that the accuracy ranking among the four estimation methodologies changes when we split our sample into investment and non-investment grade firms. The biggest surprise comes from the relative performance of EDIAV. This estimate produces a DD measure with the highest marginal contribution to R^2 for the set of non-investment-grade firms – 6.0%. For this set of firms relying on historical equity volatility appears to reduce the informational content of the IAV estimates as judged by the marginal contribution of any of the other three DD measures.

In addition to investigating the accuracy of DD, we also investigate whether the information it contains is distinct from and timelier than that contained in credit ratings. We do so by employing a Granger-causality test. We examine whether credit rating upgrades and downgrades can be forecasted with information contained in lagged distance-to-default changes. We allow for a change in firm default probability to be reflected in its debt and equity valuation up to three quarters before it is reflected in a credit rating change. That is, we use up to three 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:

$$\Pr(dRTG_{t,n}=1)=g(\beta_o+\sum_{i=1}^{3}\beta_{1i}dDD_{t-i,n}+\beta_2 DD_{t-4,n} + \sum_{j=1}^{3}\beta_{3j}dRTG_{t-j,n}+\beta_4 RTG_{t-4,n}+\sum_k \beta_k Controls_{t,n}) \quad (2\text{-}9)$$

where $dRTG_{t,n}=1$ if firm n's credit rating has been upgraded in quarter t from its rating in quarter t-1, and $dRTG_{t,n}=0$ if the rating has remained the same. Similarly, we estimate:

$$\Pr(dRTG_{t,n}=0)=g(\gamma_o+\sum_{i=1}^{3}\gamma_{1i}dDD_{t-i,n}+\gamma_2 DD_{t-4,n} + \sum_{j=1}^{3}\gamma_{3j}dRTG_{t-j,n}+\gamma_4 RTG_{t-4,n}+\sum_k \gamma_k Controls_{t,n}) \quad (2\text{-}10)$$

where $dRTG_{t,n}=0$ if the rating has remained the same and $dRTG_{t,n}=-1$ if firm n's credit rating has been downgraded in quarter t from its rating in quarter t-1. In addition to the control variables described earlier, we include two more in the estimation of the above models. The literature on the informational content of credit ratings documents that highly rated firms are very rarely downgraded. This implies that a firm's starting credit rating affects the probability of a subsequent downgrade/upgrade. Since the logit models include three lags of DD and rating changes, we choose to include the firm's rating four quarters prior to t. We also include the contemporaneous DD estimate.

Table 2-11 presents the results from a logit analysis that examines the relation between credit rating upgrades/downgrades and DD changes. The relationship between changes in credit rating and changes in distance to default appears to be of the expected direction. The negative sign on the coefficient estimates indicates that the larger the decrease in distance to default, the larger the probability of a credit rating downgrade. All three lags of all four estimates of DD are statistically significant in explaining the

probability of credit rating downgrades. This suggests that the DD estimates capture increases in default probability up to a year before these increases are reflected in an actual credit rating change. This information appears to be distinct from information contained in previous credit rating changes as indicated by the persistent statistical significance of some of the lagged rating change variables. In fact, it can be argued that the information contained in the DD estimates is better since adding DD into the model reduces the statistical significance of some of the lagged ratings. We compare the fit of the four models to that of a base model, which includes only control variables. We discover that the DD calculated from EIAV provides the highest marginal contribution to the R^2 (1.6%) and is closely followed by the marginal contribution of the DD calculated from SIAV (1.3%).

While changes in DD are highly significant in predicting credit rating downgrades, Table 2-11 shows that they lack forecasting power when it comes to rating upgrades. Only some of the lagged variables' coefficients are statistically significant and significance levels are generally lower. While the explanatory power of the model is higher for upgrades than it is for downgrades, the marginal contribution of the lagged DD changes to the R^2 is economically zero. On one hand this suggests that credit rating upgrades are easier to forecast than credit rating downgrades. On the other, it appears that lagged changes in DD do not aid in this forecasting process. This could be the result of credit rating upgrades containing little or no new information as documented in Hand *et al*. (1992) and Goh and Ederington (1993). Thus, the decrease in default probability that we use them to proxy for has been incorporated in the firm's valuation earlier than the

three quarter lags that we include. This is consistent with the fact that the most recent DD changes have the lowest statistical significance.

To sum up, all four DD estimates are able to detect credit rating downgrades up to a year before they occur. The estimate based on EIAV seems to be better at explaining subsequent downgrades than are the estimates based on EDIAV, DIAV, and SIAV. Although some of the DD estimates' lags are statistically significant in explaining credit rating upgrades, none of them improve our ability to distinguish between upgrades and no-changes as indicated by their marginal contribution to the R^2 of a base regression.

2.6.2. Tests Based on Altman's (1968) Z

Altman's (1968) Z-model provides an alternative proxy for default probability. This is probably the most popular model of bankruptcy prediction and has been extensively used in empirical research and in practice.12 The Z-model is obtained through multiple discriminant analysis of the financial ratios of industrial firms. It is given by:

$$Z = 1.2\left(\frac{WrkCapital}{TotalAssets}\right) + 1.4\left(\frac{RetainedErngs}{TotalAssets}\right) + 3.3\left(\frac{EBIT}{TotalAssets}\right) + 0.6\left(\frac{MktValEquity}{BookValEquity}\right) + \frac{Sales}{TotalAssets}$$

The Z thus obtained is a measure of financial health and a higher Z implies a lower probability of default. If IAV is the market's rational expectation of future total asset volatility, then the DD it implies should reflect expected default probability. Since Z is a measure of the same expectation then a higher DD should be associated with a higher Z.

Although Z has been documented to predict default occurrences quite accurately13, the evidence in Dichev (1998) suggests that Z is a better predictor of default when the *ex*

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[12] See Altman (1993) for an extensive review of empirical studies citing and using the Z-model.

[13] See Altman (1993) and Begley, Ming, and Watts (1997) for tests of Z's predictive abilities.

ante probability of default is high. He forms portfolios based on Z deciles and finds that the correlation between the number of distress delistings in each portfolio and the portfolio's rank is high when Z is low (portfolio 1-5). In contrast, when Z is high (portfolios 6-10) the correlations are low and sometimes with a sign reversed from expected. To account for this asymmetry in the predictive abilities of the measure, we allow the relationship between Z and DD to differ across *ex ante* default probability. Following the approach in Dichev (1998) we use each firm's Z-score at the end of each quarter and assign the firm to one of ten Z-decile portfolios.

We start our analysis with simple univariate comparisons between Z-Scores and DD estimates. Each quarter we assign firms in our sample to one of ten Z-score deciles. Table 2-12 presents medians of the four DD estimates by Z-Score deciles and shows that higher deciles are typically associated with higher DDs. It is interesting to note that the two DD estimates that incorporate information from debt prices, DD_EDIAV and DD_DIAV, are more consistent over the low-Z deciles, while the ones that incorporate information from equity prices are more consistent over the high-Z deciles.

We then estimate a model separately for low-Z (portfolios 1-5) and high-Z (portfolios 6-10) firms. That is,

$$\begin{aligned} Z_{t,n}^{low} &= \phi_0^{low} + \phi_i^{low} DD_{t,n} + \sum_k \phi_k^{low} Controls_{k,t,n} + \varepsilon_{t,n}^{low} \\ Z_{t,n}^{high} &= \phi_0^{high} + \phi_i^{high} DD_{t,n} + \sum_k \phi_k^{high} Controls_{k,t,n} + \varepsilon_{t,n}^{high} \end{aligned} \tag{2-11}$$

Table 2-13 contains the results from this OLS estimation. All four DD estimates are highly statistically significant in explaining Z whether the model includes industry or firm fixed effects. The positive sign on the DD coefficient indicates that a larger distance to default is on average associated with a higher Z score. This implies that all four of the

DD estimates contain accurate information about a firm's default probability if Z is a good proxy of this probability. The relative accuracy of the four measures can be determined by their marginal contribution to the explanatory power of a base model that includes control variables only. In the regression that includes industry fixed effects, DD_DIAV produces the highest increase in R^2 (2.74%). It is followed by DD_EIAV with 2.11%. This accuracy ranking is reversed when the regression includes firm fixed effects with DD_EIAV containing better information than DD_DIAV.

For the subset of high-Z firms, the coefficient estimates of DD are less significant and/or of a sign opposite to the one expected. Also, these variables add little or no explanatory power when included among the explanatory variables. These results might indicate that DD is a poor estimate of a firm's true distance to default, or perhaps Z is simply a poor measure of default risk. Although we cannot unambiguously distinguish between these two alternatives, the results in Dichev (1998) suggest that Z might be the flawed measure. He shows that Z score is a less accurate measure of default risk when the *ex ante* default risk is low.

We also examine whether changes in default probability, as proxied by Z, can be predicted by changes in the four DD estimates. Since an increase in a firm's distance to default implies that its financial condition is improving, then changes in DD should be associated with same-direction changes in Z. To examine whether this is the case, we estimate a model in which the dependent variable is dZ_t: the change in Z from quarter-end t-1 to quarter-end t. The main independent variable is the change in one of the four distance-to-default estimates, dDD_t. The four DD_t are calculated from the four implied asset value and volatility estimates in quarter t and the change dDD_t is from quarter-end t-

1 to quarter-end t. We include up to three lags of dDD_t to investigate whether financial markets detect changes in default probability before these are reflected in a firm's accounting reports.

We allow for our DD estimates to have different predictive power for positive and negative changes in Z. There is circumstantial evidence that when it comes to credit risk, investors tend to be surprised by negative information but not by positive information. Studies document that bank regulators' and credit rating agencies' downgrades are regarded as news while upgrades seem to have no new informational content. It has been maintained that the reason behind this asymmetry is managers' willingness to share favorable and withhold unfavorable private information. Thus, the release of the latter is eventually forced by regulators and rating agencies. We extend this argument to quarterly reports. We contend that while managers might reveal good news as soon as it becomes available, they might wait to disclose bad news until their quarterly reports are due. We estimate a model separately for increases and decreases in Z to allow for a possible asymmetry in informational content:

$$\begin{aligned} dZ^{+}_{t,n} &= \theta^{+}_{0} + \sum_{i=1}^{3} \theta^{+}_{i} dDD_{t-i,n} + \sum_{k} \theta^{+}_{k} Controls_{k,t,n} + \varepsilon^{+}_{t,n} \\ dZ^{-}_{t,n} &= \theta^{-}_{0} + \sum_{i=1}^{3} \theta^{-}_{i} dDD_{t-i,n} + \sum_{k} \theta^{-}_{k} Controls_{k,t,n} + \varepsilon^{-}_{t,n} \end{aligned} \tag{2-12}$$

All of the models in this subsection are estimated via ordinary least squares. The set of control variables includes the natural logarithm of the market value of assets, $SIZE_t$, since previous research has established that smaller firms are more likely to default all else equal. It also includes an indicator variable, REG_t, which equals 1 if the firm operates in a

regulated industry during the quarter in question, and 0 otherwise.[14] We include quarterly indicator variables designed to absorb the effect of macroeconomic changes on default probability. Finally, we include either industry or firm indicator variables in order to capture default-point differences across industries or firms respectively. In essence, this is identical to estimating a panel regression with industry or firm fixed effects.[15]

Table 2-14 presents the results from estimating Eq. 2-12. DD changes are statistically significant only for the subset of negative Z changes with industry fixed effects, and the subset of positive Z changes with firm fixed effects. When significant their coefficients are positive indicating that the larger the increase in DD, the larger the increase in Z. The marginal contribution of DD changes to the R^2 of a regression including lagged Z changes and control variables only, indicates that the former add little to no new information – the marginal contribution is always less than 0.2%. However, there is a DD estimate that stands out. An assessment of each of the four DD estimates' statistical significance and marginal explanatory power suggest that the DD calculated from EIAV performs best.

In summary, the results presented in this section indicate that when the *ex ante* probability of default is high all four DD estimates accurately reflect a firm's default risk. It seems that the DD estimate calculated from EIAV is more accurate and timely than the other DDs. Furthermore, it appears to add the most new information to the firm's lagged Z-score changes.

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[14] Regulated industries include railroads (SIC code 4011) through 1980, trucking (4210 and 4213) through 1980, airlines (4512) through 1978, telecommunications (4812 and 4813) through 1982, and gas and electric utilities (4900 and 4939). See Frank and Goyal (2003) for more. We estimate the regressions excluding regulated firms from the sample and the results remain unchanged.

[15] Our sample contains more than one industries represented by a single firm. To ensure that the model is identified we do not include both industry and firm indicator variables in the same estimation.

2.7. Sensitivity of Estimates to Alternative Model Assumptions

The analysis above examines the properties of implied asset values, volatilities, and distance-to-default measures calculated under a set of base assumptions. In this section we assess the sensitivity of the estimates to changes in the assumptions. To do so, we repeat the realized asset volatility, and the default and default probability tests discussed earlier using alternative-assumption estimates of IAV and DD. We include a sample of our results below.

2.7.1. Summary Statistics

Table 2-15 presents summary statistics under alternative assumptions. The sample statistics are largely unaffected when we use different default points, different issuer yields, or limit ourselves to non-callable bonds only. In contrast, employing alternative time-to-resolution, tax-adjustment, or debt-priority assumptions makes a significant difference.

As the time to resolution increases from one year to the duration and then the maturity of debt, median EIAV considerably increases from 15.7% to 24.2% Median DIAV is almost unchanged when instead of one year we assume that the time to resolution equals the average duration of debt. However, if time to resolution is assumed to equal the average debt maturity, then average DIAV increases. It is interesting to note that increasing the time to resolution at first decreases but then slightly increases the EDIAV estimate. While under the one-year to resolution assumption the three system-of-equations IAV estimates are significantly different, increasing the time to resolution has the effect of making their magnitudes very similar and changing their relative ranking. In fact, if the time to resolution is assumed to equal the average maturity of debt then

average EIAV is the highest, while under the one year to resolution assumption it is the lowest.

Since DIAV and EDIAV are the only estimates calculated from credit spreads, they are the only estimates affected by employing an alternative tax adjustment. Table 2-15 shows that if we do not adjust for the differential taxation of corporate and Treasury securities altogether, both DIAV and EDIAV increase. This effect is expected since not adjusting for taxes overestimates the portion of yield spreads due to default risk, which in turn overestimates the implied volatility of total assets. On the other hand, when we adjust for taxes by differencing corporate yields with the average yield on Moody's AAA-rated bonds, the two IAV estimates significantly decrease.

Finally, the sample summary statistics are most dramatically affected by changes in the debt priority assumption. Table 2-15 indicates that the DIAV and EDIAV estimates increase to unreasonable levels whenever we assume that bond yields are representative of the default risk of total debt. The increase is even more striking when we assume that senior bonds are senior to all remaining debt, and junior bonds are junior to all remaining debt. It is important to note that this latter result might be due to the loss observations. Under the second alternative debt-priority assumption the algorithm used to solve for the DIAV and EDIAV fails to converge for about 500 additional observations that tend to be characterized by low credit spreads.

2.7.2. Realized Asset Volatility Tests

Table 2-16 presents the results from re-estimating Eq. 3-5. As suggested by the summary statistics in Table 2-15, alternative assumptions about each firm's default point and credit spread do not considerable affect the informational content of the IAV estimates. Three alternative assumptions that significantly worsen the forecasting ability

of the IAV estimates are that (1) time to resolution equals the weighted average maturity of traded debt, (2) differencing corporate yields with the average yield on Moody's AAA-rated bonds is a proper tax adjustment, and (3) senior (junior) bonds are the firm's most senior (junior) debt. When we limit our sample to non-callable bonds we lose almost two-thirds of our observations. These seem to be observations that contain high-quality information, since the explanatory power for this subsample is quite lower than in our base case. Only two alternative assumptions produce IAV estimates which forecast RAV better than the base IAV estimates. Assuming that time to resolution equals the weighted average duration of each firm's traded debt or assuming that all debt is of the same priority and homogeneous default risk produces the IAV estimates with the highest explanatory power. The former assumption also generates some of the highest coefficient estimates on IAV suggesting that these estimates use information most efficiently.

2.7.3. Default and Default Probability Tests

The results from re-estimating the default forecasting model Eq. 2-7 are shown in Table 2-17. Increasing the time to resolution has the effect of decreasing the explanatory power of the DD estimates obtained through any of the system-of-equations IAV methodologies. Consistent with our realized asset volatility test, we find that alternative assumptions about default point or issuer yield do not significantly impact the explanatory power of the model. Employing no tax adjustment reduces the explanatory power of the two estimates whose calculation requires bond yields – DIAV and EDIAV. Adjusting for taxes by using the average yield on Moody's AAA-rated bonds reduces explanatory power for the whole sample but produces some of the highest $\widetilde{R}^2$ for the subsample of non-investment grade firms. The sensitivity results in Table 2-17 indicate

that some of the alternative assumptions employed affect the explanatory power of our model. However, DD_SIAV consistently produces the highest marginal contribution to $\widetilde{R}^2$ and is typically followed by DD_EDIAV. Assuming that all debt is senior and of homogeneous risk is the only assumption under which the distance to default obtained from EDIAV is relatively more informative than that produced by SIAV judging by $\Delta\widetilde{R}^2$.

Table 2-18 presents the results from re-estimating the credit ratings model (Eq. 2-9). Most of the alternative assumptions preserve the performance ranking of the four DD measures. The equity DD measure, DD_EIAV, outperforms the others in the whole sample and the investment-grade subsample estimation. For the subsample of junk firms, the DD measures which combines information from equity and debt prices typically outperforms the other DD measures. Both DD_EIAV and DD_EDIAV have the highest explanatory power when constructed under the assumption that a firm's default point equals 95% of its total debt.

The results from re-estimating the downgrade/upgrade logit model (Eq. 2-10) can be seen in Table 2-19. As we already established, the market measures are statistically significant but improve the fit of forecasting models only marginally. Table 2-19 points out that this relatively poor forecasting ability is not significantly worsened or improved by alternative model assumptions. The DD measures that rely on debt price information, DD_DIAV and DD_EDIAV, produce the best fit when credit spreads are calculated using the average yield on Moody's AAA-rated bonds rather than the yield on Treasury securities.

2.8. Summary and Conclusion

The results reported in this study have important implications for financial theory and practice. Researchers and practitioners have employed a variety of methods to obtain estimates of asset volatility for the purpose of valuing corporate debt and derivative products written on it, measuring total firm risk, or pricing deposit insurance. However, despite the variety in available methods, we know very little about the empirical properties of the implied asset volatility estimates they produce. We address this gap in the literature in two steps. First, we examine whether the source of information – debt versus equity prices, and historical versus implied equity volatility – impacts the informational content and accuracy of implied asset volatility. Second, we explore whether assumptions about the model parameters – time to resolution, default point, debt priority structure, and tax and call option adjustments – appear to be important.

To address the first issue we construct four estimates of implied asset volatility. We obtain the simplest one by de-levering historical equity volatility using the market value of equity and the book value of debt. To construct the other three we use contingent-claim pricing models to simultaneously solve for the market value and volatility of assets. The first estimate reflects information from equity prices and historical equity volatility, and the second one reflects information from debt prices and historical equity volatility. The last estimate incorporates information from contemporaneous equity and debt prices without relying on past equity volatility information. We assess the relative performance of the four implied asset volatility estimates by using them to forecast realized asset-return volatility, defaults, credit ratings, and Z scores.

We document that the implied asset volatility calculated from debt prices best explains variations in realized asset volatility. This is contrary to the commonly held

belief that debt markets are characterized by many frictions and as a result debt prices are too noisy to be useful. In addition to directly examining the relation between implied and realized volatility of asset returns, we perform a number of indirect tests that draw on the intuition that, all else equal, firms with highly volatile assets have a higher default probability. For the purpose of these tests we use firm leverage and asset volatility to construct a default risk measure, distance to default, that represents the number of asset-value standard deviations required to push a firm into default. We find that this default risk measure can successfully forecast defaults, and is highly correlated with a firm's credit rating and Z score. However, none of our four implied-asset-volatility methodologies produces a default risk measure that consistently outperforms the others. When we examine whether the distance-to-default measures are able to forecast changes in credit ratings and Z scores, we find that their predictive power is limited to negative changes in the dependent variables. This is consistent with the findings of previous studies that market participants rarely regard decreases in default probability as news. In determining which of the four methodologies analyzed in this study produces the most informative and accurate estimate of total firm risk, we examine the marginal contribution of each methodology's default risk measure to the explanatory power of a base regression. We find that although there is no consistent winner, the measure calculated from equity prices and historical equity volatility has slightly better forecasting abilities than do measures constructed through other methodologies.

The second contribution of this study is that it documents the impact of alternative model assumptions on estimates of implied asset volatility. While the choice of using equity or debt prices to extract firm risk information appears to be inconsequential, we

find that the choice of model parameters is quite important. We show that the manner in which we adjust yield spreads to account for embedded call options, and tax differences between corporate and Treasury securities has a significant effect on the level and rank ordering of firm risk measures. In addition, assumptions about the maturity of debt and debt priority structure seem to affect the forecasting ability of both implied-volatility and distance-to-default estimates. In contrast, using alternative assumptions about each firm's default point and alternative approaches to aggregating issue yields into issuer yields appear immaterial. This finding underscores the importance of robustness checks whenever equity and debt valuation is based on contingent-claim pricing models. It also provides researcher and practitioners with some guidance as to the model parameters most likely to influence results.

Table 2-1. Summary statistics. Summary statistics are for the sample of 27,723 firm-quarter observations over 1975-2001. SIAV is the simple implied asset volatility calculated by de-levering historical equity volatility. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. Implied asset volatilities are reported in percent per year. V_SIAV, V_EIAV, V_DIAV, and V_EDIAV are the corresponding estimates of the market value of assets in billion dollars. DD_SIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the corresponding distance-to-default measures.

Variable	Minimum	Maximum	Median	Mean	StdDev
V_SIAV	0.03	404.07	2.90	8.14	20.52
V_EIAV	0.02	383.08	2.77	7.76	19.37
V_DIAV	0.02	395.20	2.21	6.31	16.93
V_EDIAV	0.02	383.08	2.77	7.75	19.37
SIAV	0.6	154.6	14.8	16.9	10.6
EIAV	0.7	208.0	15.7	17.9	11.6
DIAV	1.1	141.2	20.2	22.9	12.8
EDIAV	1.9	172.4	29.5	31.9	15.3
DD_SIAV	0.05	20.34	4.83	5.08	2.12
DD_EIAV	-1.38	18.24	4.36	4.66	2.20
DD_DIAV	-0.70	19.26	1.90	2.17	1.40
DD_EDIAV	-0.34	32.56	2.02	2.23	1.26

Table 2-2. Simple and rank correlations. Correlations are for the sample of 27,723 firm-quarter observations over 1975-2001. SIAV is the simple implied asset volatility calculated by de-levering historical equity volatility. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. V_SIAV, V_EIAV, V_DIAV, and V_EDIAV are the corresponding estimates of the market value of assets. DD_SIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the corresponding distance-to-default measures. All correlations are significantly different from 0 at the 1 percent level.

	Simple Correlations				Rank Correlations			
	V_SIAV	V_EIAV	V_DIAV	V_EDIAV	V_SIAV	V_EIAV	V_DIAV	V_EDIAV
V_SIAV	1.000				1.000			
V_EIAV	1.000	1.000			1.000	1.000		
V_DIAV	0.985	0.982	1.000		0.990	0.989	1.000	
V_EDIAV	1.000	1.000	0.982	1.000	1.000	1.000	0.989	1.000
	SIAV	EIAV	DIAV	EDIAV	SIAV	EIAV	DIAV	EDIAV
SIAV	1.000				1.000			
EIAV	0.987	1.000			0.996	1.000		
DIAV	0.907	0.871	1.000		0.937	0.923	1.000	
EDIAV	0.675	0.624	0.905	1.000	0.693	0.664	0.883	1.000
	DD_SIAV	DD_EIAV	DD_DIAV	DD_EDIAV	DD_SIAV	DD_EIAV	DD_DIAV	DD_EDIAV
DD_SIAV	1.000				1.000			
DD_EIAV	0.913	1.000			0.923	1.000		
DD_DIAV	0.191	0.315	1.000		0.217	0.331	1.000	
DD_EDIAV	0.348	0.426	0.947	1.000	0.417	0.473	0.909	1.000

Table 2-3. Simple and rank correlations of implied and historical asset volatility with realized asset volatility. Correlations are for the sample of 21,570 firm-quarter observations over 1975-2001. SIAV is the simple implied asset volatility calculated by de-levering historical equity volatility. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. HAV_1 and HAV_2 are two estimates of annualized historical asset volatility calculated over the year prior to the end of each quarter. RAV_1 and RAV_2 are two estimates of annualized realized asset volatility over the year following each quarter-end. HAV_1 and RAV_1 assume that the market value of debt is the sum of the market value of traded debt and the book value of non-traded debt. HAV_2 and RAV_2 assume that the yield to maturity on non-traded debt is the same as the yield to maturity on traded debt. All correlations are significantly different from 0 and 1 at the 1 percent level.

	Simple Correlations						Rank Correlations					
	EDIAV	EIAV	DIAV	SIAV	HAV1	HAV2	EDIAV	EIAV	DIAV	SIAV	HAV1	HAV2
Whole Sample, N=21,570												
RAV1	0.251	0.285	0.312	0.310	0.321	0.320	0.425	0.533	0.514	0.567	0.563	0.490
RAV2	0.206	0.272	0.274	0.267	0.316	0.334	0.328	0.489	0.430	0.463	0.512	0.499
Assets-to-Debt Ratio, Quartile 1, N=5,428												
RAV1	0.084	0.178	0.170	0.189	0.287	0.303	0.249	0.405	0.386	0.422	0.505	0.425
RAV2	0.076	0.180	0.165	0.160	0.287	0.324	0.191	0.374	0.330	0.310	0.458	0.470
Assets-to-Debt Ratio, Quartile 2, N=5,380												
RAV1	0.207	0.289	0.304	0.333	0.344	0.308	0.262	0.520	0.450	0.537	0.562	0.501
RAV2	0.181	0.284	0.285	0.313	0.330	0.311	0.220	0.492	0.404	0.471	0.528	0.517
Assets-to-Debt Ratio, Quartile 3, N=5,410												
RAV1	0.241	0.266	0.306	0.303	0.369	0.375	0.350	0.455	0.453	0.478	0.474	0.455
RAV2	0.227	0.271	0.297	0.297	0.358	0.374	0.300	0.455	0.415	0.449	0.452	0.463
Assets-to-Debt Ratio, Quartile 4, N=5,352												
RAV1	0.337	0.332	0.391	0.366	0.394	0.386	0.405	0.431	0.459	0.446	0.422	0.411
RAV2	0.320	0.351	0.383	0.373	0.406	0.404	0.358	0.435	0.423	0.429	0.419	0.420

Table 2-4. Analysis of IAV and HAV forecasting properties. We estimate via OLS $RAV_{t,n} = \delta_0 + \delta_1 Voaltility\ Forecast_{t,n} + \varepsilon_{t,n}$. Volatility forecast is one of the five: SIAV, EIAV, DIAV, EDIAV, or HAV. SIAV is the simple implied asset volatility calculated by de-levering historical equity volatility. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. HAV is an estimate of annualized historical asset volatility calculated over the year prior to the end of each quarter. RAV is an estimate of annualized realized asset volatility over the two years following each quarter-end. Standard errors are reported in parenthesis. All coefficient estimates are statistically significant at the 1 percent level.

	IAV Methodology				
Sample Used in Estimation	EDIAV	EIAV	DIAV	SIAV	HAV
Whole Sample, N=21,570					
Intercept	0.108	0.122	0.089	0.113	0.137
	(0.002)	(0.018)	(0.003)	(0.024)	(0.014)
Slope	0.343	0.293	0.453	0.460	0.273
	(0.009)	(0.006)	(0.015)	(0.014)	(0.003)
R^2	0.063	0.081	0.097	0.096	0.103
Assets-to-Debt Ratio, Quartile 1, N=5,428					
Intercept	0.133	0.126	0.099	0.106	0.134
	(0.009)	(0.003)	(0.010)	(0.005)	(0.012)
Slope	0.202	0.233	0.427	0.649	0.186
	(0.002)	(0.008)	(0.004)	(0.024)	(0.016)
R^2	0.007	0.031	0.029	0.035	0.082
Assets-to-Debt Ratio, Quartile 2, N=5,380					
Intercept	0.091	0.109	0.063	0.079	0.107
	(0.010)	(0.005)	(0.013)	(0.015)	(0.004)
Slope	0.379	0.302	0.557	0.685	0.385
	(0.001)	(0.024)	(0.003)	(0.004)	(0.014)
R^2	0.043	0.083	0.092	0.111	0.118
Assets-to-Debt Ratio, Quartile 3, N=5,410					
Intercept	0.098	0.128	0.080	0.103	0.114
	(0.005)	(0.003)	(0.013)	(0.028)	(0.015)
Slope	0.398	0.280	0.505	0.514	0.448
	(0.002)	(0.014)	(0.003)	(0.015)	(0.003)
R^2	0.058	0.071	0.094	0.092	0.136
Assets-to-Debt Ratio, Quartile 4, N=5,352					
Intercept	0.123	0.144	0.107	0.130	0.131
	(0.009)	(0.005)	(0.014)	(0.005)	(0.015)
Slope	0.309	0.264	0.391	0.373	0.426
	(0.005)	(0.024)	(0.006)	(0.021)	(0.016)
R^2	0.113	0.110	0.153	0.134	0.155

Table 2-5. Analysis of the relative informational content of IAV and HAV in forecasting RAV. We estimate via OLS $RAV_{t,n} = \rho_0 + \rho_1 IAV_{t,n} + \rho_2 HAV_{t,n} + \varepsilon_{t,n}$ .The independent variable IAV is SIAV, EIAV, DIAV, or EDIAV. SIAV is the simple implied asset volatility obtained by de-levering historical equity volatility. EIAV is the equity-implied asset volatility obtained from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility obtained from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility obtained from contemporaneous equity and debt prices. HAV is an estimate of historical asset volatility calculated over the year prior to the end of each quarter. RAV is an estimate of realized asset volatility over the 2 years following each quarter-end. Standard errors are reported in parenthesis. All coefficient estimates are statistically significant at the 1 percent level. ΔR^2 (IAV) is the marginal contribution of the corresponding IAV to the model's R^2 when compared to a base model including HAV only.

	IAV Methodology			
Sample Used in Estimation	EDIAV	EIAV	DIAV	SIAV
Whole Sample, N=21,570				
Intercept	0.079	0.099	0.069	0.091
	(0.002)	(0.034)	(0.004)	(0.003)
IAV	0.279	0.218	0.362	0.357
	(0.007)	(0.005)	(0.012)	(0.014)
HAV	0.245	0.223	0.222	0.218
	(0.002)	(0.046)	(0.003)	(0.015)
R^2	0.143	0.144	0.161	0.157
ΔR^2 (IAV)	0.041	0.041	0.058	0.054
Assets-to-Debt Ratio, Quartile 1, N=5,428				
Intercept	0.100	0.102	0.073	0.082
	(0.002)	(0.004)	(0.031)	(0.016)
IAV	0.209	0.193	0.388	0.576
	(0.007)	(0.026)	(0.008)	(0.004)
HAV	0.186	0.175	0.180	0.177
	(0.006)	(0.003)	(0.004)	(0.014)
R^2	0.089	0.103	0.106	0.110
ΔR^2 (IAV)	0.007	0.021	0.024	0.028
Assets-to-Debt Ratio, Quartile 2, N=5,380				
Intercept	0.060	0.083	0.048	0.063
	(0.002)	(0.014)	(0.017)	(0.017)
IAV	0.263	0.192	0.384	0.475
	(0.009)	(0.005)	(0.008)	(0.005)
HAV	0.353	0.306	0.303	0.279
	(0.005)	(0.022)	(0.006)	(0.022)
R^2	0.138	0.146	0.156	0.162
ΔR^2 (IAV)	0.020	0.028	0.038	0.044

Table 2-5. Continued

	IAV Methodology			
Sample Used in Estimation	EDIAV	EIAV	DIAV	SIAV
Assets-to-Debt Ratio, Quartile 3, N=5,410				
Intercept	0.062	0.092	0.059	0.079
	(0.002)	(0.004)	(0.032)	(0.016)
IAV	0.253	0.145	0.317	0.295
	(0.010)	(0.014)	(0.008)	(0.004)
HAV	0.398	0.379	0.358	0.354
	(0.006)	(0.005)	(0.005)	(0.024)
R^2	0.158	0.152	0.167	0.160
ΔR^2 (IAV)	0.022	0.016	0.031	0.024
Assets-to-Debt Ratio, Quartile 4, N = 5,352				
Intercept	0.085	0.115	0.084	0.107
	(0.006)	(0.021)	(0.044)	(0.017)
IAV	0.206	0.130	0.263	0.214
	(0.033)	(0.004)	(0.008)	(0.004)
HAV	0.340	0.328	0.291	0.297
	(0.004)	(0.022)	(0.005)	(0.012)
R^2	0.199	0.174	0.208	0.185
ΔR^2 (IAV)	0.044	0.019	0.053	0.029

Table 2-6. Average DD statistics by default status. A firm is considered 'Defaulted' if it is delisted due to liquidation or performance, or files for bankruptcy in the three years following the fourth quarter of 1982, 1985, 1988, 1991, 1994, 1997, and 2000. SIAV is the simple 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, and represents the number of standard deviations required to push a firm into default. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively.

		Average DD Calculated from			
Default Status	N	SIAV	EIAV	DIAV	EDIAV
Investment and Non-investment Grade Observations					
All	1,795	3.29	2.89	1.30	1.39
Non-defaulting	1,760	3.32	2.91	1.32	1.40
Defaulting	35	2.06	1.65	0.72	0.89
Difference		1.25 ***	1.26 ***	0.59 ***	0.51 ***
Non-investment Grade Observations					
All	519	2.45	1.92	0.86	1.01
Non-defaulting	489	2.48	1.94	0.87	1.02
Defaulting	30	1.90	1.52	0.68	0.83
Difference		0.58 ***	0.42 **	0.19 *	0.19 ***

Table 2-7. Logit analysis of defaults. We estimate $DFLT_{t,n} = \alpha_o + \alpha_1 DD_{t,n} + \alpha_2 Controls_{t,n} + \varepsilon_{t,n}$. These are the results from a logistic regression on the sample of all 1,795 observations and the subsample of 519 non-investment-grade observations. The dependent variable DFLT equals 1 if the firm is delisted due to liquidation or performance, or files for bankruptcy in the three years following the fourth quarter of 1982, 1985, 1988, 1991, 1994, 1997, and 2000; it equals 0 otherwise. DD_SIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the simple, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. P3-P8 are period indicator variables. R^2 is max-rescaled pseudo R^2, which is an indicator of fit for logit models. ΔR^2 is the marginal contribution of each DD to R^2. It is measured as the difference between R^2 of a model including DD, and that of a base model excluding it. Standard errors are reported in parenthesis. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively.

	Investment and Non-investment Grade Observations				Non-investment Grade Observations			
	SIAV	EIAV	DIAV	EDIAV	SIAV	EIAV	DIAV	EDIAV
Intercept	-3.350 ***	-4.424 ***	-4.590 ***	-3.318 ***	-3.028 ***	-3.917 ***	-3.817 ***	-3.365 ***
	(0.867)	(0.789)	(0.760)	(0.887)	(0.904)	(0.777)	(0.773)	(0.855)
DD	-1.001 ***	-0.599 ***	-0.932 ***	-1.923 ***	-0.659 **	-0.209	-0.451	-0.870 *
	(0.240)	(0.180)	(0.253)	(0.478)	(0.306)	(0.176)	(0.290)	(0.463)
P3	2.143 ***	1.973 **	1.516 *	1.578 *	1.435	1.155	0.978	1.040
	(0.816)	(0.813)	(0.808)	(0.808)	(0.874)	(0.859)	(0.852)	(0.851)
P4	2.300 ***	1.776 **	1.281	1.384	1.420	0.965	0.763	0.786
	(0.842)	(0.846)	(0.843)	(0.848)	(0.913)	(0.888)	(0.900)	(0.906)
P6	2.053 **	1.811 **	1.394 *	1.507 *	1.560 *	1.247	1.074	1.154
	(0.832)	(0.826)	(0.827)	(0.825)	(0.859)	(0.841)	(0.835)	(0.834)
P7	2.920 ***	3.056 ***	2.900 ***	2.833 ***	2.595 ***	2.519 ***	2.463 ***	2.512 ***
	(0.837)	(0.834)	(0.834)	(0.833)	(0.881)	(0.875)	(0.872)	(0.872)
P8	2.949 ***	3.291 ***	3.597 ***	3.249 ***	2.579 ***	2.852 ***	2.912 ***	2.830 ***
	(0.830)	(0.819)	(0.809)	(0.819)	(0.852)	(0.837)	(0.831)	(0.833)
SMALL	1.464 ***	1.299 **	1.394 **	1.055 *	1.273 **	1.167 *	1.078 *	0.961
	(0.562)	(0.609)	(0.603)	(0.621)	(0.616)	(0.639)	(0.650)	(0.668)
R^2	0.223	0.196	0.190	0.209	0.156	0.134	0.138	0.145
ΔR^2 (DD)	0.073	0.046	0.040	0.059	0.029	0.007	0.011	0.018

Table 2-8. Median distance-to-default estimates by Moody's credit rating. Median statistics are on the sample of 20,298 firm-quarters for the period 1975-2001. SIAV is the simple 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. 'Prob of Default' comes from Moody's Investors Service (2000) and is the average one-year default rate over 1983-1999. For B3 and below average rates are calculated over 1998-1999, the only two cohort years available so far for the Caa subcategories.

Moody's Credit Rating	N	Prob of Default, 1983-1999 (%)	DD_EDIAV	DD_EIAV	DD_DIAV	DD_SIAV
Investment Grade						
Aaa	1,070	0.00	2.11	3.71	2.16	4.02
Aa1	358	0.00	1.48	3.63	1.56	3.89
Aa2	2,164	0.00	1.59	3.46	1.66	3.81
Aa3	1,151	0.10	1.53	3.18	1.58	3.53
A1	2,083	0.00	1.49	3.26	1.54	3.59
A2	4,532	0.00	1.54	3.04	1.52	3.48
A3	2,176	0.00	1.49	3.10	1.48	3.47
Baa1	1,496	0.00	1.48	3.09	1.44	3.44
Baa2	2,283	0.10	1.41	2.88	1.34	3.32
Baa3	1,360	0.30	1.38	2.73	1.30	3.14
Non-Investment Grade						
Ba1	696	0.60	1.30	2.37	1.21	2.81
Ba2	914	0.50	1.21	2.13	1.16	2.57
Ba3	1,090	2.50	1.15	2.10	1.09	2.44
B1	2,905	3.50	1.01	1.62	0.91	2.18
B2	882	6.90	0.99	1.67	0.91	2.10
B3	479	8.04	0.95	1.53	0.88	1.87
Caa1	17	10.78	0.74	0.95	0.54	1.64
Caa2	42	15.79	0.70	1.27	0.46	2.04
Caa3	1	28.87	0.71	1.15	0.58	1.68
Ca	2	N/A	-0.26	0.14	-0.93	2.96

Table 2-9. Median changes in distance-to-default estimates by Moody's credit rating change. Median statistics are on the sample of 20,298 firm-quarters for the period 1975-2001. SIAV is the simple 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. dDD is the quarterly change in the distance-to-default measure calculated from the corresponding asset values and volatilities.

Credit Rating Change	N	dDD_EDIAV	dDD_EIAV	dDD_DIAV	dDD_SIAV
Downgrade Crossing the Investment Grade Boundary	107	-0.0483	0.0123	-0.0786	0.1546
Downgrade Without Crossing the Investment Grade Boundary	1,009	-0.0048	-0.0256	-0.0027	-0.0265
No Change	18,228	0.0036	0.0182	0.0038	0.0130
Upgrade Without Crossing the Investment Grade Boundary	855	0.0071	0.0434	0.0104	0.0541
Upgrade Crossing the Investment Grade Boundary	99	0.0509	0.0746	0.0889	0.0680

Table 2-10. Analysis of Moody's credit ratings. We estimate via OLS $RTG_{t,n} = \chi_0 + \chi_1 DD_{t,n} + \sum_k \chi_k Controls_{k,t,n} + \varepsilon_{t,n}$ for the sample of 25,701 firm-quarters for the period 1975-2001. Moody's rating of Aaa to Caa is coded as 1 to 19 respectively, so that as ratings deteriorate, the dependent variable increases. The dependent variable is not discrete since firm rating is the average rating of its debt issues which does not have to be the same. DD_SIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the simple, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. SIZE is the log of the market value of assets. REG is an indicator variable that equals 1 if the firm operates in a regulated industry during that quarter and 0 otherwise. ΔR^2 is the contribution of DD to the R^2 of a model including control variables only. Standard errors are reported in parenthesis. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively.

	EDIAV	EIAV	DIAV	SIAV
Investment and Non-Investment Grade Firms				
Intercept	21.36 ***	21.23 ***	21.30 ***	21.60 ***
	(0.25)	(0.24)	(0.25)	(0.24)
DD	-0.72 ***	-0.65 ***	-0.65 ***	-0.60 ***
	(0.01)	(0.01)	(0.01)	(0.01)
SIZE	-1.64 ***	-1.56 ***	-1.65 ***	-1.56 ***
	(0.01)	(0.01)	(0.01)	(0.01)
REG	-1.34 ***	-1.06 ***	-1.32 ***	-0.92 ***
	(0.21)	(0.20)	(0.21)	(0.21)
R^2	0.611	0.645	0.610	0.633
ΔR^2 (DD)	0.036	0.070	0.035	0.058
Investment Grade Firms				
Intercept	13.65 ***	14.08 ***	13.62 ***	14.18 ***
	(0.23)	(0.23)	(0.23)	(0.23)
DD	-0.37 ***	-0.33 ***	-0.35 ***	-0.31 ***
	(0.01)	(0.01)	(0.01)	(0.01)
SIZE	-0.85 ***	-0.87 ***	-0.85 ***	-0.85 ***
	(0.01)	(0.01)	(0.01)	(0.01)
REG	-0.90 ***	-0.74 ***	-0.90 ***	-0.62 ***
	(0.17)	(0.17)	(0.17)	(0.17)
R^2	0.403	0.420	0.405	0.413
ΔR^2 (DD)	0.032	0.049	0.034	0.042
Non-Investment Grade Firms				
Intercept	16.48 ***	16.38 ***	16.26 ***	16.42 ***
	(0.26)	(0.26)	(0.27)	(0.27)
DD	-0.75 ***	-0.24 ***	-0.43 ***	-0.19 ***
	(0.03)	(0.01)	(0.02)	(0.01)
SIZE	-0.41 ***	-0.45 ***	-0.45 ***	-0.45 ***
	(0.01)	(0.01)	(0.01)	(0.01)
REG	0.20	-1.09 ***	-0.40	-1.32 ***
	(0.30)	(0.29)	(0.30)	(0.29)
R^2	0.366	0.351	0.342	0.337
ΔR^2 (DD)	0.060	0.045	0.036	0.031

Table 2-11. Logit analysis of credit rating changes. We estimate

$$dRTG_{t,n} = \beta_o + \sum_{i=1}^{3} \beta_{1i} dDD_{t-i,n} + \beta_2 DD_{t-4,n} + \sum_{j=1}^{3} \beta_{3j} dRTG_{t-i,n} + \beta_4 RTG_{t-4,n} + \sum_k \beta_k Controls_{t,n} + \varepsilon_{t,n}$$

for the sample of 20,298 firm-quarters during the period 1975-2001. Moody's rating change, dRTG, equals -1 if a firm is downgraded, 0 if the credit rating remains the same, and 1 if the firm is upgraded. When credit rating change is the dependent variable, we further distinguish between upgrades/downgrades that cross the investment grade threshold (dRTG=2/dRTG=-2) and those that do not (dRTG=1/dRTG=-1). The model estimates the probability of the lower rating change values. dDD_SIAV, dDD_EIAV, dDD_DIAV, and dDD_EDIAV are quarterly changes in the distance-to-default measures calculated from the simple, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. SIZE is the log of the market value of assets. Lags of variables are so indicated. Indicator variables are not presented for ease of exposition. The model's fit is indicated by the max rescaled pseudo R^2. ΔR^2 is the contribution of all lags of DD and dDD to R^2 of a model including all but these variables. Standard errors are reported in parenthesis. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively.

	Credit Rating Downgrades				Credit Rating Upgrades			
Variable	SIAV	EIAV	DIAV	EDIAV	SIAV	EIAV	DIAV	EDIAV
Intercept	-5.77 ***	-5.72 ***	-5.82 ***	-5.84 ***	9.29 ***	9.91 ***	9.75 ***	9.71 ***
	(1.11)	(1.11)	(1.11)	(1.11)	(0.61)	(0.62)	(0.61)	(0.61)
dDD_lag1	-0.25 ***	-0.30 ***	-0.25 ***	-0.33 ***	0.02	-0.06	-0.07	-0.06
	(0.04)	(0.04)	(0.06)	(0.08)	(0.05)	(0.05)	(0.06)	(0.07)
dDD_lag2	-0.44 ***	-0.48 ***	-0.29 ***	-0.41 ***	0.06	-0.05	-0.13 **	-0.12
	(0.05)	(0.05)	(0.07)	(0.09)	(0.05)	(0.05)	(0.07)	(0.09)
dDD_lag3	-0.34 ***	-0.34 ***	-0.39 ***	-0.45 ***	0.02	-0.12 **	-0.19 ***	-0.18 **
	(0.05)	(0.05)	(0.07)	(0.09)	(0.05)	(0.05)	(0.07)	(0.09)
DD_lag4	-0.28 ***	-0.29 ***	-0.47 ***	-0.50 ***	0.04	-0.11 ***	-0.13 **	-0.12
	(0.04)	(0.04)	(0.06)	(0.08)	(0.04)	(0.04)	(0.06)	(0.08)
SIZE	0.18 ***	0.15 ***	0.16 ***	0.17 ***	-0.62 ***	-0.62 ***	-0.61 ***	-0.61 ***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
dRTG_lag1	-0.07	-0.04	-0.07	-0.08	0.05	0.06	0.06	0.06
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
dRTG_lag2	-0.25 ***	-0.23 ***	-0.24 ***	-0.25 ***	0.05	0.06	0.07	0.06
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
dRTG_lag3	-0.23 ***	-0.22 ***	-0.22 **	-0.23 ***	-0.10	-0.08	-0.08	-0.08
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
RTG_lag4	-0.01	-0.02	-0.02 *	-0.01	-0.27 ***	-0.29 ***	-0.28 ***	-0.28 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.096	0.099	0.092	0.090	0.155	0.156	0.156	0.155
ΔR^2 (dDD and DD)	0.013	0.016	0.009	0.007	0.000	0.001	0.001	0.001

Table 2-12. Average statistics by Z-score deciles. Z-score is a measure of default probability proposed by Altman (1969) where a higher Z implies lower default probability. SIAV is the simple 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.

Z-Score Decile	N	DD_EDIAV	DD_EIAV	DD_DIAV	DD_SIAV
All	23,600	1.40	2.79	1.36	3.14
1	2,409	1.11	2.37	0.85	2.93
2	2,354	1.28	3.29	1.03	3.72
3	2,364	1.31	2.63	1.11	3.19
4	2,358	1.36	2.48	1.22	3.02
5	2,344	1.45	2.59	1.37	3.04
6	2,373	1.48	2.73	1.44	3.10
7	2,369	1.49	2.81	1.49	3.12
8	2,352	1.50	2.89	1.55	3.17
9	2,366	1.46	2.98	1.56	3.18
10	2,311	1.38	3.06	1.54	3.17

Table 2-13. Analysis of Z-score. We estimate via OLS $Z_{t,n} = \phi_0 + \phi_i \; DD_{t,n} + \sum_k \phi_k Controls_{k,t,n} + \varepsilon_{t,n}$ for the sample of 23,600 firm-quarter observations for 1975-2001. The dependent variable is Z-Score as calculated in Altman (1969) and is a measure of default probability based on accounting reports. A higher Z-Score implies lower probability of default. SIZE is the log of market value of assets. REG is an indicator variable that equals one if the firm operates in an industry regulated during the quarter in question. DD_SIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the simple, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities and values respectively. Control variables (industry and year-quarter indicator variables) are not presented for ease of exposition. ΔR^2 (DD) is the contribution of DD to the R^2 of a model including all but these variables. Standard errors are reported in parenthesis. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively.

	Industry Fixed Effects				Firm Fixed Effects			
	EDIAV	EIAV	DIAV	SIAV	EDIAV	EIAV	DIAV	SIAV
Low Z-Score Firms								
DD	0.090 ***	0.053 ***	0.082 ***	0.039 ***	0.029 ***	0.042 ***	0.032 ***	0.022 ***
	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
SIZE	0.011 ***	0.012 ***	0.012 ***	0.015 ***	0.090 ***	0.081 ***	0.089 ***	0.085 ***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)	(0.009)
REG	-0.003	-0.006	-0.001	-0.013	-0.084 *	-0.082 *	-0.077	-0.094 *
	(0.032)	(0.032)	(0.032)	(0.032)	(0.049)	(0.049)	(0.049)	(0.049)
R^2	0.240	0.241	0.247	0.231	0.709	0.714	0.710	0.709
ΔR^2 (DD)	0.021	0.021	0.027	0.011	0.002	0.007	0.003	0.002
High Z-Score Firms								
DD	-0.111 ***	0.019 **	0.024 **	-0.058 ***	-0.036 ***	0.049 ***	0.014 *	0.012 *
	(0.014)	(0.009)	(0.011)	(0.008)	(0.010)	(0.007)	(0.008)	(0.006)
SIZE	0.147 ***	0.123 ***	0.123 ***	0.142 ***	0.611 ***	0.613 ***	0.611 ***	0.613 ***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.017)	(0.017)	(0.017)	(0.017)
REG	0.275	0.194	0.176	0.204	-0.354 *	-0.345 *	-0.337 *	-0.347 *
	(0.210)	(0.210)	(0.210)	(0.210)	(0.190)	(0.190)	(0.190)	(0.190)
R^2	0.218	0.214	0.214	0.217	0.730	0.731	0.729	0.729
ΔR^2 (DD)	0.004	0.000	0.000	0.003	0.000	0.001	0.000	0.000

Table 2-14. Analysis of Z-score changes. We estimate via OLS $dZ_{t,n} = \theta_0 + \sum_{i=1}^{3} \theta_i \, dDD_{t-i,n} + \sum_k \theta_k Controls_{k,t,n} + \varepsilon_{t,n}$ on the sample of 19,800 firm-quarter observations for 1975-2001. The dependent variable is Altman's (1969) Z-Score. A higher Z-Score implies a lower probability of default. SIZE_lag is the one quarter lag of the log of market value of assets. REG is an indicator variable that equals one if the firm operates in an industry regulated during the quarter in question. DD_SIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the simple, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities and values respectively. Control variables (industry and year-quarter indicator variables) are not presented for ease of exposition. ΔR^2 (DD) is the contribution of all lags of dDD to the R^2 of a model including all but these variables. Standard errors are reported in parenthesis. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively.

	Industry Fixed Effects				Firm Fixed Effects			
	SIAV	EIAV	DIAV	EDIAV	SIAV	EIAV	DIAV	EDIAV
Negative Z Score Changes								
dDD_lag1	0.010 ***	0.013 ***	0.008 **	0.008 *	0.000	0.003	0.001	0.001
	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)
dDD_lag2	0.008 **	0.011 ***	0.007 *	0.009 *	0.002	0.004	0.002	0.000
	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)
dDD_lag3	0.004	0.006 *	0.003	0.004	0.001	0.003	0.001	0.002
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
dZ_lag1	-0.186 ***	-0.188 ***	-0.186 ***	-0.186 ***	-0.338 ***	-0.340 ***	-0.338 ***	-0.338 ***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
dZ_lag2	-0.122 ***	-0.124 ***	-0.122 ***	-0.122 ***	-0.213 ***	-0.215 ***	-0.213 ***	-0.213 ***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
dZ_lag3	-0.122 ***	-0.123 ***	-0.122 ***	-0.122 ***	-0.145 ***	-0.147 ***	-0.145 ***	-0.145 ***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
SIZE	0.007 ***	0.007 ***	0.007 ***	0.007 ***	-0.044 ***	-0.044 ***	-0.044 ***	-0.044 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.009)	(0.009)	(0.009)	(0.009)
REG	0.038	0.038	0.040	0.040	0.059	0.059	0.058	0.059
	(0.032)	(0.032)	(0.032)	(0.032)	(0.044)	(0.044)	(0.044)	(0.044)
R^2	0.1748	0.1754	0.1743	0.1742	0.3355	0.3357	0.3355	0.3356
ΔR^2 (dDD)	0.0010	0.0017	0.0006	0.0004	0.0001	0.0003	0.0001	0.0001

Table 2-14. Continued

	Industry Fixed Effects				Firm Fixed Effects			
	SIAV	EIAV	DIAV	EDIAV	SIAV	EIAV	DIAV	EDIAV
Positive Z Score Changes								
dDD_lag1	-0.001	0.000	0.001	0.001	0.007	0.010 **	0.005	0.008 *
	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)	(0.005)	(0.006)	(0.005)
dDD_lag2	0.001	0.003	0.001	0.001	0.001	0.009 *	0.002	0.006
	(0.003)	(0.003)	(0.003)	(0.004)	(0.009)	(0.006)	(0.007)	(0.005)
dDD_lag3	0.003	0.004	-0.001	-0.001	0.001	0.011 **	0.002	0.008 *
	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)	(0.005)	(0.006)	(0.005)
dZ_lag1	-0.047 ***	-0.048 ***	-0.048 ***	-0.048 ***	-0.272 ***	-0.273 ***	-0.272 ***	-0.272 ***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
dZ_lag2	0.007	0.007	0.007	0.008	-0.142 ***	-0.143 ***	-0.142 ***	-0.142 ***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
dZ_lag3	0.006	0.006	0.007	0.007	-0.143 ***	-0.144 ***	-0.143 ***	-0.143 ***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
SIZE	-0.011 ***	-0.011 ***	-0.011 ***	-0.011 ***	0.041 ***	0.042 ***	0.041 ***	0.042 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.014)	(0.014)	(0.014)	(0.014)
REG	-0.010	-0.010	-0.009	-0.009	0.125	0.115	0.126	0.117
	(0.029)	(0.029)	(0.029)	(0.029)	(0.149)	(0.149)	(0.149)	(0.149)
R^2	0.1107	0.1107	0.1105	0.1105	0.2281	0.2287	0.2281	0.2285
ΔR^2 (dDD)	0.0002	0.0002	0.0000	0.0000	0.0001	0.0006	0.0001	0.0004

Table 2-15. Sensitivity of summary statistics to alternative input assumptions. SIAV is the simple implied asset volatility calculated by de-levering historical equity volatility. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. Implied asset volatilities are reported in percent per year. V_SIAV, V_EIAV, V_DIAV, and V_EDIAV are the corresponding estimates of the market value of assets in billion dollars. DD_SIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the corresponding distance-to-default measures.

	Time to Firm Resolution				Default Point				Issuer Yield			
	Weighted Average Debt Duration		Weighted Average Debt Maturity		95% of Total Debt		99% of Total Debt		Weighted Averge Issue Yields		Largest Issue's Yield	
	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean
V_SIAV	2.92	8.35	2.91	8.31	2.90	8.16	2.90	8.15	2.91	8.29	2.91	8.28
V_EIAV	2.21	6.55	1.79	5.57	2.74	7.69	2.77	7.76	2.82	8.01	2.82	8.00
V_DIAV	2.20	6.66	1.88	6.03	2.20	6.28	2.21	6.31	2.23	6.46	2.23	6.45
V_EDIAV	2.22	6.59	1.81	5.63	2.74	7.69	2.77	7.76	2.82	8.00	2.82	7.99
SIAV	14.7	16.7	14.8	16.8	14.8	16.9	14.8	16.9	14.8	16.9	14.8	16.9
EIAV	20.0	23.4	24.2	28.2	15.9	18.1	15.7	17.9	15.5	17.7	15.5	17.7
DIAV	21.1	22.5	25.2	26.0	20.2	23.0	20.2	22.9	20.3	23.1	20.3	23.1
EDIAV	22.8	23.8	25.9	26.6	29.3	31.7	29.5	31.9	30.0	32.4	30.1	32.4
DD_SIAV	3.18	3.57	3.27	3.86	4.83	5.09	4.83	5.09	4.83	5.08	4.83	5.08
DD_EIAV	1.68	1.79	1.20	1.29	4.05	4.32	4.17	4.46	4.36	4.66	4.36	4.66
DD_DIAV	1.29	1.69	0.99	1.45	1.81	2.07	1.86	2.13	1.88	2.16	1.89	2.15
DD_EDIAV	1.31	1.55	1.00	1.27	1.97	2.15	1.99	2.19	2.00	2.22	2.00	2.21
N	28,236		28,113		27,750		27,754		27,735		27,717	

Table 2-15. Continued

	Tax Adjustment				Debt Priority					
	None		Moody's AAA-Rated Yield		All Debt Assumed Senior		Senior (Junior) Bonds Senior (Junior) to Remaining Debt		Credit Spreads Calculated from Non-Callable Bonds Only	
	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean
V_SIAV	2.91	8.32	5.32	12.09	2.88	8.23	1.71	4.17	5.76	13.75
V_EIAV	2.83	8.06	5.18	11.64	2.75	7.83	1.52	3.89	5.64	13.30
V_DIAV	2.18	6.35	4.83	11.26	2.03	5.88	1.07	2.75	4.34	10.86
V_EDIAV	2.82	8.04	5.18	11.64	2.73	7.78	1.51	3.88	5.63	13.29
SIAV	14.8	16.9	14.8	16.2	14.8	17.0	25.1	27.1	13.9	15.3
EIAV	15.5	17.7	15.4	16.8	15.8	18.0	27.6	30.7	14.3	15.8
DIAV	20.9	23.6	16.7	18.1	23.8	27.0	43.3	43.1	18.9	21.2
EDIAV	31.5	33.8	20.3	21.8	38.6	40.8	49.5	49.6	28.9	30.7
DD_SIAV	4.81	5.06	5.22	5.54	4.82	5.06	3.38	3.66	5.29	5.56
DD_EIAV	4.36	4.66	4.78	5.09	4.15	4.42	2.76	2.99	4.90	5.20
DD_DIAV	1.82	1.97	4.22	4.20	1.13	1.47	1.02	1.43	2.12	2.38
DD_EDIAV	1.94	2.05	4.61	4.02	1.41	1.65	1.08	1.33	2.22	2.46
N	27,740		7,425		27,802		27,412		10,031	

Table 2-16. Analysis of IAV and HAV forecasting properties under alternative assumptions. We estimate $RAV_{t,n} = \delta_0 + \delta_1 Voaltility\ Forecast_{t,n} + \varepsilon_{t,n}$. Volatility forecast is one of the five: SIAV, EIAV, DIAV, EDIAV, or HAV. SIAV is the simple implied asset volatility calculated by de-levering historical equity volatility. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. HAV is an estimate of annualized historical asset volatility calculated over the year prior to the end of each quarter. RAV is an estimate of annualized realized asset volatility over the two years following each quarter-end. Standard errors are reported in parenthesis. All coefficient estimates are statistically significant at the 1 percent level.

	EDIAV	EIAV	DIAV	SIAV	HAV	EDIAV	EIAV	DIAV	SIAV	HAV
Time to Resolution	Average Duration of Traded Debt					Average Maturity of Traded Debt				
Intercept	0.095	0.114	0.075	0.103	0.122	0.106	0.116	0.090	0.104	0.112
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
Slope	0.382	0.305	0.498	0.496	0.331	0.298	0.244	0.369	0.490	0.391
	(0.010)	(0.006)	(0.010)	(0.010)	(0.005)	(0.009)	(0.006)	(0.009)	(0.010)	(0.006)
R^2	0.062	0.083	0.095	0.100	0.132	0.044	0.066	0.064	0.098	0.157
Default Point	95% of Total Debt					99% of Total Debt				
Intercept	0.109	0.106	0.097	0.104	0.123	0.108	0.107	0.096	0.104	0.124
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Slope	0.242	0.447	0.395	0.491	0.329	0.243	0.450	0.396	0.490	0.328
	(0.007)	(0.009)	(0.008)	(0.010)	(0.005)	(0.007)	(0.009)	(0.008)	(0.010)	(0.005)
R^2	0.052	0.096	0.093	0.097	0.131	0.052	0.096	0.093	0.097	0.130
Issuer Yield	Weighted Average Issue Yield					Largest Isssue Yield				
Intercept	0.110	0.107	0.097	0.104	0.123	0.109	0.107	0.097	0.104	0.123
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Slope	0.239	0.449	0.393	0.491	0.328	0.240	0.449	0.395	0.491	0.328
	(0.007)	(0.009)	(0.008)	(0.010)	(0.005)	(0.007)	(0.009)	(0.008)	(0.010)	(0.005)
R^2	0.051	0.096	0.092	0.097	0.130	0.051	0.096	0.092	0.097	0.130
Tax Adjustment	None					Average Yield on Moody's AAA-rated Bonds				
Intercept	0.109	0.107	0.097	0.104	0.123	0.124	0.102	0.100	0.101	0.088
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Slope	0.231	0.449	0.382	0.491	0.329	0.231	0.426	0.415	0.453	0.501
	(0.007)	(0.009)	(0.008)	(0.010)	(0.005)	(0.017)	(0.020)	(0.022)	(0.022)	(0.012)
R^2	0.049	0.096	0.090	0.097	0.131	0.028	0.064	0.054	0.063	0.208
Debt Priority	All Debt Assumed Senior					Senior Bonds Assumed Senior to all other Debt				
Intercept	0.094	0.107	0.089	0.104	0.123	0.107	0.107	0.099	0.101	0.123
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
Slope	0.230	0.453	0.370	0.495	0.332	0.158	0.261	0.202	0.318	0.333
	(0.006)	(0.009)	(0.007)	(0.010)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
R^2	0.061	0.100	0.103	0.102	0.133	0.032	0.067	0.045	0.073	0.134
Non-callable Bonds Only										
Intercept	0.107	0.092	0.094	0.091	0.092					
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)					
Slope	0.200	0.477	0.349	0.504	0.451					
	(0.011)	(0.017)	(0.014)	(0.018)	(0.010)					
R^2	0.036	0.080	0.067	0.078	0.177					

Table 2-17. Logit analysis of defaults under alternative assumptions. We estimate the logistic regression $DFLT_{t,n} = \alpha_o + \alpha_1 DD_{t,n} + \alpha_2 Controls_{t,n} + \varepsilon_{t,n}$ on the sample of all 1,795 observations and the subsample of 519 non-investment-grade observations. The dependent variable DFLT equals 1 if the firm is delisted due to liquidation or performance, or files for bankruptcy in the three years following the fourth quarter of 1982, 1985, 1988, 1991, 1994, 1997, and 2000; it equals 0 otherwise. DD_SIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the simple, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. R^2 is max-rescaled pseudo R^2, which is an indicator of fit for logit models. ΔR^2 is the marginal contribution of each DD to R^2, which is the difference between R^2 of a model including DD, and that of a base model excluding it.

	Investment and Non-investment Grade Observations				Non-investment Grade Observations			
	DD_SIAV	DD_EIAV	DD_DIAV	DD_EDIAV	DD_SIAV	DD_EIAV	DD_DIAV	DD_EDIAV
Time to Resolution: Weighted Average Duration of Traded Debt								
R^2	0.227	0.168	0.156	0.156	0.158	0.143	0.131	0.134
ΔR^2 (DD)	0.079	0.020	0.008	0.008	0.034	0.018	0.006	0.009
Time to Resolution: Weighted Average Maturity of Traded Debt								
R^2	0.208	0.151	0.139	0.137	0.136	0.128	0.112	0.113
ΔR^2 (DD)	0.077	0.020	0.007	0.006	0.033	0.024	0.008	0.009
Deafult Point: 95% of Total Debt								
R^2	0.212	0.197	0.189	0.204	0.149	0.134	0.137	0.143
ΔR^2 (DD)	0.062	0.047	0.039	0.054	0.022	0.007	0.010	0.016
Deafult Point: 99% of Total Debt								
R^2	0.235	0.192	0.185	0.203	0.165	0.134	0.139	0.148
ΔR^2 (DD)	0.085	0.043	0.036	0.054	0.038	0.007	0.012	0.021
Issuer Yield: Weighted Average Issue Yields								
R^2	0.223	0.196	0.191	0.211	0.156	0.134	0.138	0.146
ΔR^2 (DD)	0.073	0.046	0.042	0.061	0.029	0.007	0.011	0.019
Issuer Yield: Largest Issue Yield								
R^2	0.223	0.196	0.190	0.209	0.156	0.134	0.139	0.146
ΔR^2 (DD)	0.073	0.046	0.041	0.060	0.029	0.007	0.012	0.019
Tax Adjustment: None								
R^2	0.222	0.196	0.182	0.193	0.156	0.134	0.138	0.145
ΔR^2 (DD)	0.073	0.047	0.032	0.043	0.029	0.007	0.011	0.019
Tax Adjustment: Average Yield on Moody's AAA-rated Bonds								
R^2	0.489	0.478	0.511	0.514	0.590	0.576	0.598	0.586
ΔR^2 (DD)	0.011	0.001	0.034	0.037	0.039	0.025	0.046	0.034
Debt Priority: All Debt Assumed Senior								
R^2	0.230	0.196	0.198	0.233	0.164	0.141	0.156	0.178
ΔR^2 (DD)	0.075	0.041	0.043	0.078	0.032	0.008	0.024	0.046
Debt Priority: Senior (Junior) Bonds Assumed Senior (Junior) to Remaining Debt								
R^2	0.244	0.241	0.197	0.215	0.180	0.174	0.150	0.160
ΔR^2 (DD)	0.087	0.084	0.040	0.057	0.043	0.037	0.013	0.023
Non-callable Bonds Only								
R^2	0.344	0.335	0.425	0.411	0.392	0.414	0.402	0.361
ΔR^2 (DD)	0.010	0.000	0.090	0.077	0.056	0.078	0.066	0.025

Table 2-18. Analysis of Moody's credit ratings under alternative assumptions. We estimate $RTG_{t,n} = \chi_0 + \chi_1 DD_{t,n} + \sum_k \chi_k Controls_{k,t,n} + \varepsilon_{t,n}$ via OLS for the sample of 25,701 observations over 1975-2001. Moody's rating of Aaa to Caa is coded as 1 to 19 respectively, so that as ratings deteriorate, the dependent variable increases. The dependent variable is not discrete since firm rating is the average rating of its debt issues which does not have to be the same. DD_SIAV, DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the simple, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. ΔR^2 is the contribution of DD to the R^2 of a model including control variables only. Standard errors are reported in parenthesis. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively.

	All Observations			
	DD_SIAV	DD_EIAV	DD_DIAV	DD_EDIAV
Time to Resolution: Weighted Average Duration of Traded Debt				
R^2	0.590	0.636	0.615	0.627
ΔR^2 (DD)	0.000	0.047	0.026	0.038
Time to Resolution: Weighted Average Maturity of Traded Debt				
R^2	0.607	0.643	0.622	0.629
ΔR^2 (DD)	0.000	0.035	0.015	0.022
Deafult Point: 95% of Total Debt				
R^2	0.638	0.662	0.618	0.629
ΔR^2 (DD)	0.060	0.085	0.040	0.052
Deafult Point: 99% of Total Debt				
R^2	0.636	0.655	0.614	0.623
ΔR^2 (DD)	0.060	0.079	0.038	0.047
Issuer Yield: Weighted Average Issue Yields				
R^2	0.633	0.645	0.616	0.616
ΔR^2 (DD)	0.059	0.070	0.041	0.041
Issuer Yield: Largest Issue Yield				
R^2	0.633	0.645	0.609	0.611
ΔR^2 (DD)	0.059	0.070	0.035	0.037
Tax Adjustment: None				
R^2	0.634	0.644	0.601	0.604
ΔR^2 (DD)	0.060	0.070	0.027	0.030
Tax Adjustment: Average Yield on Moody's AAA-rated Bonds				
R^2	0.453	0.476	0.486	0.440
ΔR^2 (DD)	0.063	0.086	0.096	0.050
Debt Priority: All Debt Assumed Senior				
R^2	0.636	0.659	0.622	0.630
ΔR^2 (DD)	0.056	0.079	0.042	0.050
Debt Priority: Senior (Junior) Bonds Assumed Senior (Junior) to Remaining Debt				
R^2	0.628	0.637	0.621	0.624
ΔR^2 (DD)	0.016	0.025	0.010	0.012
Non-callable Bonds Only				
R^2	0.488	0.498	0.499	0.497
ΔR^2 (DD)	0.073	0.083	0.083	0.082

Table 2-18. Continued

	Investment-Grade Firms				Non-Investment-Grade Firms			
	DD_SIAV	DD_EIAV	DD_DIAV	DD_EDIAV	DD_SIAV	DD_EIAV	DD_DIAV	DD_EDIAV
Time to Resolution: Weighted Average Duration of Traded Debt								
R^2	0.376	0.408	0.400	0.406	0.318	0.358	0.342	0.363
ΔR^2 (DD)	0.000	0.032	0.024	0.030	0.000	0.040	0.024	0.045
Time to Resolution: Weighted Average Maturity of Traded Debt								
R^2	0.391	0.415	0.406	0.409	0.337	0.369	0.352	0.364
ΔR^2 (DD)	0.000	0.025	0.016	0.018	0.000	0.032	0.015	0.027
Deafult Point: 95% of Total Debt								
R^2	0.418	0.437	0.413	0.418	0.340	0.367	0.348	0.383
ΔR^2 (DD)	0.044	0.063	0.039	0.044	0.032	0.060	0.040	0.075
Deafult Point: 99% of Total Debt								
R^2	0.417	0.430	0.409	0.413	0.339	0.362	0.346	0.376
ΔR^2 (DD)	0.044	0.058	0.036	0.041	0.031	0.054	0.039	0.069
Issuer Yield: Weighted Average Issue Yields								
R^2	0.413	0.420	0.413	0.410	0.337	0.351	0.339	0.362
ΔR^2 (DD)	0.043	0.050	0.043	0.039	0.031	0.045	0.033	0.056
Issuer Yield: Largest Issue Yield								
R^2	0.413	0.420	0.403	0.402	0.337	0.351	0.335	0.355
ΔR^2 (DD)	0.042	0.050	0.033	0.031	0.031	0.045	0.029	0.049
Tax Adjustment: None								
R^2	0.412	0.418	0.389	0.389	0.338	0.351	0.344	0.365
ΔR^2 (DD)	0.043	0.049	0.020	0.020	0.032	0.045	0.038	0.059
Tax Adjustment: Average Yield on Moody's AAA-rated Bonds								
R^2	0.402	0.425	0.410	0.385	0.533	0.531	0.541	0.546
ΔR^2 (DD)	0.039	0.062	0.047	0.022	0.007	0.006	0.016	0.020
Debt Priority: All Debt Assumed Senior								
R^2	0.412	0.429	0.415	0.419	0.344	0.368	0.350	0.386
ΔR^2 (DD)	0.041	0.058	0.044	0.048	0.031	0.055	0.037	0.073
Debt Priority: Senior (Junior) Bonds Assumed Senior (Junior) to Remaining Debt								
R^2	0.431	0.441	0.430	0.436	0.315	0.320	0.312	0.311
ΔR^2 (DD)	0.019	0.029	0.018	0.024	0.004	0.009	0.001	0.000
Non-callable Bonds Only								
R^2	0.442	0.451	0.464	0.458	0.506	0.503	0.494	0.498
ΔR^2 (DD)	0.034	0.044	0.057	0.050	0.023	0.020	0.011	0.015

Table 2-19. Analysis of credit rating changes under alternative assumptions. We estimate the logit model

$$dRTG_{t,n} = \beta_o + \sum_{i=1}^{3} \beta_{1i} dDD_{t-i,n} + \beta_2 DD_{t-4,n} + \sum_{j=1}^{3} \beta_{3j} dRTG_{t-i,n} + \beta_4 RTG_{t-4,n} + \sum_k \beta_k Controls_{t,n} + \varepsilon_{t,n}$$

for the period 1975-2001. Moody's rating change, dRTG, equals -1 if a firm is downgraded, 1 if it is upgraded, and 0 if its rating remains the same. When rating change is the dependent variable, we further distinguish upgrades and downgrades that cross the investment grade threshold from those that do not. The model estimates the probability of the lower rating change values. dDD_SIAV, dDD_EIAV, dDD_DIAV, and dDD_EDIAV are quarterly changes in the distance-to-default measures calculated from the simple, equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. Lags of variables are so indicated. The model's fit is measured by the max re-scaled pseudo R^2. ΔR^2 is the contribution of all lags of DD and dDD to the R^2 of a model including all but these variables.

	Credit Rating Downgrades				Credit Rating Upgrades			
	DD_SIAV	DD_EIAV	DD_DIAV	DD_EDIAV	DD_SIAV	DD_EIAV	DD_DIAV	DD_EDIAV
Time to Resolution: Weighted Average Duration of Traded Debt								
R^2	0.0919	0.0934	0.0854	0.0899	0.1572	0.1591	0.1587	0.1607
ΔR^2 (DD)	0.0136	0.0151	0.0071	0.0116	0.0004	0.0023	0.0019	0.0038
Time to Resolution: Weighted Average Maturity of Traded Debt								
R^2	0.0916	0.0953	0.0866	0.0910	0.1589	0.1589	0.1590	0.1595
ΔR^2 (DD)	0.0134	0.0171	0.0084	0.0128	0.0003	0.0003	0.0005	0.0009
Deafult Point: 95% of Total Debt								
R^2	0.0934	0.0988	0.0916	0.0888	0.1552	0.1561	0.1556	0.1552
ΔR^2 (DD)	0.0104	0.0158	0.0086	0.0058	0.0006	0.0014	0.0010	0.0005
Deafult Point: 99% of Total Debt								
R^2	0.0991	0.0997	0.0939	0.0920	0.1551	0.1564	0.1562	0.1555
ΔR^2 (DD)	0.0153	0.0159	0.0101	0.0082	0.0002	0.0015	0.0013	0.0006
Issuer Yield: Weighted Average Issue Yields								
R^2	0.0964	0.0995	0.0961	0.0948	0.1554	0.1565	0.1559	0.1557
ΔR^2 (DD)	0.0130	0.0161	0.0127	0.0114	0.0004	0.0015	0.0009	0.0007
Issuer Yield: Largest Issue Yield								
R^2	0.0959	0.0990	0.0928	0.0906	0.1553	0.1564	0.1558	0.1554
ΔR^2 (DD)	0.0129	0.0159	0.0098	0.0076	0.0004	0.0015	0.0009	0.0005
Tax Adjustment: None								
R^2	0.0953	0.0982	0.0924	0.0892	0.1551	0.1562	0.1559	0.1554
ΔR^2 (DD)	0.0128	0.0157	0.0098	0.0066	0.0003	0.0014	0.0010	0.0006
Tax Adjustment: Average Yield on Moody's AAA-rated Bonds								
R^2	0.0874	0.0986	0.1097	0.1064	0.1563	0.1539	0.1523	0.1542
ΔR^2 (DD)	0.0010	0.0122	0.0233	0.0200	0.0055	0.0031	0.0016	0.0034
Debt Priority: All Debt Assumed Senior								
R^2	0.0956	0.0983	0.0926	0.0909	0.1544	0.1555	0.1572	0.1561
ΔR^2 (DD)	0.0129	0.0155	0.0098	0.0082	0.0008	0.0019	0.0036	0.0025
Debt Priority: Senior (Junior) Bonds Assumed Senior (Junior) to Remaining Debt								
R^2	0.0935	0.1132	0.0857	0.0916	0.1628	0.1642	0.1639	0.1646
ΔR^2 (DD)	0.0165	0.0362	0.0087	0.0146	0.0006	0.0020	0.0017	0.0024
Non-callable Bonds Only								
R^2	0.1387	0.1561	0.1262	0.1202	0.1732	0.1643	0.1599	0.1619
ΔR^2 (DD)	0.0323	0.0496	0.0198	0.0137	0.0098	0.0009	-0.0035	-0.0015

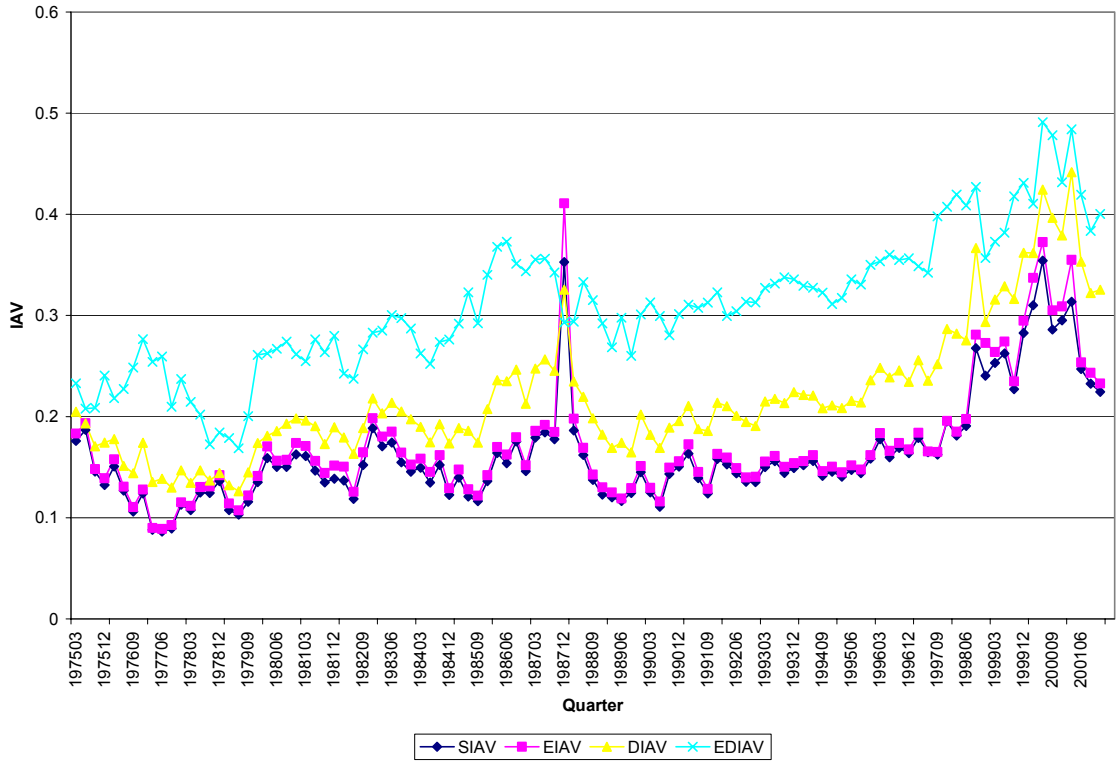

Figure 2-1. Median implied asset volatility over 1975-2001

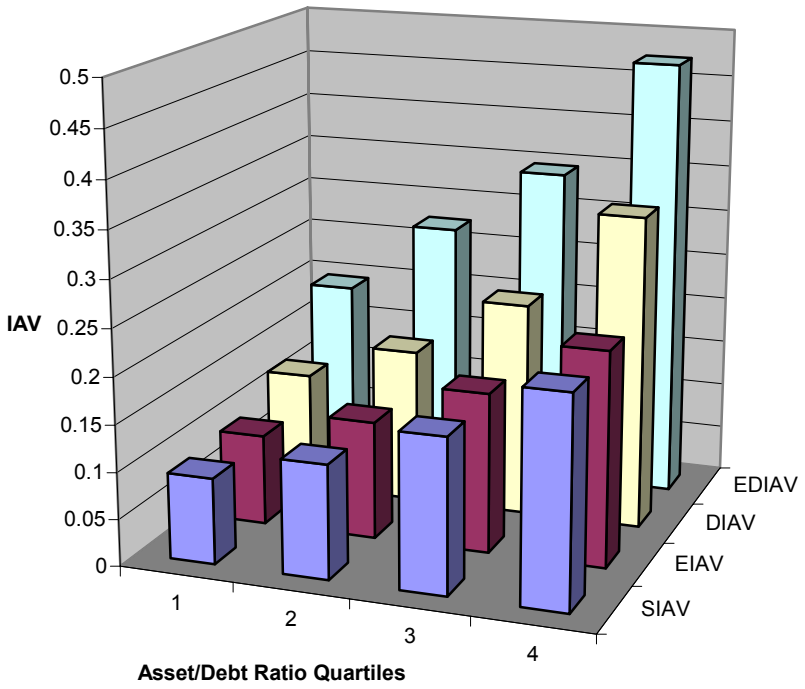

Figure 2-2. Median implied asset volatility by assets-to-debt ratio quartile

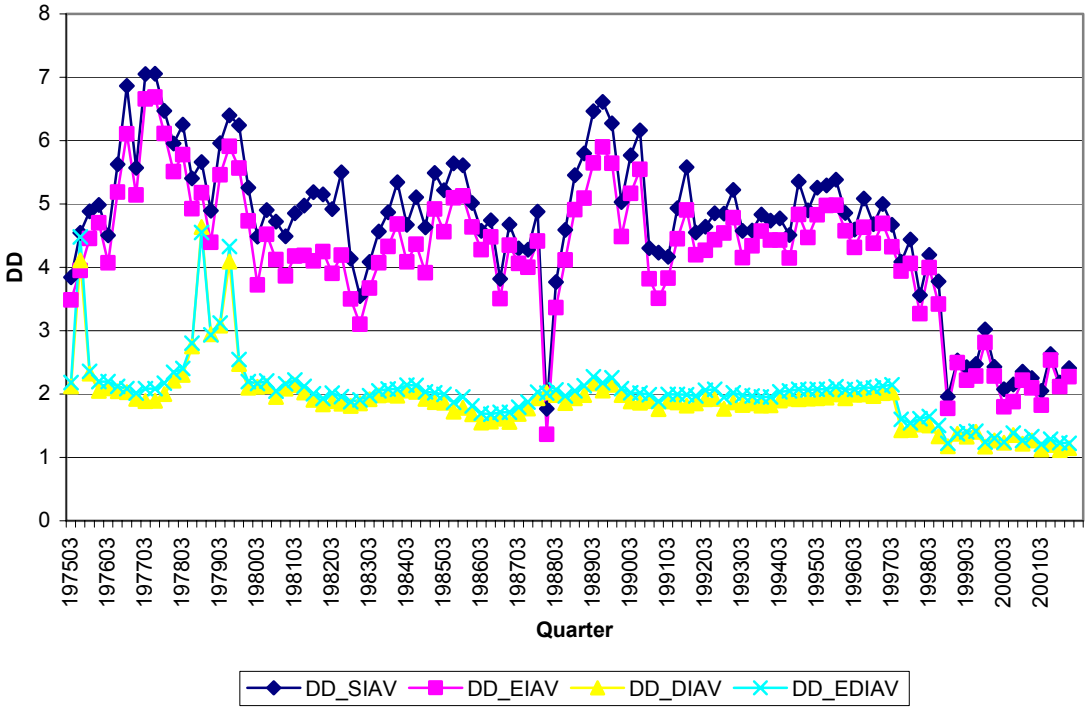

Figure 2-3. Median distance to default over 1975-2001

CHAPTER 3
BANK RISK REFLECTED IN SECURITY PRICES: EQUITY AND DEBT MARKET INDICATORS OF BANK CONDITION

3.1. Introduction

The banking industry is one of the most heavily regulated industries in the U.S. There are two commonly cited reasons for this extensive oversight. Banks play an important role in the economy, which creates the concern that bank failures might have a ripple effect and de-stabilize the financial system. In addition, bank claimholders are thought to be unable or unwilling to curb a bank's appetite for risk. These widely held beliefs have resulted in a complex set of government regulations that attempt to limit the risk-taking activities of banking firms. It was not until recently that bank supervisors warmed up to the idea that market discipline can aid them in this task:

> The real pre-safety-net discipline was from the market, and we need to adopt policies that promote private counterparty supervision as the first line of defense for a safe and sound banking system. (Greenspan, 2001)

Regulators have started to view market discipline as a desirable and necessary supplement to government oversight. Market discipline was proposed as one of the three pillars discussed in the Basel II proposal, and the Gramm-Leach-Bliley legislation required the study of mandatory subordinated debt proposals as a tool of improving market discipline.

In order to determine whether market discipline can deliver the benefits ascribed to it, researchers have examined whether the information in bank-issued securities is

accurate and timely, and whether it can improve supervisory assessments.[1] The general consensus is that bank risk is reflected in the valuation of all the securities that a bank issues. Most studies focus on the information in uninsured liabilities. They document a positive contemporaneous association between bank subordinated debt yields or large deposit rates, and indicators of risk (Evanoff and Wall 2002, Hall *et al*. 2002, Jagtiani and Lemieux 2000, Jagtiani and Lemieux 2001, Jagtiani *et al*. 2002, Krishnan *et al*. 2003, Morgan and Stiroh 2001, Sironi 2002). Although there are fewer studies that investigate the informational content of equity prices, they reach the same conclusion – market prices reflect a bank's current condition (Gropp *et al*. 2002, Krainer and Lopez 2002). Event studies provide further evidence that the prices of publicly traded debt and equity respond to relevant news in a rational manner (Allen *et al*. 2001, Berger and Davies 1998, Harvey *et al*. 2003, Jordan *et al*. 2000).

Even if market information is timely and accurate, there is also the question of whether it can add value to supervisory information. Numerous studies document that equity-market and debt-market indicators can aid regulators in their monitoring of banks by marginally increasing the explanatory power of regulatory-rating forecasting models. Berger *et al*. (2000) find that supervisory assessments are less accurate than equity market indicators in reflecting the bank's condition except when the supervisory assessment is based on recent inspections. Gunther *et al*. (2001) show that equity data in the form of expected default frequency adds value to BOPEC forecasting models. Elmer and Fissel (2001) and Curry *et al*. (2001) find that simple equity-market indicators (price, return, and dividend information) add explanatory power to CAMEL forecasting models

[1] See Flannery (1998) for an overview of the literature on the market discipline of financial firms.

based on accounting information. Evanoff and Wall (2001) show that yield spreads are slightly better than capital ratios in predicting bank condition. Krainer and Lopez (2003) find that equity and debt-market indicators are in alignment with subsequent BOPEC ratings and that including these in BOPEC off-site monitoring model helps identify additional risky firms.

These studies suggest that regulators can benefit from explicitly or implicitly including market information into supervisory models. However, they do not address the question of which market information to include. Previous research has argued that using debt prices is better suited for the purpose of oversight, since the incentives of debt holders are more closely aligned with those of regulators in that neither group likes an increase in asset risk.[2] However, this advantage of debt market prices is balanced out by a number of disadvantages. Debt prices are notoriously difficult to collect. While some corporate bonds trade on NYSE and Amex, they account for no more than 2% of market volume (Nunn *et al*. 1986). The accuracy of bond data is also problematic. Data quotes on OTC trades tend to be diffuse, and based on matrix valuation rather than on actual trades, and Warga and Welch (1993) document that there are large disparities between matrix prices and dealer quotes. Hancock and Kwast (2001) compare bond-price data from four sources, and find that the correlation among bond yields from the different sources are only about 70-80%. Finally, Saunders *et al*. (2002) document that the

[2] Gorton and Santomero (1990) are the first to point out that this statement is not necessarily true. The payoff to subordinated debt-holders is a nonlinear function of risk. Thus, at low leverage levels, subordinated debtholders have incentives similar to those of equityholders. However, the authors document that none of the banks in their sample have low enough leverage for this to occur. Furthermore, this describes an extreme situation that supervisors are likely to have already detected.

corporate bond market is characterized by a small number of bidders, slow trade execution, and large spreads between the best and second-best price bids.

Even if bond data were readily available and accurate, extracting risk information from debt spreads is complicated. The typical approach is to use debt prices, and calculate yield spreads as the difference between a corporate yield and the yield on a Treasury security of the same maturity. This spread is assumed to be a measure of credit risk. However, corporate yields will differ from Treasury yields for a number of reasons other than credit risk (Delianedis and Geske 2001, Elton *et al*. 2001, Longstaff 2002). They include premiums for tax, liquidity, and expected recovery differences between corporate and Treasury bonds, as well as compensation for common bond-market factors. Yield spreads also reflect redemption and convertibility options, sinking fund provisions, and other common bond features. The complexity of bond spreads raises new questions about their interpretation.

In contrast to debt markets, equity markets are liquid and deep, and equity prices of high frequency and quality can be easily obtained. Offsetting this data advantage is the difficulty in extracting firm risk information from equity prices. Increases in stock values do not always correspond to a safer bank, and by extension to a lower expected claim on the federal safety net. Under some circumstances, an insured institution's equity value can rise simply because its portfolio risk has risen, which leaves the bank's failure probability higher than before. This calls for using equity-market indicators other than prices or returns to extract information about firm risk. One such way is proposed by KMV (Crosbie and Bohn 2002, Gropp *et al*. 2002), who use equity prices and historical

equity volatility to calculate estimates of implied asset volatility. These are then combined with firm leverage to construct equity-based measures of default risk.

Since both debt and equity prices can impose challenges in inferring a bank's condition, perhaps the best way to overcome these challenges is to combine the information from these two sources. Saunders (2001) points out that contingent-claim models of firm valuation imply that in perfect markets both equity and debt prices will reflect the same information about firm market value and portfolio risk. To the extent that debt (or equity) prices contain noise, or fail to conform to the Black-Scholes assumptions used to back out risk parameters, using both securities (where they are available) might provide more accurate information. Gropp, Vesala and Vulpes (GVV) (2002) and Krainer and Lopez (KL) (2003) document the advantage of this approach by showing that a model using both equity-market and debt-market indicators to forecast bank risk outperforms a model using either set of indicators alone.

We address the general question of whether market information can aid regulators in their assessment of bank risk. More specifically, we evaluate the relative informational content and accuracy of firm risk measures obtained from equity or debt prices, and examine whether combining information from both markets can produce a more accurate risk assessment. We extend the analysis of KL and GVV in a number of ways. First, we argue that the equity and debt market indicators that these papers analyze are not necessarily comparable. KL compare debt credit spreads to equity abnormal returns but the link between changes in equity prices and changes in bank risk is not an obvious one. Positive abnormal returns can result from an increase in the market value of assets which reduces bank default probability, or from an increase in asset volatility which increases

default probability. GVV compare debt credit spreads to a distance-to-default measure extracted from equity prices using a structural credit risk model. Although theoretically appealing, structural models have attracted a lot of criticism for their limitations in explaining observed prices. Thus, the forecasting ability of the equity distance-to-default measure might be affected by its construction. To avoid such issues, we construct the exact same risk measure – a distance-to-default measure – first from equity prices and then from debt prices. We believe that this allows for a fairer comparison of the accuracy and informational content of equity and debt prices. Second, we conduct a larger set of tests in assessing the relative usefulness of equity and debt market indicators. The analysis in KL and GVV focuses on the forecasting ability of market indicators. However, even if market information cannot systematically improve supervisory assessments of a bank's future condition, contemporaneous affirmation of supervisory information can still provide substantial value. It may enable supervisors to act sooner when they perceive a problem, or it may cause appropriate forbearance if it suggests that the supervisory view is too bearish. We recognize this and as our second extension conduct both contemporaneous and forecasting tests on the accuracy of market indicators. Third, our data covers the period 1986-1999 which is a longer time series than in either KL or GVV. This also allows us to document the changes in market participants' behavior after the passage of the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991.

We start this study by constructing three implied asset volatility estimates for a set of 84 U.S. bank holding companies (BHCs) over the period 1986-1999. We model equity as a call option written on the market value of the firm's assets (Black and Scholes 1973),

and risky debt as riskless debt short a put (default) option (Merton 1974). Since both the equity-call and debt-put options are written on the same underlying, the firm's total assets, they are functions of the same set of variables: the market value of firm's assets, the volatility of the firm's assets, the face value of debt, interest rates, and the time to firm resolution (debt maturity). We use this framework to extract implied asset volatility from equity prices alone, debt prices alone, and equity and debt prices together. These asset volatilities are then combined with firm leverage to produce three versions of a single measure of default risk – distance to default (DD).

We then investigate the contemporaneous association between the three DD measures and other indicators of bank risk – (1) credit ratings, (2) asset portfolio quality, and (3) a composite financial-health score calculated from accounting-report variables. We find that all three DD measures are significantly related to the three risk proxies. This relationship is stronger for the measure constructed from debt prices than it is for the one constructed from equity prices, suggesting that the debtholders are relatively more informed about BHC risk. However, in the post-FDICIA period, the DD measure that combines information from equity and debt prices outperforms the other market indicators. It is more closely related to bank risk than is equity volatility, credit spread, or any of the other DD estimates.

Next, we compare the forecasting abilities of the three DD estimates. Since prices are inherently forward-looking, risk measures derived from them might detect changes in a bank's condition before these changes are observed in the bank's balance sheet or have resulted in a revised credit rating. We examine whether changes in the above proxies of bank risk can be forecasted using our three DD estimates. We document that these

estimates can predict which banks will be downgraded from investment grade to junk as much as three quarters prior to the downgrade. Once again, the DD measure constructed from debt performs better than the one constructed from equity prices. We also document that all five measures can foresee quarter-to-quarter changes in asset-portfolio quality and overall firm condition up to a year before these changes materialize in the firm's accounting reports. Finally, all of the forecasting tests confirm the contemporaneous tests result that combining information from equity and debt prices is superior to using either set of information alone. All of the "combination" models have better fit than their equity or debt counterparts.

Some of the above risk measures are constructed using contingent-claim models of firm valuation which require a set of theoretical assumptions. The final goal of this study is to investigate whether deviations from these assumptions are empirically important. We initially produce asset value and volatility estimates under a set of base assumptions and later explore the sensitivity of these estimates to alternative model assumptions. We document that while the estimates' magnitude and explanatory power changes, varying the model assumptions does not significantly affects our main findings.

3.2. Extracting Information about Firm Risk from Security Prices

3.2.1. Review of Contingent Claim Valuation Models

Black and Scholes (1973) were the first to recognize that their approach to valuing exchange-traded options could also be used to value firm equity. 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 τ .

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

$$E = VN(d_1) - De^{-R_f\tau}N(d_2) \tag{3-1}$$

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 returns,
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 that consists 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. Re-arranging the formula in Merton (1974) allows us to express the credit-risk premium as the spread between the yield on risky debt, R, and the yield on risk-free debt with otherwise the same characteristics:

$$R - R_f = -\ln\left\{\frac{V}{D}e^{R_f\tau}N(-d_1) + N(d_2)\right\}/\tau \tag{3-2}$$

One of the basic assumptions underlying Merton's (1974) derivation is that the firm issues a single homogenous class of debt. In reality, the characteristics of debt are highly variable, which makes his model intuitively useful, but not precisely 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. Thus, while knowing the precise breakdown of debt into priority classes is crucial for debt valuation, it does not affect the valuation of equity.

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

$$X_2 = V\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - D_1 e^{-R_f \tau} N(\tilde{d}_2) + (D_1 + D_2) e^{-R_f \tau} N(\hat{d}_2) \qquad \text{(3-3')}$$

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.

The Black-Cox model most frequently appears in the literature as the spread between the yield on subordinated debt (R_2) and the risk-free rate (R_f) of the same maturity:

$$R_2 - R_f = -\ln\left\{\frac{V}{D_2}e^{R_f\tau}\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - \frac{D_1}{D_2}N(\tilde{d}_2) + \frac{D_1 + D_2}{D_2}N(\hat{d}_2)\right\}/\tau \quad (3\text{-}3)$$

3.2.2. Methodologies for Calculating Implied Asset Value and Volatility

The above contingent-claim models of firm valuation suggest that information about a firm's asset value and volatility is embedded in both equity and debt prices. This section summarizes the two methodologies traditionally used to extract this information. It then describes a new one that relies on contemporaneous equity and debt prices to obtain V and σ_V.

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

$$E = VN(d_1) - De^{-R_f\tau}N(d_2) \quad (3\text{-}1)$$

$$\sigma_V = \sigma_E \frac{E}{VN(d_1)} \quad (3\text{-}4)$$

for σ_V and V. For the starting value of V, we use the sum of the market value of assets and book value of debt, and for the starting value of σ_V we use de-levered historical equity volatility.[3] 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 returns over the quarter. Marcus and Shaked (1984), Ronn and Verma (1986), Pennacchi (1987), Dale *et al*. (1991), and King and O'Brien (1991) apply this methodology to the analysis of deposit insurance premiums. It has also been used to calculate the market value of assets for savings and loan associations (Burnett *et al*. 1991), and insurance companies and

[3] We ensure that the asset value and volatility estimates produced by all three methodologies are not sensitive to the starting values used.

investment banks (Santomero and Chung 1992). We are aware of only one study that investigates whether the market value estimates obtained through this methodology are correct. Diba *et al*. (1995) use a contingent-claim model to calculate the equity values of failed banks and find that these values 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.

The debt-implied asset volatility (DIAV) is calculated by solving the system of nonlinear equations[4]

$$R_2 - R_f = -\ln\left\{\frac{V}{D_2}e^{R_f\tau}\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - \frac{D_1}{D_2}N(\tilde{d}_2) + \frac{D_1 + D_2}{D_2}N(\hat{d}_2)\right\}/\tau \qquad (3\text{-}3)$$

$$\sigma_V = \sigma_E \frac{E}{VN(d_1)} \qquad (3\text{-}4)$$

for σ_V and V. Once again, for the starting value of V we use the sum of the market value of equity and book value of debt, but for the starting value of σ_V we use 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 returns at the end of the quarter. This methodology is proposed in Gorton and Santomero (1990) and has since been used in Hassan (1993) and Hassan *et al*. (1993) to calculate implied asset volatilities, and in Flannery and Sorescu (1996) to obtain theoretical credit risk spreads.

[4] For the purpose of this study we use the subordinated debt valuation model under the assumption that a BHC's publicly issued bonds are subordinated to at least deposits. This assumption is quite reasonable. One of the statutes in the Omnibus Budget Reconciliation Act of 1993 established a national depositor preference in distributing the assets of a failed institution. That is, a failed bank's depositors have priority over nondepositors' claims. Such statutes were already in force in twenty-eight states.

The equity-and-debt implied asset volatility (EDIAV) is obtained by solving the system of nonlinear equations

$$E = VN(d_1) - De^{-R_f\tau}N(d_2) \tag{3-1}$$

$$R_2 - R_f = -\ln\left\{\frac{V}{D_2}e^{R_f\tau}\left[N(\tilde{d}_1) - N(\hat{d}_1)\right] - \frac{D_1}{D_2}N(\tilde{d}_2) + \frac{D_1 + D_2}{D_2}N(\hat{d}_2)\right\}/\tau \tag{3-3}$$

for σ_V and V. We use the same starting values for V and σ_V as in the calculation of DIAV. Note that unlike the previous three methodologies, this one needs no historical information about the standard deviation of equity. To the best of our knowledge this methodology has been used only in Schellhorn and Spellman (1996). They examine the difference between EIAV and EDIAV for four banks over 1987-1988. The authors conclude that the two volatility 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 equity prices and historical equity volatility.

These three methodologies are based on contingent-claim valuation and as a result require that the theoretical assumptions of Black and Scholes (1976) and Black and Cox (1979) be met. Bliss (2000) points out that this is 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 theoretical assumptions, applying contingent-claim valuation techniques requires 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 affect 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 an audit indicates that the market value of assets is found to be less than the value of total liabilities, regulators can choose to close the bank. 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 address in the current study. In the application of contingent-claim models to the valuation of industrial firms there is much less uniformity in the time-to-expiration assumption. Huang and Huang (2002) use the actual maturity of debt, Delianedis and Geske (2001) use the duration of debt, and Crosbie and Bohn (2002) use an interval of one year. Since the empirical properties of implied asset volatility are not the focus of these studies, they offer little evidence on the sensitivity of their results to alternative time-to-expiration assumptions. The study at hand fills this gap in the literature. To start with, we assume that the time to resolution equals one year. We later explore the effects of two alternative assumptions – time to resolution equals to either the weighted average duration or the weighted average maturity of the firm's bond issues.

Although it is often assumed 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 (p.881). They do not examine the relative accuracy of the estimates obtained under alternative default-point assumptions which is an issue that we address.

In summary, we employ the following base assumptions when calculating the three implied asset volatility estimates. The time to debt resolution equals one year; the default point is at 100% of total debt; the issuer's yield is the yield on the most recently issued bonds (Hancock and Kwast 2001); and, the adjustment for taxes is based on Cooper and Davydenko (2002). In the following sections we present detailed results obtained under this initial set of assumptions and in Section 3.4 investigate the sensitivity of our findings to alternative assumptions.

3.2.3. Distance-to-Default Measures

Three elements determine the probability that a firm will default – the market value of its assets, the market value of its liabilities, and the probability distribution of its asset returns. The difference between the first two determines the default of the firm. The last element captures the business, industry, and market risks faced by the firm and is measured by asset volatility. If the implied asset volatility estimates calculated in this

study offer a correct assessment of the firm's risk exposure, then along with asset and liability values they should reflect default probability accurately. We combine asset volatility with the value of assets and liabilities into a single measure of default risk and refer to it as distance to default (DD). This measure compares a firm's net worth to the size of one standard deviation move in asset value and is calculated as:

$$DD = \frac{\ln(V/D) + \left(R_f - 0.5\sigma_V^2\right)\cdot T}{\sigma_V \sqrt{T}}$$

Intuitively, a DD value of X tells us that a firm is X standard deviations of asset returns 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.

We calculate a DD measure based on each of the three asset volatility and value estimates discussed above: EIAV (uses equity values and historical equity volatility), DIAV (uses debt values and historical equity volatility), and EDIAV (uses debt and equity values). In the tests that follow we assess the relative accuracy and forecasting abilities of these three measures and compare their performance to that of more traditional risk measures – equity volatility and credit spreads.

3.3. Data Sources

This study combines a number of data sources for the period of January 1986 – December 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, accounting data comes from the Y-9 reports filed by bank holding companies.

Combining equity-characteristic, debt-characteristic, and accounting data from these four 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.

3.3.1. 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. BHC-issued fixed-rate coupon-paying debentures that are not

convertible, putable, secured, or backed by mortgages/assets. We collect data on their month-end yield, prepayment options, and amount outstanding. 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, non-putable, and non-secured debentures issued by U.S. BHCs. 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 the 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 spread, we need to subtract from each corporate yield the yield on a debt security that is risk-free but otherwise has the same characteristics as the corporate bond. The most common approach to calculating a credit spread is to

difference the yield on a corporate bond with that on a Treasury bond of the same remaining maturity. To do so we collect 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 measure of the raw credit spread. These spreads are further adjusted for tax and call-option premiums, and are then aggregated to obtain an issuer credit spread.

3.3.1.1. Tax adjustment

There is growing evidence that corporate yield spreads calculated as above cannot be entirely attributed to the risk of default. Huang and Huang (2002) and Delianedis and Geske (2001) demonstrate that at best less than half of the difference between corporate and Treasury bonds is due to default risk. Elton *et al*. (2001) suggest that this difference can be explained by the differential taxation of the income from corporate and Treasury bonds. Since interest payments on corporate bonds are taxed at the state and local level while interest payments on government bonds are not, corporate bonds have to offer a higher pre-tax return to yield the same after-tax return. Thus, the difference between the yield on a corporate and the yield on a Treasury bond must include a tax premium. Elton *et al*. (2001) illustrate that this tax premium accounts for a significantly larger portion of the difference than does a default risk premium. For example, they find that for 10-year A-rated bonds, taxes account for 36.1% of the yield spread over Treasuries compared to the 17.8% accounted for by expected losses. Cooper and Davydenko (2002) derive an

explicit formula for the tax adjustment proposed by Elton *et al*. (2001). They calculate that the tax-induced yield spread over Treasuries is:

$$\Delta y^{tax} = \frac{1}{t_M} \ln\left[\frac{1-\tau}{1-\tau \exp\left(-r_{t_M}^{rf} t_M\right)}\right]$$

where t_M is the time to maturity for both the corporate and the Treasury bonds, τ is the applicable tax rate, and $r_{t_M}^{rf}$ is the Treasury yield.[5] We use this formulation along with the estimated relevant tax rate of 4.875% from Elton *et al*. (2001) to calculate a hypothetical Treasury yield if Treasuries were to be taxed on the state and local level.[6] The difference between a corporate yield and a corresponding "taxable" Treasury rate is a measure of the tax-adjusted raw credit-risk spread.

Alternatively, we can difference corporate yields with the yield on the highest rated bonds under the assumption that these almost never default. We obtain Moody's average yield on AAA-rated bonds from the Federal Reserve Board's H.15 releases. It is important to note that differencing a corporate yield with the AAA yield might allow us to extract a more accurate estimate of the credit-risk premium by controlling for liquidity as well as tax differential between corporate and Treasury bonds. However, it is also the case that the AAA yield has a number of drawbacks – it averages the yields on bonds of different maturity and different convertibility/callability options. Nevertheless, for the non-AAA-rated bonds in our sample we use the difference between their yield and the average AAA yield as an alternative tax adjustment for the raw credit-risk spread. We

[5] This formulation of the yield spread due to taxes assumes that capital gains and losses are treated symmetrically and that the capital gain tax is the same as the income tax on coupons.

[6] Corporate bonds are subject to state tax with maximum marginal rates generally between 5% and 10% depending on the state. This yields an average maximum state tax rate in the U.S. of 7.5%. Since in most states, state tax for financial institutions (the main holder of bonds) is paid on income subject to federal taxes, Elton *et al.* (2001) use the maximum federal tax rate of 35% and the maximum state tax rate of 7.5% to obtain an estimate for τ of 4.875%. An alternative estimate is produced by Severn and Stewart (1992) and equals to 5%.

start by differencing the corporate yields with the hypothetical taxable Treasury yields. However, in the spirit of this study we later investigate whether using the average AAA yields significantly affects the accuracy and informational content of the implied asset volatility estimates.

3.3.1.2. Call-option adjustment

The tax-adjusted yield spreads calculated above might still contain some non-credit related components. 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 spread over Treasuries whether adjusted for taxes or not, will 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 "taxable" 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 adjusted for taxes. 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 tax-adjusted spreads calculated earlier to obtain option-adjusted credit spreads.

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.

In a small number of cases these credit spreads turn out to be negative. A cursory examination of these occurrences indicates when the term structure of interest rates is relatively flat and interest rate volatility high, our option-adjustment methodology produces higher option values. When combined with an initially low yield (high-rated bonds) these high option values lead to negative credit spreads. Since the theoretical motivation used in this study does not allow for negative credit spread values and since negative credit spreads are heavily concentrated in high-rated bonds, we winsorize our set of credit spreads at zero.[7]

3.3.1.3. Yield spread aggregation

To obtain a firm yield spread, YS, 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

[7] We intend to investigate the resulting statistical bias by repeating all test after having excluded negative yield spreads altogether.

most recent issue as our third measure. We investigate whether different aggregation approaches produce significantly different IAV estimates.

3.3.2. 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 annualized standard deviation of 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 fewer than fifty equity-return observations in a quarter. These data filters attempt to reduce the effect of the bid-ask bounce on the estimate of equity-return volatility, and attempt to provide enough observations to make the quarterly volatility estimate meaningful.

3.3.3. Accounting Data

Quarterly accounting data for the bank holding companies is obtained from the "Consolidated Financial Statements" (Y-9 reports) filed with the Federal Reserve Board. These statements consolidate the balance sheets of the parent corporation with those of its subsidiaries. For each BHC in our sample we collect information on the book value of total assets V_B, the book value of subordinated notes and debentures, D_2, loan quality, profitability, and capitalization at the end of each calendar quarter during 1986-1999.

3.4. Sample Selection and Summary Statistics

Merging data from the above sources produces a sample of 98 unique BHCs which give us 2,110 firm-quarter observations for 1986-1999. We require each BHC to have

filed at least four quarters of supervisory data in order to be able to conduct our forecasting analysis. We then employ the methodologies and the input assumptions described earlier to compute our three estimates of implied asset value and volatility using the Newton iterative method for solving systems of nonlinear equations.[8] Our final sample contains 2,060 observations for 84 different BHCs.

Table 3-1 presents summary statistics on the 2,060 firm-quarters. The BHCs in our sample are quite large which is not surprising given that they have both publicly traded debt and equity. The average market value of assets is in the range of $40-42 billion and is very similar across methodologies. The estimates of implied asset volatility show relatively more variation – the average is 3.02% for EIAV, 3.16% for DIAV, and 4.55% for EDIAV. The magnitude of EDIAV is consistent with that reported in Schellhorn and Spellman (1996) who find EDIAV to be on average 40% higher than EIAV.

We investigate whether the implied asset volatility estimates vary across quarters. Figure 3-1 plots median implied asset volatility for each quarter during 1986-1999, and makes three noteworthy points. First, the three IAV measures appear to follow a similar time pattern. The one notable exception is the last quarter of 1987 when median EIAV and DIAV dramatically increase, while EDIAV falls. This is likely due to the reliance of the first two estimates on historical equity volatilities calculated over the three-month period that includes the October 1987 crash. EDIAV on the other hand is not affected by the crash-induced historical equity volatility and as a result is a more forward-looking assessment of asset volatility. In fact, EDIAV increases in the second quarter of 1987

[8] For a small set of observations, the Newton 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 three asset value and volatility estimates for the majority of the original observations.

possibly in anticipation of the crisis to come. Finally, the plot shows a general upward trend in the three IAV estimates suggesting that the risk of BHC assetss has been increasing over time.

We also explore whether our estimates of implied asset volatility are affected by BHC capitalization. At the end of each quarter in 1986-1999, we use each firm's book value of assets to debt ratio ranking to assign it to one of four quartiles. Figure 3-2 shows median implied asset volatilities from our four methodologies by assets-to-debt ratio quartile. It is apparent that the higher the amount of debt relative to assets, the lower the implied volatility. A possible explanation for this finding is that a firm's capital structure and asset volatility are simultaneously determined. BHCs that are relatively better capitalized might be willing to take on more risk since they have a significant equity cushion to absorb changes in total asset value. This is consistent with the findings of Shrieves and Dahl (1992) and Calomiris and Wilson (1998) that increases in bank risk are positively related to increases in bank capital.

The distance-to-default measures (DD) can possibly avoid problems resulting from the endogenous relationship between implied volatility and leverage since it combines them into a single measure of credit risk. Table 3-1 presents summary statistics on DD calculated from the three estimates of implied asset volatility. The average DD is 3.91 if calculated from EIAV, 2.32 if calculated from DIAV, and 2.43 if calculated from EDIAV. Figure 3-3 shows the time series behavior of the three DD estimates. While the estimate calculated from EIAV is very volatile, those calculated from DIAV and EDIAV are very stable. For instance, during 1986-1999 the median DD_EDIAV and DD_DIAV

have remained in the range of 1.5-2.5 while the median DD_EIAV has fluctuated in the much wider range of 1.5-5.5.

Table 3-2 examines more closely the differences among the three implied asset value, volatility, and distance-to-default estimates. Panel A indicates that the estimate of market value of assets is largely independent of the methodology used to compute it – simple and rank correlations among all of the three estimates are essentially 1. Panel B shows that this is not the case for the three implied asset volatility estimates. Two of them are still very similar – EIAV and DIAV have simple and rank correlations in the 90% range – while the third one appears to be quite different. The simple (rank) correlation of EDIAV with EIAV and DIAV is 70% (66%) and 80% (73%) respectively. Panel C presents the correlations among the three DD estimates and points to a strong association between DD_DIAV and DD_EDIAV, and low association between these two and DD_EIAV. Interestingly enough, these do not simply reflect differences in implied asset volatility. Comparing the results in Panel B with those in Panel C suggests that high correlation between any two implied volatility estimates does not necessarily translate into high correlation between the corresponding distances to default.

The wide range of correlation among the distance-to-default measures reported in Table 3-2, Panel C suggests that different methodologies produce very different estimates. Although all of the simple and rank correlations are statistically different from zero, all of them are also statistically different from one. By using information from different sources these three methodologies produce risk measures not only of different magnitude but also of different ranking. In the two sections that follow we investigate

whether these differences translate into differences in informational content and accuracy.

3.4. Relative Accuracy of Market Indicators of Risk

Our comparison of market indicators of risk starts with an assessment of their relative accuracy. If market participants are able to correctly evaluate a BHC's condition and promptly reflect it in the BHC's security prices, then risk measures constructed from these prices will be significantly related to other indicators of bank risk. That is, if a bank's risk increases, so will its default probability, which implies a lower distance to default, higher equity volatility, and higher yield spread.

To measure a BHC's risk we employ three proxies. The first one, RTG, is the average Moody's rating of each bank's subordinated notes and debentures (SNDs) weighted by its amount outstanding. RTG is designed to capture the risk assessment of rating agencies. The Moody's rating of each SND issue is coded as a discrete number varying from 1 (Aaa) to 20 (Ca). Since most BHCs in our sample have more than one SND issue outstanding, their rating turns out to be non-discrete variable between 1 and 20 where a higher RTG indicates a riskier bank.[9] The second proxy is a set of balance sheet variables that previous studies have found to reflect the financial health of banks. These include profitability, asset quality, and capitalization measures, which are summarized in Table 3-1. Our third proxy, SCORE, is a composite score of the firm's condition based on five indicators: CAP (Capital Adequacy), LLAGL (Asset Quality), EFFIC (Management), ROA (Earnings), and LIQ (Liquidity). For every year in our sample, we consider each bank's percentile ranking for all five indicators. We divide the

[9] I also used Moody's ratings without notches and the results were even stronger.

ranking distributions into quartiles and assign a score varying from 1 (best) to 4 (worst) to each bank based on its ranking. We obtain our composite score by summing up the scores for each indicator yielding a variable between 5 and 20 where a lower composite score indicates a healthier firm.

We start our analysis with several univariate examinations of whether the five market measures of risk are generally consistent with the above three indicators of BHCs' financial health. Table 3-3 provides summary statistics on the average market indicator estimates by Moody's credit rating. It shows that the market indicators derived from debt prices (DD_DIAV and YS), or from equity and debt prices (DD_EDIAV) agree with credit ratings. The average DDs decrease and average YS increases as rating deteriorates. Except for the highest rating categories, equity market indicators are also consistent in that average DD_EIAV decreases and average EV increases as we move from Aaa-rated to Caa-rated firms.

We also examine whether our five market indicator estimates are consistent with BHC asset quality. Each year we assign firms in our sample to one of ten asset quality deciles. We use two proxies for asset quality – (1) loan loss allowances as a proportion of total loans (LLAGL), and (2) the sum of past-due loans, non-accruing loans, and other real estate owned as a proportion of total loans (BADLOANS). Table 3-4 presents averages of the three DD estimates by asset quality deciles and shows that higher deciles are typically associated with lower DDs. The relationship between average market indicator estimates and asset quality deciles appears to be non-monotonic, but a closer look at the data suggests that this is due to the effect of outliers.

Finally, we use the same approach to explore the relationship between a BHC's overall financial condition and the five market indicators. As above, each year we assign firms to one of ten SCORE deciles. Table 3-5 presents averages of the three DD estimates, EV, and YS by SCORE decile. It documents that BHCs in relatively worse condition typically have lower DDs, higher equity volatility, and higher credit spreads. It is interesting to note that the market measures are typically more consistent over the higher SCORE deciles, which suggests that they might be more accurate for firms in a weaker financial state.

We test the contemporaneous accuracy of the five market indicators of BHC risk – three DD measures, equity volatility (EV), and credit spread (YS) – by estimating the model below with two-way fixed effects:

$$MktInd_{it} = \alpha_0 + \alpha_1 FH_{it} + \alpha_2 Size_{it} + \varepsilon_{it} \qquad (3\text{-}6)$$

For each firm i at the end of quarter t, $MktInd_{it}$ is one of the five market indicators: DD_EIAV, DD_DIAV, DD_EDIAV, EV, or YS; FH_{it} is one of the three financial health proxies described earlier; and $Size_{it}$ is the natural logarithm of the market value of assets. The model also includes cross-sectional and time-series fixed effects. Previous studies have found that the passage of FDICIA has limited the implicit and explicit government guarantees and has thus affected the informational content of market measures of risk. To account for this regime shift in late 1991, we estimate the above model for separately for the pre-FDICIA (June 1986 – September 1991) and post-FDICIA (December 1991 – December 1999) periods.

Table 3-6 contains the results from the multivariate analysis using Moody's ratings as the main independent variable. In all five models the BHC Moody's rating, RTG, is

statistically significant in explaining each of the five market indicators of risk. This implies that investors are both willing and able to accurately assess BHCs' underlying risk, and that they promptly price it in these firms' debt and equity securities. In comparing the informational content of equity and debt prices, we examine the fit statistics for Model 1 versus Model 2, and Model 4 versus Model 5. We find that debt-price-only indicators (DD_DIAV and YS) always outperforms equity-price-only indicators (DD_EIAV and EV) suggesting that debtholders are on average more accurate in their assessment of BHC risk. We also document that using more complex market indicators (distance-to-default measures) over simpler ones (credit spreads or equity volatilities) increases the explanatory power of debt-market indicators and reduces that of equity-market indicators. Finally, we show that using both equity and debt prices in constructing a market risk measure is superior to using either set of prices alone. In the post-FDICIA period DD_EDIAV – the distance to default measure calculated from contemporaneous equity and debt prices without reliance on historical volatility – is most closely related to BHC credit rating. The R^2 of the model in which DD_EDIAV is the dependent variable is at least 2.5 percentage points higher than those of any of the other models.

Table 3-7 shows the results from a multivariate analysis that uses a set of asset quality measures to explain BHC market indicators of risk. These are consistent with the results presented in Table 3-6. BHCs with less low-quality assets (past-due loans, non-accruing loans, and other real estate owned) have higher DD measures, lower EV, and lower YS. The interactions of these variables with firm leverage (equity-to-debt ratio) are expected to capture the non-linear effect of asset quality and leverage. Their positive

coefficients in the DD models and negative coefficients in the EV and YS models suggest that asset quality is more relevant for banks with higher leverage. Profitability (ROA) is typically not statistically significant but whenever significant it enters with a positive sign in the DD models and negative sign in the EV and YS models. This implies that BHCs with higher return-on-assets ratio are perceived as having lower credit risk. The explanatory power in these regressions follows a pattern similar to that in Table 3-6. First, debt-only market indicators (DD_DIAV and YS) outperform equity-only market indicators (DD_EIAV and EV). Second, in the post-FDICIA period of 1991-1999, the DD_EDIAV model has the best fit (R^2 of at least 2.2 percentage points higher than that of any of the other models), thus suggesting that the DD measure calculated from contemporaneous equity and debt prices is more closely related to accounting measures of asset quality than are other market indicators of risk. It is interesting to note that while the equity-derived DD is related to OREOGL and the debt-derived DD is related to NALGL, the equity-and-debt DD is significantly related to both OREOGL and NALGL. This supports the idea the using equity and debt market indicators performs better because it combined risk information from two sources.

Finally, Table 3-8 presents the results in which the main explanatory variable is the composite score of the BHC financial health. The negative coefficient on SCORE in the DD models implies that weaker firms (as indicated by a higher SCORE) are characterized by lower DD measures. It is interesting to note the change in sign and statistical significance of SIZE across the two subperiods in the fixed-effects estimation. During pre-FDICIA period firm size is either not significant or has a negative coefficient in the EV and YS models, thus suggesting that larger firms have lower credit risk. This is

consistent with the existence of implicit or explicit government guarantees for banks considered "too big to fail". In the post-FDICIA period, larger banks are associated with lower DD measures, higher EV, and higher YS. One possible explanation for this finding is that larger banks are more flexible and better able to handle adverse shocks. Another explanation is that investors have come to believe regulators' claims that "too big to fail" guarantees are over. Bank managers, on the other hand, might know that political pressures in the face of a big bank failure can make it difficult for regulators to keep their word.

Our findings on the relative accuracy of the five market indicators in the post-FDICIA period are consistent with those presented in Table 3-6 and Table 3-7. First, debt-price indicators outperform equity-price indicators. Second, using more complex risk indicators improves the model fit for debt-price indicators and worsens that for equity-market indicators. Finally, judging by the explanatory power of the five models, DD_EDIAV is the most accurate measure as indicated by the highest R^2 of that model which is at least 1.9 percentage points higher than that of any of the other models.

In summary, the above tests suggest that all five market indicators of BHC risk are closely related to credit agency assessments, asset portfolio quality, and overall firm condition as indicated by accounting variables. This confirms the findings of previous studies[10] that both equity and debt prices of BHC-issued securities accurately and promptly reflect information about the firm's financial condition. Comparison of the explanatory power of the five models reveals three noteworthy points. First, market indicators based on debt prices alone outperform market indicators based on equity prices

[10] See Flannery (1998) for a review of these studies.

alone. Second, the use of structural credit risk models to construct market indicators tends to improve the informational content of debt measures and worsen that of equity measures. Finally, as indicated by the model's fit, the distance-to-default measure calculated from both equity and debt prices displays the closest association with the three proxies of BHC true risk. This suggests that combining information from equity and debt prices can improve the quality of market measures of risk.

3.5. Relative Forecasting Ability of Market Indicators of Risk

In this section we empirically examine the forecasting ability of market indicators of BHC risk. Since market prices are investors' expectations of future outcomes, risk indicators constructed from them might reflect not only current but also future bank condition. To test this conjecture we examine (1) whether market indicators of BHC risk can predict material changes in the firm's default probability, and (2) whether changes in the indicators can foresee quarter-to-quarter changes in the firm's asset portfolio quality and composite financial health score.

3.5.1. Forecasting Material Changes in Default Probability

We first examine the ability of market indicators to predict significant changes in the BHCs' default probability. The clearest manifestation of such a change would be a default, but large U.S. BHCs almost never fail – only three firms in our sample do. In the absence of BHC failures, we consider a downgrade from investment to non-investment grade by Moody's as a signal of a material weakening of the BHC's financial condition (an approach similar to that in Gropp *et al*. 2002).

We start our analysis with simple mean-comparison tests to determine whether market risk indicators can distinguish the financially weak banks in our sample. Table 3-9 presents the results. As hypothesized, BHCs that eventually experience a material

negative change in their financial condition have lower DD measures, higher EV, and higher YS. All five of our market indicators have predictive power up to two quarters prior to the event. Three quarters prior only the measures derived from debt prices can distinguish between BHCs that will be significantly downgraded from those that are not.

As a second step in testing whether our market indicators of risk can predict material changes in BHC default probability, we estimate a standard logit model of the form:

$$\Pr\left[Change_{i,t} = 1\right] = g\left(\beta_0 + \beta_1 MktInd_{i,t-k} + \beta_2 RTG_{i,t-k} + \beta_3 Size_{i,t-k}\right) \qquad (3\text{-}7)$$

where

$$Change_{i,t} = \begin{cases} 1 \; if \;\; bank \; is \; downgraded \;\; from \; investment \; to \; non-investment \; grade \\ 0 \; otherwise \end{cases}$$

The cumulative logistic distribution is denoted by $g(\cdot)$. $MktInd_{i,t-k}$ is one of the five market indicators – DD_EIAV, DD_DIAV, DD_EDIAV, EV, or YS – for firm i, k quarters prior to quarter t. $RTG_{i,t-k}$ is firm i's Moody's rating k quarters prior to quarter t.[11] $Size_{i,t-k}$ is the natural logarithm of firm i's market value of assets k quarters prior to quarter t. We explicitly control for size for at least two reasons. Large BHCs might attract more government oversight and this might have the effect of preventing small problems escalating into more serious ones. It might also be the case that credit rating agencies pay different attention to the financial health of small versus large firms.

[11]In an alternative model specification we substitute the continuous variable RTG with indicator variables for each of the major rating categories. The results are basically the same with DD_EDIAV having higher explanatory power one and two quarters prior to the event.

The results from the logit analysis are presented in Table 3-10. Consistent with the mean difference tests, we find that all five market indicators are statistically significant in explaining the probability of experiencing a material negative change one and two quarters prior to the change occurring. Only, DD_DIAV, DD_EDIAV, and YS have predictive power three quarters prior.[12] This is in contrast to the findings of Gropp *et al*. (2002) that equity-market indicators are the first to respond to European financial institutions' weakening condition.

In order to compare the informational content of equity-market indicators to that of debt-market indicators of risk, we estimate two models which include both sets of indicators as explanatory variables. The last two columns of Table 3-10 show that in these specifications equity indicators are not statistically significant. This suggests that when it comes to predicting downgrades from investment to junk, the information available from equity prices is a subset of the information available from debt prices. That is, equityholders do not know more than debtholders when it comes to material negative changes in BHC default probability.

Finally, information from both equity and debt prices is neither better nor worse than debt-price information in predicting significant credit downgrades. The fit of the models which include equity-price and debt-price information is the same as that of the models including debt-price information alone. This is the direct result of equity prices containing redundant information about material changes in default probability.

[12] Four quarters prior, DD_DIAV and DD_EDIAV are marginally significant (at the 10 percent level) in explaining the probability of a material negative change in BHC condition.

3.5.2. Forecasting Changes in Asset Quality

After confirming that our five market indicators can foresee material changes in BHC financial conditions, we investigate whether their forecasting power extends to changes of any (low and high) magnitude. In this section we explore whether changes in any of the five market indicators can explain future changes in BHC asset quality beyond what can be explained by historical asset quality information. As in Section 3.4, we use two proxies for asset quality – (1) loan loss allowances as a proportion of total loans (LLAGL), and (2) past-due loans, non-accruing loans, and other real estate owned as a proportion of total loans (BADLOANS). To test our hypothesis we estimate the following model:

$$dAQ_{i,t} = \gamma_0 + \sum_{k=1}^{3} \gamma_{1,k} dMktInd_{i,t-k} + \gamma_2 MktInd_{i,t-4} + \sum_{k=1}^{3} \gamma_{3,k} dAQ_{i,t-k} + \gamma_4 AQ_{i,t-4} + \gamma_5 SIZE_{i,t-1} + \varepsilon_{i,t} \quad (3\text{-}8)$$

where for each BHC i in quarter t $AQ_{i,t}$ is one of the two asset quality proxies at the end of quarter t and $dAQ_{i,t}$, is the change from quarter t-1 to t; $MktInd_{i,t}$ is one of the five market indicators of risk at the end of quarter t and $dMktInd_{i,t}$ is the change from quarter t-1 to t; $SIZE_{i,t}$ is the natural logarithm of the market value of assets at time t.

Tables 3-11 and 3-12 present the results from an OLS estimation of Eq. 3-8 in which AQ is proxied by LLAGL and BADLOANS respectively. It is interesting to note that our findings depend on the asset quality proxy used. Table 3-11 shows that in the pre-FDICIA period none of the five market indicators can explain subsequent changes in LLAGL. The results are dramatically different for the post-FDICIA period. All five of our market indicators foresee changes in LLAGL up to four quarters prior to the changes occurring, and all of them contribute significantly to the model's fit. A comparison of the explanatory power of equity versus debt indicators (columns 1 and 2) reveals that debt

indicators' marginal contribution to the model's R^2 is twice that of equity indicators. This suggests that the information available from debt prices is a more accurate forecaster of future LLAGL changes than is the information available from equity prices. Had we evaluated the explanatory power of equity volatility against that of credit spreads, we would have reached the opposite conclusion which underscores the importance of analyzing comparable equity and debt indicators.

Consistent with the contemporaneous tests results, we document that using information from both equity and debt prices is better than using information from either set of prices alone. DD_EDIAV produces a better fit than DD_EIAV or DD_DIAV. Including both DD_EIAV and DD_DIAV in the set of explanatory variables increases the explanatory power of the model even further. The latter specification allows us to assess the relative informational content of equity-price and debt-price indicators. Since both DD_EIAV and DD_DIAV retain their statistical significance and estimates magnitude, we conclude that the credit risk information contained in equity prices has little or no overlap with the information contained in debt prices when it comes to forecasting LLAGL changes.

Table 3-12 presents the results from an OLS estimation of Eq. 3-8 in which we use BADLOANS as a proxy of BHC asset quality. In contrast to our findings for LLAGL above, we document that market indicators can foresee changes in BADLOANS even before FDICIA is passed. Equity indicators have lower statistical significance and lower explanatory power, mostly concentrated in the first three lags. On the other hand, all four lags of the debt indicators are strongly significant. The estimation results for the post-

FDICIA period are similar to those in Table 3-11 where BHC asset quality is proxied by LLAGL.

Finally, we examine whether changes in a firm's overall financial condition can be forecasted using market indicators from up to four lags. This requires the estimation of a logit model analogous to Eq. 3-8:

$$\begin{aligned}\Pr\left[CHG_{i,t}=1\right]=g(\gamma_0&+\sum_{k=1}^{3}\gamma_{1,k}dMktInd_{i,t-k}+\gamma_2 MktInd_{i,t-4}\\&+\sum_{k=1}^{3}\gamma_{3,k}dSCORE_{i,t-k}+\gamma_4 SCORE_{i,t-4}+\gamma_5 SIZE_{i,t})\end{aligned} \tag{3-9}$$

where

$$CHG_{i,t}=\begin{cases}1\ if\ \ SCORE\ decreases\\0\ if\ \ SCORE\ does\ not\ change\\-1\ if\ \ SCORE\ increases\end{cases}$$

and other variables are as defined earlier. Recall that SCORE increases when the BHC's financial condition weakens.

The results are presented in Table 3-13. In the pre-FDICIA period, market indicators either do not foresee changes in a BHC's SCORE or do so only in the quarter prior to the change occurring. In the post-FDICIA period, market indicators seem to react much sooner. Both DD_DIAV and DD_EDIAV are statistically significant one, two, and three quarters before SCORE changes. This causes the explanatory power of the models to more than double from the early to the latter part of the sample period. As in the previous tests, debt-price indicators seem to outperform equity price indicators. All three lagged changes of DD_DIAV are strongly significant, while only two lagged changes of DD_EIAV are significant at the 10% level. Furthermore, debt indicators produce a better model fit as judged by a pseudo R^2 of at least 2-3 percentage points higher than that of

equity indicators. Finally, combining risk information from equity and debt prices is only marginally better than using debt prices alone as judged by the relevant models' fit. It appears that equity indicators lose most of their statistical significance while debt indicators continue to be significant at the 1% level. This suggests that changes in equity indicators contain little risk information beyond what is already contained in debt indicator changes. That is, when it comes to forecasting changes in BHC overall condition relative to its peers, the default risk information in equity prices is a subset of that in debt prices.

3.6. Sensitivity of Market Indicators to Alternative Model Assumptions

In this study we use contingent-claim models for firm valuation in order to construct some of the market indicators of firm risk. The application of such models requires that a set of simplifying assumptions be made. So far in the analysis we examine distance-to-default (DD) measures calculated under the following base assumptions. The time to debt resolution equals one year; the default point is at 100% of total debt; the issuer's yield is the yield on the most recently issued bonds (Hancock and Kwast 2001); and, the adjustment for taxes is based on Cooper and Davydenko (2002). In this section we investigate the sensitivity of our findings to alternative assumptions.

Table 3-14 presents summary statistics for the new estimates of implied asset value, implied asset volatility, and distance-to-default (DD). Increasing the time to expiration from one year to the weighted average duration or maturity of the firm's outstanding debt issues decreases asset value, increases asset volatility, and decreases DD. Reducing the firm's default point has a similar effect. An assumption that appears to have little or no effect on our estimates is that the issuer credit spread can be represented by the credit spread on the firm's most recently issued bonds. If we instead use the weighted average

issue credit spreads or the credit spread on the firm's largest issues, then the median asset value, volatility, and DD estimates remain the same. Not adjusting credit spreads for taxes causes our estimates of DD to decrease slightly. If we calculate credit spreads by using the average yield on Moody's AAA-rated bonds instead of Treasury securities tends to increase the average DD estimates that use debt prices. Finally, excluding all callable issues from our bond data sample leaves summary statistics effectively unchanged.

Having established that some of the model assumptions affect the magnitude of the DD estimates, we then explore whether they affect the estimates' informational content as well. We re-estimate the contemporaneous and forecasting models described earlier in the paper using each set of new market indicators. We document that the statistical significance of the DD measures stays essentially the same while the models' fit shows slight variation. Tables 3-15 presents the results from estimating Eq. 3-6 where financial health is proxied by a set of accounting measures of BHC asset quality. Judging by the models' fit, the only assumption that dramatically affects the explanatory power of the three DD measures is the default point assumption. In the post-FDICIA period, reducing the default point to 97% or 95% of total debt increases the R^2 of all three DD models. Furthermore, it also underscores the outperformance of the DD measure which combines information from equity and debt prices. Table 3-15 points out that the R^2 of the DD_EDIAV model is at least 15 percentage points higher than that of the other models. An estimation of Eq. 3-6 in which financial health is proxied by credit rating (RTG) or overall condition (SCORE) confirms the results in Table 3-15. Once again, the R^2 of the DD_EDIAV model is at least 9 percentage points (when RTG is the explanatory variable)

and 8 percentage points (when SCORE is the explanatory variable) higher than that of the other models.[13] Alternative time-to-expiration and issuer-yield assumptions do not significantly alter the models' fit. It is interesting to note that employing no adjustment for taxes produces the best model fit. Using the Cooper and Davydenko (2002) adjustment or the yield on Moody's AAA-rated bonds reduces the association between DD estimates and proxies of the BHC financial health. Finally, alternative model assumptions tend to preserve the ranking of the DD estimates and leave the main findings of this study unchanged. In the post-FDICIA period DD measures constructed from debt prices are more closely related to BHC credit rating, asset quality, and overall condition than are DD measures constructed from equity prices. However, both measures are further outperformed by the equity-and-debt DD.

Re-estimating the forecasting models (Equations 3-7, 3-8, and 3-9) under alternative model assumptions produces results similar to those above. Once again, the assumption that most significantly affects our DD estimates is the BHC default point. When we reduce it to 95% of total debt, we obtain the DD estimates with the highest explanatory power. Table 3-16 indicates that the R^2 of a model forecasting changes in BADLOANS increases by 5 percentage points if we assume that BHC default point is at 95% of total debt. Table 3-17 shows that such an assumption improves the fit of a model forecasting changes in SCORE as well – pseudo R^2 increases by 3 to 5 percentage points. Employing alternative model assumptions preserves our main findings that the forecasting ability of debt indicators is slightly better than that of equity indicators, and

[13] Results are available from the author upon request.

that combining information from equity and debt prices produces an even better forecast of changes in BHC risk.

3.7. Conclusions

The literature on market discipline of banks and BHCs offers voluminous evidence that market prices reflect information about firm condition in an accurate and timely manner, and that this information can be different from that available to regulators. This evidence has been used as justification for supplementing government oversight with information from the equity and debt markets. However, research to date has offered little guidance as to which set of market information to use and how to use it. This paper addresses both questions.

First, we compare information from equity prices with that from debt prices to determine which set produces risk estimates that more accurately reflect a bank's true condition. We construct the same credit risk indicators (distance-to-default (DD) measures) from equity prices as we do from debt prices and then assess their relative performance in contemporaneous and forecasting models. We document that the contemporaneous association between the debt implied DD and BHC credit rating, asset-portfolio quality, and overall financial condition than is higher than it is between these and equity implied DD. In addition, debt-price indicators have slightly higher explanatory power than equity-price indicators when it comes to forecasting significant credit downgrades, changes in accounting proxies of risk, and changes in the BHC overall standing relative to its peers. When both equity and debt DD measures are used to forecast changes in BHC credit risk, the explanatory power is concentrated in the debt measures. This finding is in contrast to the commonly held belief that debt prices are too

noisy for the information in them to be useful. It appears that despite the noise, debt prices are a better overall source of BHC risk information than are equity prices.

We further propose that combining information from both equity and debt prices might be superior to using either source alone. Judging by the explanatory power of the contemporaneous models, the DD measure calculated from contemporaneous equity and debt prices is the one most closely related to indicators of BHC credit risk in the post-FDICIA period. It produces an R^2 that is at least 2 percentage points higher than that produced by any of the other market indicator. The forecasting regressions also confirm the benefits of combining information from equity and debt prices. "Combination" models improve on the explanatory power of equity-only or debt-only models and the magnitude of the improvement depends on how similar the information in equity and debt prices is. Both equity and debt markets are characterized by frictions and as a result both equity and debt prices reflect a BHC's true credit risk with noise. Statistical theory tells us that combining two forecasts that are not perfectly correlated can produce a better estimate. Our findings are consistent with this explanation.

A final dimension of the analysis evaluates how market information is to aid regulators in the assessment of a BHC's financial condition. Is it to be used as contemporaneous affirmation, or as a forecasting tool? The contemporaneous analysis suggests that risk measures constructed from equity and/or debt prices are related to indicators of BHC risk. This implies that market information can be used by regulators to confirm a BHC's current condition. In that sense, it can also be used as a tripwire for supervisory actions, which might help reduce regulatory forbearance (Evanoff and Wall 2000). The DD measure using information from both equity and debt prices provide the

most accurate affirmation of BHC credit risk in the post-FIDICIA period as indicated by the model's fit. Our forecasting analysis indicates that market indicators can also be used to predict material changes in the firm's default probability and quarter-to-quarter changes in the firm's asset-portfolio quality and overall condition. Once again, models that combine information from equity and debt prices produce the best fit.

Table 3-1. Summary statistics. Summary statistics are for the sample of 2,060 firm-quarter observations over 1986-1999.

Variable	Definition	Min	Max	Median	Mean	StdDev
V_EIAV	Equity-implied asset value calculated from equity prices and historical equity volatility	0.97	391.41	23.71	42.25	53.93
V_DIAV	Debt-implied asset value calculated from debt prices and historical equity volatility	0.92	398.30	22.95	40.81	52.09
V_EDIAV	Equity-and-debt-implied asset value calculated from contemporaneous equity and debt prices	0.97	391.01	23.71	42.25	53.91
EIAV	Equity-implied asset volatility calculated from equity prices and historical equity volatility	0.48	20.55	2.66	3.02	1.86
DIAV	Debt-implied asset volatility calculated from debt prices and historical equity volatility	0.64	19.65	2.84	3.16	1.79
EDIAV	Equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices	0.49	19.48	4.36	4.55	2.19
DD_EIAV	Distance to default calculated from equity-implied asset value and volatility	0.14	13.31	3.85	3.91	1.42
DD_DIAV	Distance to default calculated from debt-implied asset value and volatility	0.78	5.58	2.25	2.32	0.63
DD_EDIAV	Distance to default calculated from equity-and-debt-implied asset value and volatility	0.81	5.82	2.33	2.43	0.74
EV	equity volatility over the quarter.	8.23	122.56	29.11	32.73	14.58
YS	credit spread of the firm's most recently issued subordinated debt	0.00	18.82	0.68	1.11	1.44
LEV	Market value of equity / Book value of debt	0.01	1.19	0.10	0.11	0.09
ROA	Net income / Total assets	-0.027	0.028	0.005	0.005	0.005
LLAGL	Loan and lease allowance / Total loans	0.007	0.128	0.021	0.025	0.014
NALGL	Non-performing loans / Total loans	0.000	0.104	0.012	0.018	0.018
PDL90GL	Total loans past due more than 90 days / Total loans	0.000	0.038	0.003	0.003	0.003
OREOGL	Other real estate owned /Total loans	0.000	0.064	0.003	0.006	0.008
BADLOANS	Sum of non-performing loans, loans past due more than 90 days, and OREO / Total loans	0.000	0.173	0.020	0.028	0.024
SIZE	Log(Market value of assets)	6.9	12.9	10.1	10.1	1.1
RTG	Weighted average Moody's rating	1.0	20.0	7.0	7.2	2.4

Table 3-2. Simple and rank correlations. Correlations are for the sample of 2,060 firm-quarter observations over 1986-1999. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. V_EIAV, V_DIAV, and V_EDIAV are the corresponding estimates of the market value of assets. DD_EIAV, DD_DIAV, and DD_EDIAV are the corresponding distance-to-default measures. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. All correlations are significantly different from 0 at the 1 percent level.

	Simple Correlations			Rank Correlations		
Panel A: Implied Market Value of Assets						
	V_EIAV	V_DIAV	V_EDIAV	V_EIAV	V_DIAV	V_EDIAV
V_EIAV	1.00			1.00		
V_DIAV	1.00	1.00		1.00	1.00	
V_EDIAV	1.00	1.00	1.00	1.00	1.00	1.00
Panel B: Implied Asset Volatility						
	EIAV	DIAV	EDIAV	EIAV	DIAV	EDIAV
EIAV	1.00			1.00		
DIAV	0.98	1.00		0.99	1.00	
EDIAV	0.70	0.80	1.00	0.67	0.74	1.00
Panel C: Market Measures of Risk						
	DD_EIAV	DD_DIAV	DD_EDIAV	DD_EIAV	DD_DIAV	DD_EDIAV
DD_EIAV	1.00			1.00		
DD_DIAV	0.09	1.00		0.18	1.00	
DD_EDIAV	0.14	0.98	1.00	0.32	0.97	1.00

Table 3-3. Average market indicators of risk by Moody's credit rating. Average statistics are on the sample of 2,022 firm-quarters for the period 1986-1999. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. DD_EIAV, DD_DIAV, and DD_EDIAV are the corresponding distance-to-default measures. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. 'Prob of Default' is the average one-year default rate over 1980-1999, obtained from Moody's Investors Service (2000).

Moody's Credit Rating	N	Prob of Default, 1980-1999 (%)	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS
Investment Grade							
Aaa-Aa	132	0.00-0.02	3.88	2.35	2.39	0.28	0.006
A	1,101	0.02	4.06	2.32	2.39	0.27	0.006
Baa	621	0.19	3.69	2.20	2.28	0.31	0.007
Non-Investment Grade							
Ba	118	1.40	2.86	1.65	1.72	0.40	0.028
B	42	6.60	1.69	1.55	1.56	0.63	0.046
Caa-C	8	25.35	1.41	1.49	1.48	0.71	0.060

Table 3-4. Average market indicators of risk by asset quality deciles. Average statistics are on the sample of 2,022 firm-quarters for the period 1986-1999. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. DD_EIAV, DD_DIAV, and DD_EDIAV are the corresponding distance-to-default measures. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. LLAGL is the ratio of loan loss allowances to gross loans. BADLOANS is the sum of non-performing loans, past due loans, and other real estate owned as a proportion of gross loans.

Asset Quality	Nobs	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS
LLAGL Decile						
1 (Healthy BHCs)	214	4.03	2.58	2.68	0.293	0.010
2	204	4.02	2.34	2.42	0.288	0.011
3	207	4.05	2.46	2.55	0.295	0.008
4	205	3.96	2.44	2.54	0.306	0.008
5	205	4.07	2.36	2.47	0.304	0.008
6	207	3.92	2.29	2.38	0.322	0.011
7	207	3.61	2.17	2.28	0.358	0.015
8	205	4.13	2.23	2.37	0.345	0.010
9	206	3.63	2.15	2.29	0.390	0.014
10 (Weak BHCs)	200	3.69	2.14	2.25	0.374	0.015
BADLOANS Decile						
1 (Healthy BHCs)	214	3.95	2.51	2.61	0.306	0.009
2	204	4.15	2.46	2.58	0.308	0.009
3	207	4.05	2.49	2.61	0.304	0.009
4	205	4.06	2.34	2.44	0.314	0.011
5	205	4.12	2.36	2.46	0.298	0.011
6	207	4.11	2.35	2.45	0.310	0.010
7	207	3.75	2.30	2.40	0.329	0.010
8	205	3.68	2.23	2.35	0.349	0.012
9	206	3.73	2.15	2.27	0.357	0.012
10 (Weak BHCs)	200	3.49	1.97	2.07	0.401	0.019

Table 3-5. Average market indicators of risk by SCORE deciles. Average statistics are on the sample of 2,022 firm-quarters for the period 1986-1999. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. DD_EIAV, DD_DIAV, and DD_EDIAV are the corresponding distance-to-default measures. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. SCORE is a composite index of the firm's financial condition based on its capitalization, asset quality, management, earnings, and liquidity relative to other firms. It is a variable between 5 and 20 where a lower score indicates a healthier firm.

SCORE Decile	Nobs	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS
1 (Healthy BHCs)	374	4.13	2.51	2.62	0.297	0.0086
2	219	4.01	2.43	2.52	0.305	0.0094
3	225	4.05	2.49	2.59	0.300	0.0086
4	244	4.28	2.25	2.34	0.289	0.0093
5	176	4.12	2.40	2.55	0.300	0.0086
6	186	3.77	2.27	2.37	0.335	0.0113
7	193	3.83	2.23	2.33	0.332	0.0106
8	153	3.79	2.25	2.36	0.355	0.0118
9	171	3.58	2.11	2.24	0.379	0.0147
10 (Weak BHCs)	119	3.09	1.86	1.95	0.452	0.0266

Table 3-6. Analysis of Moody's credit ratings. We estimate $MktInd_{it} = \alpha_0 + \alpha_1 RTG_{it} + \alpha_2 Size_{it} + \varepsilon_{it}$ via two-way fixed effects for the sample of 843 and 1,179 firm-quarters for the pre-FDICIA and post-FDICIA period respectively. The dependent variable is one of the five market indicators: DD_EIAV, DD_DIAV, DD_EDIAV, EV, or YS. DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. The main independent variable, RTG, is the weighted average Moody's rating for the firm's debt issues outstanding, RTG. Moody's ratings are coded as Aaa=1 to Caa=19, so that as ratings deteriorate, the variable RTG increases. SIZE is the log of the market value of assets. Fixed effects are excluded from the table for ease of exposition. Standard errors are reported in parenthesis. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively. F^a is the F-statistic for the hypothesis that all time series effects are jointly zero. F^b is the F-statistic testing the hypothesis that all cross section fixed effects are jointly zero.

	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS
Pre-FDICIA Period (Jun 1986 - Sept 1991)					
RTG	-0.158 ***	-0.097 ***	-0.103 ***	0.032 ***	0.006 ***
	(0.029)	(0.013)	(0.016)	(0.003)	(0.000)
SIZE	-0.065	-0.393 ***	-0.380 ***	0.003	0.001
	(0.255)	(0.112)	(0.145)	(0.025)	(0.002)
R^2	0.617	0.752	0.710	0.709	0.748
F^a (df = 22, [nobs-ncoef])	37.10 ***	5.42 ***	5.34 ***	55.38 ***	14.15 ***
F^b (df = 68, [nobs-ncoef])	5.55 ***	23.67 ***	18.89 ***	5.09 ***	12.29 ***
Post-FDICIA Period (Dec 1991 - Dec 1999)					
RTG	-0.193 ***	-0.056 ***	-0.056 ***	0.027 ***	0.002 ***
	(0.033)	(0.006)	(0.005)	(0.003)	(0.000)
SIZE	-0.800 ***	-0.111 ***	-0.126 ***	0.084 ***	0.006 ***
	(0.227)	(0.041)	(0.037)	(0.018)	(0.002)
R^2	0.561	0.721	0.746	0.655	0.705
F^a (df = 32, [nobs-ncoef])	14.03 ***	13.68 ***	19.00 ***	16.57 ***	10.57 ***
F^b (df = 66, [nobs-ncoef])	6.85 ***	13.10 ***	9.96 ***	6.19 ***	12.47 ***

Table 3-7. Analysis of asset quality measures. We estimate $MktInd_{it} = \alpha_0 + \sum_m \alpha_1^m AssetQualityMeasures_{it}^m + \alpha_2 Size_{it} + \varepsilon_{it}$ via two-way fixed effects using the sample of 860 and 1,200 firm-quarters for the pre-FDICIA and post-FDICIA period respectively. The dependent variable is one of the five market indicators: DD_EIAV, DD_DIAV, DD_EDIAV, EV, or YS. DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. ROA is the ratio of net income (loss) to total assets. OREOGL, NALGL, and PDL90GL are asset-quality proxies defined in Table 3-1. ROALEV, OREOGLLEV, NALGLLEV, and PDL90GLLEV are ROA, OREOGL, NALGL, and PDL90GL interacted with leverage (LEV). LEV is the ratio of the market value of equity to the book value of debt. SIZE is the log of the market value of assets. Fixed effects are excluded from the table for ease of exposition. Standard errors are reported in parenthesis. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively. The R^2 of the model with the highest explanatory power is in bold. F^a is the F-statistic testing that all fixed effects are jointly zero (df=nfe, [nobs-ncoeff]). F^b is the F-statistic for the hypothesis that all three interaction variables are jointly zero (df=3, [nobs=ncoff]). F^c is the F-statistics for testing that all six loan quality variables are jointly zero (df=6, [nobs-ncoeff]).

	Pre-FDICIA Period (Jun 1986 - Sept 1991)					Post-FDICIA Period (Dec 1991- Dec 1999)				
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS
Intercept	0.00	4.34 ***	4.56 ***	0.85 ***	0.06 ***	5.21 **	1.77 ***	1.78 ***	0.39 **	0.05 ***
	(2.19)	(0.95)	(1.23)	(0.21)	(0.02)	(2.19)	(0.39)	(0.36)	(0.16)	(0.02)
ROA	30.83 **	-1.88	0.89	-6.94 ***	-0.98 ***	-8.02	2.39	2.86	0.71	-0.17
	(14.90)	(6.47)	(8.39)	(1.42)	(0.13)	(14.71)	(2.65)	(2.42)	(1.10)	(0.11)
OREOGL	-50.23 ***	-38.65 ***	-42.94 ***	11.50 ***	2.09 ***	-48.71 ***	-2.97	-4.23 **	6.06 ***	0.38 ***
	(14.08)	(6.12)	(7.93)	(1.34)	(0.12)	(14.09)	(2.53)	(2.31)	(1.05)	(0.10)
NALGL	-4.06	-3.91 *	-3.65	-0.48	-0.05	-9.26	-5.40 ***	-5.04 ***	1.92 ***	0.12 **
	(5.49)	(2.39)	(3.09)	(0.52)	(0.05)	(7.71)	(1.39)	(1.27)	(0.58)	(0.06)
PDL90GL	-21.80	0.08	-0.45	-1.03	0.09	-16.85	-1.46	-1.99	-0.33	0.49 ***
	(34.96)	(15.18)	(19.69)	(3.33)	(0.30)	(20.83)	(3.75)	(3.42)	(1.56)	(0.15)
ROALEV	-289.00	163.03 *	140.80	44.35 **	9.45 ***	12.77	-1.33	-3.37	-2.24	0.45 *
	(215.34)	(93.53)	(121.26)	(20.54)	(1.84)	(35.37)	(6.36)	(5.81)	(2.64)	(0.25)
OREOGLLEV	318.66	328.06 ***	361.73 **	-79.88 ***	-22.36 ***	319.12 *	-8.04	3.19	-47.37 ***	-3.04 **
	(259.63)	(112.77)	(146.20)	(24.76)	(2.22)	(167.64)	(30.14)	(27.55)	(12.53)	(1.20)
NALGLLEV	-44.78	53.97	58.80	9.09	1.03	-47.21	82.38 ***	70.70 ***	-10.73 *	-1.44 **
	(79.57)	(34.56)	(44.81)	(7.59)	(0.68)	(79.04)	(14.21)	(12.99)	(5.91)	(0.57)
PDL90GLLEV	389.23	-302.04	-435.81 *	-4.68	-2.04	32.33	3.42	3.23	4.31	-0.84 *
	(455.96)	(198.05)	(256.76)	(43.49)	(3.89)	(70.51)	(12.68)	(11.59)	(5.27)	(0.51)
SIZE	0.27	-0.29 **	-0.32 **	-0.04 *	0.00 **	-0.43 *	-0.02	-0.03	0.03 *	0.00
	(0.26)	(0.11)	(0.15)	(0.03)	(0.00)	(0.23)	(0.04)	(0.04)	(0.02)	(0.00)

Table 3-7. Continued

	Pre-FDICIA Period (Jun 1986 - Sept 1991)					Post-FDICIA Period (Dec 1991- Dec 1999)				
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS
R^2	0.624	0.761	0.720	0.721	0.771	0.573	0.726	0.748	0.687	0.723
F^a	12.25 ***	24.64 ***	20.32 ***	14.90 ***	13.27 ***	9.40 ***	13.43 ***	13.67 ***	9.77 ***	12.20 ***
F^b	0.82	5.17 ***	3.84 ***	3.51 **	36.78 ***	1.81	22.99 ***	22.37 ***	19.20 ***	18.31 ***
F^c	4.13 ***	10.82 ***	8.19 ***	14.41 ***	58.29 ***	9.71 ***	16.26 ***	18.20 ***	31.95 ***	19.93 ***

Table 3-8. Analysis of financial health SCORE. We estimate $MktInd_{it} = \alpha_0 + \alpha_1 SCORE_{it} + \alpha_2 Size_{it} + \varepsilon_{it}$ via two-way fixed effects for the sample of 860 and 1,200 firm-quarters for the pre-FDICIA and post-FDICIA period respectively. The dependent variable is one of the five market indicators: DD_EIAV, DD_DIAV, DD_EDIAV, EV, or YS. DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. The main dependent variable is the firm's financial health score, SCORE. This is a composite index of the firm's financial condition based on its capitalization, asset quality, management, earnings, and liquidity relative to other firms. It is a variable between 5 and 20 where a lower score indicates a healthier firm. SIZE is the log of the market value of assets. Quarter indicators variables are included in the set of independent variables but excluded from the table for ease of exposition. Standard errors are reported in parenthesis. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively. F^a is the F-statistic testing that all fixed effects are jointly zero (df=nfe, [nobs-ncoeff]).

	Pre-FDICIA Period (Jun 1986 - Sept 1991)					Post-FDICIA Period (Dec 1991- Dec 1999)				
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS
Intercept	-2.091	1.927 **	1.633	1.439 ***	0.166 ***	7.777 ***	2.645 ***	2.681 ***	-0.109	0.007
	(2.054)	(0.897)	(1.159)	(0.204)	(0.021)	(2.136)	(0.385)	(0.355)	(0.169)	(0.016)
SCORE	-0.074 ***	-0.064 ***	-0.067 ***	0.017 ***	0.002 ***	-0.076 ***	-0.029 ***	-0.027 ***	0.011 ***	0.001 ***
	(0.020)	(0.009)	(0.011)	(0.002)	(0.000)	(0.020)	(0.004)	(0.003)	(0.002)	(0.000)
SIZE	0.578 **	0.074	0.110	-0.133 ***	-0.020 ***	-0.799 ***	-0.096 **	-0.116 ***	0.088 ***	0.005 ***
	(0.257)	(0.112)	(0.145)	(0.025)	(0.003)	(0.227)	(0.041)	(0.038)	(0.018)	(0.002)
R^2	0.612	0.751	0.709	0.689	0.670	0.550	0.710	0.729	0.630	0.688
F^a	15.39 ***	27.60 ***	22.91 ***	20.52 ***	17.21 ***	11.32 ***	19.95 ***	21.88 ***	14.62 ***	17.78 ***

Table 3-9. Mean value tests of forecasting ability of market indicators. CHANGE equals 1 if the firm is downgraded from investment into non-investment grade by Moody's during quarter t; it equals 0 otherwise. DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. We test the hypothesis that the mean value of each market indicator is different for BHCs experiencing a material change in condition versus those that do not. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively.

		One Quarter Prior		Two Quarters Prior		Three Quarters Prior		Four Quarters Prior	
Variable	CHANGE	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
DD_EIAV	0	4.01	1.38	4.02	1.38	4.01	1.38	4.00	1.38
	1	2.76	1.33	2.66	1.27	3.60	0.79	3.97	1.04
	Diff (0-1)	1.25 ***		1.36 ***		0.41		0.03	
DD_DIAV	0	2.37	0.61	2.37	0.61	2.36	0.61	2.35	0.61
	1	1.61	0.34	1.65	0.21	1.86	0.26	2.11	0.56
	Diff (0-1)	0.76 ***		0.72 ***		0.51 ***		0.25	
DD_EDIAV	0	2.48	0.73	2.48	0.73	2.47	0.73	2.47	0.73
	1	1.68	0.35	1.70	0.21	1.95	0.24	2.34	1.02
	Diff (0-1)	0.81 ***		0.78 ***		0.53 ***		0.13	
EV	0	0.31	0.13	0.31	0.13	0.31	0.13	0.32	0.13
	1	0.49	0.19	0.50	0.18	0.34	0.08	0.31	0.09
	Diff (0-1)	-0.18 ***		-0.19 ***		-0.03		0.01	
YS	0	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	1	0.04	0.02	0.03	0.02	0.02	0.01	0.01	0.01
	Diff (0-1)	-0.03 ***		-0.02 ***		-0.01 ***		0.00	
Nobs	0	1,897		1,823		1,752		1,683	
	1	15		16		15		14	

Table 3-10. Logit analysis of material changes in firm condition. We estimate $\Pr[Change_{i,t} = 1] = g(\beta_0 + \beta_1 MktInd_{i,t-k} + \beta_2 RTG_{i,t-k} + \beta_3 SIZE_{i,t-k})$ via logistic regression for the samples of 1,912, 1,839, and 1,767 observations respectively 1, 2, or 3 quarters prior to the event during 1986-1999. The dependent variable CHANGE equals 1 if the firm is downgraded from investment to non-investment grade by Moody's during quarter t; it equals 0 otherwise. DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
				Panel A: One Quarter Prior			
DD_EIAV	-0.80 ***					-0.07	
	(0.28)					(0.25)	
DD_DIAV		-6.84 ***				-6.67 ***	
		(1.25)				(1.36)	
DD_EDIAV			-6.52 ***				
			(1.17)				
EV				5.35 ***			0.83
				(1.40)			(2.26)
YS					95.97 ***		92.05 ***
					(16.10)		(19.20)
R^2	0.023	0.044	0.044	0.024	0.041	0.044	0.041
				Panel B: Two Quarters Prior			
DD_EIAV	-0.82 ***					-0.32	
	(0.24)					(0.25)	
DD_DIAV		-4.96 ***				-4.42 ***	
		(0.87)				(0.94)	
DD_EDIAV			-5.00 ***				
			(0.84)				
EV				4.88 ***			2.57
				(1.18)			(1.63)
YS					69.41 ***		57.62 ***
					(12.48)		(14.33)
R^2	0.025	0.041	0.043	0.026	0.034	0.042	0.035
				Panel C: Three Quarters Prior			
DD_EIAV	-0.10					0.04	
	(0.23)					(0.20)	
DD_DIAV		-2.64 ***				-2.69 ***	
		(0.88)				(0.91)	
DD_EDIAV			-2.55 ***				
			(0.87)				
EV				0.09			-2.19
				(2.14)			(2.72)
YS					33.38 **		42.89 **
					(16.82)		(19.71)
R^2	0.004	0.010	0.010	0.004	0.006	0.010	0.006

Table 3-11. Analysis of asset quality changes (LLAGL). We estimate via OLS

$$dAQ_{i,t} = \gamma_0 + \sum_{k=1}^{3}\gamma_{1,k} dMktInd_{i,t-k} + \gamma_2 MktInd_{i,t-4} + \sum_{k=1}^{3}\gamma_{3,k} dAQ_{i,t-k} + \gamma_4 AQ_{i,t-4} + \gamma_5 SIZE_{i,t} + \varepsilon_{i,t}$$

for the sample of 555 and 1,000 firm-quarters for the pre-FDICIA and post-FDICIA period respectively. The dependent variable dAQ is the change in asset quality as proxied by LLAGL. LLAGL is the ratio of loan loss allowances to gross loans. MktInd is one of the following equity (EInd), debt (DInd), or equity-and-debt (EDInd) indicators of risk: DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively; EV is the annualized daily equity volatility over the quarter; YS is the credit spread of the firm's most recently issued subordinated debt. A change in variable X is denoted by dX. Control variables are excluded from the table for ease of exposition. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively. F^a is the F-statistic testing that all MktInd are jointly zero (df=4 or 8, [nobs-ncoeff]). F^b is the F-statistic for the hypothesis that all equity indicators are jointly zero (df=4, [nobs=ncoff]). F^c is the F-statistics for testing that all debt indicators are jointly zero (df=4, [nobs-ncoeff]).

	Pre-FDICIA Period (Jun 1986 - Jan 1991)						
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS
dEInd_lag1	-0.0002			0.0014		-0.0002	0.0005
	(0.000)			(0.002)		(0.000)	(0.002)
dEInd_lag2	0.0003			-0.0005		0.0003	-0.0015
	(0.000)			(0.002)		(0.000)	(0.002)
dEInd_lag3	0.0002			-0.0007		0.0002	-0.0018
	(0.000)			(0.003)		(0.000)	(0.003)
EInd_lag4	0.0001			-0.0027		0.0001	-0.0035
	(0.000)			(0.003)		(0.000)	(0.003)
dDInd_lag1		-0.0003			0.0473	-0.0004	0.0455
		(0.001)			(0.040)	(0.001)	(0.041)
dDInd_lag2		-0.0005			0.0448	-0.0004	0.0441
		(0.001)			(0.052)	(0.001)	(0.053)
dDInd_lag3		-0.0009			0.0675	-0.0008	0.0649
		(0.001)			(0.057)	(0.001)	(0.059)
DInd_lag4		-0.0002			0.0127	-0.0002	0.0209
		(0.000)			(0.034)	(0.000)	(0.035)
dEDInd_lag1			-0.0003				
			(0.001)				
dEDInd_lag2			-0.0004				
			(0.001)				
dEDInd_lag3			-0.0006				
			(0.001)				
EDInd_lag4			0.0000				
			(0.000)				
R^2	0.034	0.026	0.026	0.028	0.030	0.029	0.027
ΔR^2 (MktInd)	0.003	-0.004	-0.004	-0.002	-0.001	-0.001	-0.004
F^a	1.48	0.39	0.39	0.67	0.88	0.91	0.72
F^b						0.34	0.76
F^c						1.42	0.55

Table 3-11. Continued

	Post-FDICIA Period (Jan 1993 - Dec 1999)						
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS
dEInd_lag1	-0.0003 ***			0.0067 ***		-0.0003 ***	0.0051 ***
	(0.000)			(0.001)		(0.000)	(0.001)
dEInd_lag2	-0.0004 ***			0.0083 ***		-0.0004 ***	0.0076 ***
	(0.000)			(0.001)		(0.000)	(0.001)
dEInd_lag3	-0.0005 ***			0.0078 ***		-0.0005 ***	0.0085 ***
	(0.000)			(0.001)		(0.000)	(0.001)
EInd_lag4	-0.0004 ***			0.0053 ***		-0.0004 ***	0.0067 ***
	(0.000)			(0.001)		(0.000)	(0.001)
dDInd_lag1		-0.0035 ***			0.0979 ***	-0.0036 ***	0.0757 ***
		(0.001)			(0.014)	(0.001)	(0.015)
dDInd_lag2		-0.0029 ***			0.0677 ***	-0.0027 ***	0.0278 *
		(0.001)			(0.014)	(0.001)	(0.015)
dDInd_lag3		-0.0016 **			0.0539 ***	-0.0013 **	0.0050
		(0.001)			(0.015)	(0.001)	(0.016)
DInd_lag4		-0.0014 ***			0.0403 ***	-0.0011 ***	-0.0056
		(0.000)			(0.011)	(0.000)	(0.013)
dEDInd_lag1			-0.0043 ***				
			(0.001)				
dEDInd_lag2			-0.0032 ***				
			(0.001)				
dEDInd_lag3			-0.0022 ***				
			(0.001)				
EDInd_lag4			-0.0018 ***				
			(0.000)				
R^2	0.128	0.148	0.163	0.175	0.156	0.171	0.201
ΔR^2 (MktInd)	0.023	0.044	0.058	0.070	0.052	0.067	0.096
F^a	6.95 ***	12.42 ***	16.41 ***	19.90 ***	14.60 ***	9.91 ***	14.38 ***
F^b						12.51 ***	8.21 ***
F^c						7.05 ***	13.34 ***

Table 3-12. Analysis of asset quality changes (BADLOANS). We estimate

$$dAQ_{i,t} = \gamma_0 + \sum_{k=1}^{3}\gamma_{1,k}dMktInd_{i,t-k} + \gamma_2 MktInd_{i,t-4} + \sum_{k=1}^{3}\gamma_{3,k}dAQ_{i,t-k} + \gamma_4 AQ_{i,t-4} + \gamma_5 SIZE_{i,t} + \varepsilon_{i,t}$$

via OLS for the sample of 555 and 1,000 firm-quarters for the pre-FDICIA and post-FDICIA period respectively. The dependent variable dAQ is the change in asset quality as proxied by BADLOANS. This is the sum of non-performing loans, past due loans, and other real estate owned as a proportion of gross loans. MktInd is one of the following equity (EInd), debt (DInd), or equity-and-debt (EDInd) indicators of risk: DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively; EV is the annualized daily equity volatility over the quarter; YS is the credit spread of the firm's most recently issued subordinated debt. A change in variable X is denoted by dX. Control variables are excluded from the table for ease of exposition. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively. F^a is the F-statistic testing that all MktInd are jointly zero (df=4 or 8, [nobs-ncoeff]). F^b is the F-statistic for the hypothesis that all equity indicators are jointly zero (df=4, [nobs=ncoff]). F^c is the F-statistics for testing that all debt indicators are jointly zero (df=4, [nobs-ncoeff]).

	Pre-FDICIA Period (Jun 1986 - Jan 1991)						
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS
dEInd_lag1	-0.042 ***			0.438 ***		-0.043 ***	0.232
	(0.016)			(0.142)		(0.016)	(0.142)
dEInd_lag2	-0.040 **			0.416 **		-0.041 **	0.175
	(0.018)			(0.180)		(0.018)	(0.177)
dEInd_lag3	-0.066 ***			0.496 **		-0.072 ***	0.331
	(0.021)			(0.214)		(0.020)	(0.210)
EInd_lag4	-0.031			0.220		-0.042 **	0.110
	(0.020)			(0.241)		(0.020)	(0.235)
dDInd_lag1		-0.160 ***			19.481 ***	-0.176 ***	18.834 ***
		(0.052)			(3.044)	(0.052)	(3.100)
dDInd_lag2		-0.163 ***			14.212 ***	-0.169 ***	13.518 ***
		(0.055)			(3.980)	(0.055)	(4.036)
dDInd_lag3		-0.188 ***			11.873 ***	-0.178 ***	9.267 **
		(0.055)			(4.285)	(0.055)	(4.425)
DInd_lag4		-0.105 ***			7.627 ***	-0.106 ***	7.402 ***
		(0.028)			(2.704)	(0.028)	(2.726)
dEDInd_lag1			-0.112 ***				
			(0.041)				
dEDInd_lag2			-0.103 **				
			(0.044)				
dEDInd_lag3			-0.147 ***				
			(0.042)				
EDInd_lag4			-0.092 ***				
			(0.023)				
R^2	0.051	0.063	0.062	0.049	0.123	0.084	0.125
ΔR^2 (MktInd)	0.019	0.031	0.030	0.017	0.091	0.052	0.094
F^a	3.76 ***	5.50 ***	5.31 ***	3.42 ***	15.07 ***	4.83 ***	8.27 ***
F^b						5.77 ***	12.82 ***
F^c						4.04 ***	1.42

Table 3-12. Continued

	Post-FDICIA Period (Jan 1993 - Dec 1999)						
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS
dEInd_lag1	-0.047 ***			0.877 ***		-0.048 ***	0.846 ***
	(0.014)			(0.163)		(0.014)	(0.172)
dEInd_lag2	-0.021			0.779 ***		-0.025	0.873 ***
	(0.017)			(0.187)		(0.017)	(0.203)
dEInd_lag3	-0.055 ***			0.934 ***		-0.055 ***	1.277 ***
	(0.018)			(0.206)		(0.018)	(0.228)
EInd_lag4	-0.025			0.482 **		-0.027	0.851 ***
	(0.017)			(0.198)		(0.017)	(0.229)
dDInd_lag1		-0.196 **			6.484 ***	-0.244 ***	3.589
		(0.092)			(2.332)	(0.093)	(2.391)
dDInd_lag2		-0.411 ***			4.882 **	-0.377 ***	0.938
		(0.093)			(2.245)	(0.093)	(2.384)
dDInd_lag3		-0.083			-0.304	-0.107	-6.333 **
		(0.100)			(2.442)	(0.099)	(2.607)
DInd_lag4		-0.029			-1.118	-0.026	-5.604 ***
		(0.068)			(1.886)	(0.068)	(2.130)
dEDInd_lag1			-0.342 ***				
			(0.100)				
dEDInd_lag2			-0.415 ***				
			(0.099)				
dEDInd_lag3			-0.175				
			(0.107)				
EDInd_lag4			-0.062				
			(0.076)				
R^2	0.225	0.229	0.232	0.241	0.223	0.241	0.253
ΔR^2 (MktInd)	0.013	0.017	0.020	0.029	0.011	0.029	0.041
F^a	4.74 ***	5.74 ***	6.66 ***	9.44 ***	3.99 ***	5.18 ***	7.08 ***
F^b						5.52 ***	4.57 ***
F^c						4.52 ***	10.00 ***

Table 3-13. Logit analysis of SCORE changes. We estimate the logit model

$$\Pr[CHG_{i,t}=1]=g(\gamma_0+\sum_{k=1}^{3}\gamma_{1,k}dMktInd_{i,t-k}+\gamma_2 MktInd_{i,t-4}+\sum_{k=1}^{3}\gamma_{3,k}dSCORE_{i,t-k}+\gamma_4 SCORE_{i,t-4}+\gamma_5 SIZE_{i,t})$$

for the sample of 555 and 1,000 firm-quarters for the pre-FDICIA and post-FDICIA periods respectively. The dependent variable CHG equals 1 if a firm's SCORE decreases, 0 if it remains the same, and -1 if it increases. SCORE is a composite index of the firm's financial health. It is a number between 5 and 20 with a lower number indicating a healthier firm. MktInd is one of the following equity (EInd), debt (DInd), or equity-and-debt (EDInd) indicators of risk: DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively; EV is the annualized daily equity volatility over the quarter; YS is the credit spread of the firm's most recently issued subordinated debt. A change in variable X is denoted by dX. Control variables are excluded from the table for ease of exposition. Statistical significance at the 1, 5, and 10 percent level is denoted by ***, **, and * respectively. W^a is the Wald statistic testing that all MktInd are jointly zero (df=4 or 8, [nobs-ncoeff]). W^b is the Wald statistic testing that all EInd are jointly zero (df=4, [nobs=ncoff]). W^c is the Wald statistics testing that all DInd are jointly zero (df=4, [nobs-ncoeff]).

	Pre-FDICIA Period (Jun 1986 - Jan 1991)						
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS
dEInd_lag1	0.30 ***			-2.97 ***		0.32 ***	-2.92 ***
	0.07			0.60		0.07	0.62
dEInd_lag2	-0.13 *			0.32		-0.12	0.56
	0.08			0.78		0.08	0.82
dEInd_lag3	-0.05			0.94		-0.04	1.04
	0.08			0.88		0.08	0.92
Eind_lag4	0.02			0.63		0.03	0.59
	0.08			0.97		0.08	1.00
dDInd_lag1		0.21			-25.59 **	0.33	-15.23
		0.21			12.17	0.21	12.54
dDInd_lag2		0.34			-15.97	0.32	-27.07 *
		0.22			15.55	0.22	16.25
dDInd_lag3		0.20			-14.79	0.07	-2.25
		0.22			17.27	0.22	18.52
Dind_lag4		0.01			-6.51	0.01	-6.53
		0.11			10.77	0.11	11.10
dEDInd_lag1			0.23				
			0.16				
dEDInd_lag2			0.24				
			0.17				
dEDInd_lag3			0.08				
			0.16				
EDind_lag4			0.01				
			0.09				
R^2	0.17	0.10	0.11	0.18	0.11	0.17	0.18
ΔR^2	0.07	0.00	0.01	0.08	0.01	0.07	0.08
W^a	37.19 ***	2.92	3.06	39.19 ***	6.08	40.85 ***	43.63 ***
W^b						3.59	4.21
W^c						38.09 ***	37.95 ***

Table 3-13. Continued

	Post-FDICIA Period (Jan 1993 - Dec 1999)						
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS
dEInd_lag1	0.14 *			-1.63 *		0.12	-0.15
	0.07			0.84		0.08	0.93
dEInd_lag2	0.02			-3.25 ***		0.00	-1.37
	0.08			0.91		0.09	1.04
dEInd_lag3	0.17 *			-5.04 ***		0.15 *	-4.36 ***
	0.09			0.98		0.09	1.15
Eind_lag4	-0.08			0.47		-0.09	-0.93
	0.08			0.82		0.08	1.11
dDInd_lag1		1.26 ***			-35.89 ***	1.37 ***	-33.87 ***
		0.48			11.79	0.48	12.82
dDInd_lag2		3.30 ***			-68.81 ***	3.15 ***	-59.00 ***
		0.49			12.36	0.50	13.68
dDInd_lag3		2.39 ***			-61.11 ***	2.62 ***	-37.94 **
		0.53			14.01	0.55	15.34
Dind_lag4		0.39			9.78	0.49	18.25
		0.33			9.74	0.34	12.34
dEDInd_lag1			1.43 ***				
			0.52				
dEDInd_lag2			3.15 ***				
			0.52				
dEDInd_lag3			2.66 ***				
			0.57				
EDind_lag4			0.15				
			0.34				
R^2	0.34	0.37	0.37	0.36	0.38	0.38	0.39
ΔR^2	0.01	0.04	0.04	0.03	0.04	0.05	0.06
W^a	15.35 ***	56.24 ***	56.69 ***	42.00 ***	52.14 ***	66.94 ***	68.27 ***
W^b						54.01 ***	31.40 ***
W^c						13.65 ***	18.56 ***

Table 3-14. Sensitivity of summary statistics to alternative input assumptions. EIAV is the equity-implied asset volatility calculated from equity prices and historical equity volatility. DIAV is the debt-implied asset volatility calculated from debt prices and historical equity volatility. EDIAV is the equity-and-debt-implied asset volatility calculated from contemporaneous equity and debt prices. Implied asset volatilities are reported in percent per year. V_EIAV, V_DIAV, and V_EDIAV are the corresponding estimates of the market value of assets in billion dollars. DD_EIAV, DD_DIAV, and DD_EDIAV are the corresponding distance-to-default measures.

	Time to Resolution				Default Point				Issuer Yield				Tax Adjustment					
	Weighted Average Duration of Traded Debt		Weighted Average Maturity of Traded Debt		95% of Total Debt		97% of Total Debt		Weighted Average Issue Yields		Largest Issue Yield		None		Average Yield on Moody's AAA-rated Bonds		Credit Spreads Calculated from Non-Callable Bonds Only	
	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean
V_EIAV	17.16	31.60	15.01	27.10	22.28	40.23	23.09	41.11	23.76	42.26	23.76	42.26	23.82	42.36	23.37	41.90	27.52	44.85
V_DIAV	17.93	32.70	16.22	29.01	20.57	38.16	21.59	39.34	22.94	40.81	22.99	40.88	22.91	40.79	23.52	42.21	27.13	43.68
V_EDIAV	17.49	31.78	15.43	27.84	21.34	38.91	22.18	40.24	23.75	42.26	23.73	42.25	23.81	42.35	23.41	41.93	28.05	45.29
EIAV	3.95	5.12	4.84	6.72	2.81	3.18	2.73	3.10	2.66	3.02	2.66	3.02	2.65	3.01	2.68	3.05	2.68	3.04
DIAV	3.69	3.98	4.24	4.62	2.99	3.35	2.90	3.24	2.84	3.16	2.84	3.16	2.85	3.18	2.71	2.96	2.88	3.22
EDIAV	3.51	3.58	3.79	3.89	3.87	4.13	3.90	4.12	4.33	4.50	4.40	4.50	4.52	4.74	2.58	2.67	4.55	4.73
DD_EIAV	1.50	1.51	1.17	1.16	1.98	1.84	2.67	2.63	3.85	3.90	3.85	3.90	3.85	3.90	3.85	3.90	3.87	3.92
DD_DIAV	1.72	1.83	1.60	1.74	1.19	1.14	1.69	1.71	2.25	2.35	2.25	2.37	2.13	2.20	4.11	3.66	2.24	2.20
DD_EDIAV	1.71	1.87	1.59	1.75	1.55	1.42	1.95	1.88	2.33	2.46	2.33	2.50	2.21	2.31	4.82	4.27	2.32	2.27
Nobs	2,030		1,970		1,832		1,919		2,059		2,060		2,060		2,057		1,608	

Table 3-15. Analysis of asset quality measures under alternative assumptions. We estimate via two-way fixed effects $MktInd_{it} = \alpha_0 + \sum_m \alpha_1^m AssetQualityMeasures_{it}^m + \alpha_2 Size_{it} + \varepsilon_{it}$ for the sample of 860 and 1,200 firm-quarters for the pre-FDICIA and post-FDICIA period respectively. The dependent variable is one of the five market indicators: DD_EIAV, DD_DIAV, DD_EDIAV, EV, or YS. DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively. EV is the annualized daily equity volatility over the quarter. YS is the credit spread of the firm's most recently issued subordinated debt. ROA is the ratio of net income (loss) to total assets. OREOGL is the ratio of other real estate owned to gross loans. NALGL is the ratio of non-accruing loans to gross loans. PDL90GL is the ratio of loans past due more than 90 days to gross loans. ROALEV, OREOGLLEV, NALGLLEV, and PDL90GLLEV are the last four variables interacted with firm leverage. LEV is the ratio of the market value of equity to the book value of liabilities. SIZE is the log of the market value of assets. Each model's fit is indicated by the R^2. ΔR^2 is the contribution of all lags of DD and dDD to the pseudo R^2 of a model including all but these variables.

	Pre-FDICIA Period (Jun 1986 - Jan 1991)					Post-FDICIA Period (Jan 1993 - Dec 1999)				
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS
Base Case										
R^2	0.62	0.76	0.72	0.72	0.77	0.57	0.73	0.75	0.69	0.72
Time to Resolution: Weighted Average Duration of Traded Debt										
R^2	0.68	0.72	0.71	0.74	0.77	0.56	0.73	0.73	0.69	0.72
Time to Resolution: Weighted Average Maturity of Traded Debt										
R^2	0.71	0.72	0.67	0.72	0.80	0.59	0.74	0.75	0.68	0.72
Default Point: 95% of Total Debt										
R^2	0.76	0.53	0.88	0.72	0.79	0.71	0.75	0.90	0.66	0.72
Default Point: 97% of Total Debt										
R^2	0.70	0.50	0.83	0.74	0.75	0.63	0.75	0.86	0.66	0.72
Issuer Yield: Weighted Average Issue Yields										
R^2	0.62	0.77	0.72	0.73	0.79	0.59	0.75	0.73	0.70	0.73
Issuer Yield: Largest Issue Yield										
R^2	0.62	0.61	0.67	0.73	0.76	0.59	0.72	0.69	0.70	0.71
Tax Adjustment: None										
R^2	0.62	0.76	0.73	0.73	0.78	0.59	0.75	0.78	0.70	0.71
Tax Adjustment: Average Yield on Moody's AAA-rated Bonds										
R^2	0.62	0.67	0.62	0.73	0.67	0.59	0.68	0.56	0.70	0.66
Non-callable Bonds Only										
R^2	0.69	0.77	0.73	0.78	0.79	0.59	0.77	0.80	0.71	0.76

Table 3-16. Analysis of asset quality changes. We estimate via OLS

$$dAQ_{i,t} = \gamma_0 + \sum_{k=1}^{3} \gamma_{1,k} dMktInd_{i,t-k} + \gamma_2 MktInd_{i,t-4} + \sum_{k=1}^{3} \gamma_{3,k} dAQ_{i,t-k} + \gamma_4 AQ_{i,t-4} + \gamma_5 SIZE_{i,t} + \varepsilon_{i,t}$$ f

or the sample of 555 and 1,000 firm-quarters for the pre-FDICIA and post-FDICIA period respectively. The dependent variable dAQ is the change in asset quality as proxied by BADLOANS. This is the sum of non-performing loans, past due loans, and other real estate owned as a proportion of gross loans. MktInd is one of the following equity (EInd), debt (DInd), or equity-and-debt (EDInd) indicators of risk: DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively; EV is the annualized daily equity volatility over the quarter; YS is the credit spread of the firm's most recently issued subordinated debt. A change in variable X is denoted by dX. The model's fit is indicated by the pseudo R^2. ΔR^2 is the contribution of all lags of DD and dDD to the pseudo R^2 of a model including all but these variables.

	Pre-FDICIA Period (Jun 1986 - Jan 1991)						
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS
Base Case							
R^2	0.051	0.063	0.062	0.049	0.123	0.084	0.125
ΔR^2	0.019	0.031	0.030	0.017	0.091	0.052	0.094
Time to Resolution: Weighted Average Duration of Traded Debt							
R^2	0.055	0.070	0.069	0.080	0.194	0.085	0.201
ΔR^2	0.016	0.031	0.031	0.042	0.155	0.046	0.163
Time to Resolution: Weighted Average Maturity of Traded Debt							
R^2	0.076	0.066	0.066	0.103	0.227	0.099	0.239
ΔR^2	0.032	0.023	0.022	0.059	0.183	0.055	0.196
Default Point: 95% of Total Debt							
R^2	0.057	0.020	0.104	0.043	0.089	0.077	0.104
ΔR^2	0.037	0.000	0.083	0.023	0.068	0.057	0.084
Default Point: 97% of Total Debt							
R^2	0.123	0.087	0.183	0.129	0.300	0.137	0.307
ΔR^2	0.037	0.001	0.097	0.043	0.214	0.051	0.222
Issuer Yield: Weighted Average Issue Yields							
R^2	0.051	0.060	0.055	0.049	0.142	0.075	0.142
ΔR^2	0.019	0.028	0.023	0.017	0.110	0.043	0.111
Issuer Yield: Largest Issue Yield							
R^2	0.056	0.045	0.051	0.054	0.128	0.066	0.133
ΔR^2	0.021	0.010	0.016	0.018	0.093	0.031	0.098
Tax Adjustment: None							
R^2	0.051	0.059	0.061	0.049	0.126	0.081	0.129
ΔR^2	0.019	0.028	0.029	0.017	0.094	0.049	0.097
Tax Adjustment: Average Yield on Moody's AAA-rated Bonds							
R^2	0.094	0.107	0.109	0.102	0.126	0.136	0.147
ΔR^2	0.028	0.042	0.043	0.036	0.060	0.070	0.081
Non-callable Bonds Only							
R^2	0.063	0.045	0.042	0.060	0.063	0.089	0.083
ΔR^2	0.049	0.031	0.028	0.046	0.049	0.075	0.068

Table 3-16. Continued

	Post-FDICIA Period (Jan 1993 - Dec 1999)						
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS
Base Case							
R^2	0.225	0.229	0.232	0.241	0.223	0.241	0.253
ΔR^2	0.013	0.017	0.020	0.029	0.011	0.029	0.041
Time to Resolution: Weighted Average Duration of Traded Debt							
R^2	0.243	0.242	0.242	0.256	0.236	0.252	0.262
ΔR^2	0.011	0.010	0.010	0.024	0.004	0.020	0.030
Time to Resolution: Weighted Average Maturity of Traded Debt							
R^2	0.215	0.231	0.231	0.228	0.245	0.237	0.252
ΔR^2	0.013	0.028	0.029	0.026	0.042	0.035	0.050
Default Point: 95% of Total Debt							
R^2	0.262	0.282	0.291	0.260	0.267	0.294	0.274
ΔR^2	0.009	0.029	0.038	0.007	0.014	0.040	0.020
Default Point: 97% of Total Debt							
R^2	0.246	0.261	0.267	0.245	0.241	0.265	0.250
ΔR^2	0.011	0.025	0.032	0.010	0.005	0.030	0.015
Issuer Yield: Weighted Average Issue Yields							
R^2	0.226	0.229	0.227	0.242	0.226	0.240	0.255
ΔR^2	0.013	0.016	0.014	0.029	0.013	0.028	0.042
Issuer Yield: Largest Issue Yield							
R^2	0.225	0.227	0.223	0.241	0.219	0.236	0.249
ΔR^2	0.013	0.014	0.011	0.029	0.007	0.024	0.036
Tax Adjustment: None							
R^2	0.225	0.229	0.233	0.241	0.223	0.241	0.253
ΔR^2	0.013	0.017	0.021	0.029	0.010	0.029	0.040
Tax Adjustment: Average Yield on Moody's AAA-rated Bonds							
R^2	0.226	0.230	0.237	0.241	0.224	0.239	0.250
ΔR^2	0.013	0.017	0.025	0.029	0.012	0.026	0.037
Non-callable Bonds Only							
R^2	0.236	0.246	0.258	0.261	0.248	0.265	0.278
ΔR^2	0.017	0.027	0.039	0.042	0.029	0.046	0.060

Table 3-17. Logit analysis of SCORE changes. We estimate the logit model $\Pr[CHG_{i,t}=1]=g(\gamma_0+\sum_{k=1}^{3}\gamma_{1,k}dMktInd_{i,t-k}+\gamma_2 MktInd_{i,t-4}+\sum_{k=1}^{3}\gamma_{3,k}dSCORE_{i,t-k}+\gamma_4 SCORE_{i,t-4}+\gamma_5 SIZE_{i,t})$ for the sample of 555 and 1,000 firm-quarters for the pre-FDICIA and post-FDICIA periods respectively. The dependent variable CHG equals 1 if the firm's SCORE decreases, 0 if it remains the same, and -1 if it increases. SCORE is a composite index of the firm's financial condition based on its capitalization, asset quality, management, earnings, and liquidity relative to other firms. It is a variable between 5 and 20 where a lower score indicates a healthier firm. MktInd is one of the following: DD_EIAV, DD_DIAV, and DD_EDIAV are the distance-to-default measures calculated from the equity-implied, debt-implied, and equity-and-debt-implied asset volatilities respectively; EV is the annualized daily equity volatility over the quarter; YS is the credit spread of the firm's most recently issued subordinated debt. A change in variable X is denoted by dX. Control variables are excluded from the table for ease of exposition.

	Pre-FDICIA Period							Post-FDICIA Period						
	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS	DD_EIAV	DD_DIAV	DD_EDIAV	EV	YS	DD_EIAV and DD_DIAV	EV and YS
Base Case														
Pseudo R^2	0.167	0.105	0.105	0.176	0.109	0.172	0.182	0.343	0.374	0.375	0.364	0.376	0.383	0.388
Time to Resolution: Weighted Average Duration of Traded Debt														
Pseudo R^2	0.150	0.098	0.099	0.163	0.118	0.158	0.178	0.345	0.372	0.373	0.359	0.371	0.380	0.382
Time to Resolution: Weighted Average Maturity of Traded Debt														
Pseudo R^2	0.132	0.101	0.105	0.145	0.122	0.136	0.161	0.357	0.387	0.388	0.370	0.384	0.397	0.394
Default Point: 95% of Total Debt														
Pseudo R^2	0.214	0.139	0.159	0.216	0.131	0.217	0.229	0.392	0.400	0.415	0.396	0.397	0.416	0.407
Default Point: 97% of Total Debt														
Pseudo R^2	0.211	0.122	0.138	0.204	0.140	0.214	0.229	0.393	0.399	0.406	0.397	0.394	0.415	0.404
Issuer Yield: Weighted Average Issue Yields														
Pseudo R^2	0.167	0.110	0.106	0.176	0.104	0.174	0.178	0.344	0.372	0.370	0.364	0.380	0.382	0.392
Issuer Yield: Largest Issue Yield														
Pseudo R^2	0.167	0.108	0.108	0.176	0.106	0.174	0.181	0.343	0.363	0.359	0.364	0.377	0.374	0.390
Tax Adjustment: None														
Pseudo R^2	0.167	0.106	0.104	0.176	0.108	0.169	0.182	0.343	0.378	0.380	0.364	0.376	0.389	0.389
Tax Adjustment: Average Yield on Moody's AAA-rated Bonds														
Pseudo R^2	0.162	0.099	0.100	0.173	0.097	0.168	0.179	0.343	0.356	0.355	0.364	0.361	0.366	0.377
Non-callable Bonds Only														
Pseudo R^2	0.120	0.100	0.103	0.114	0.084	0.148	0.120	0.386	0.412	0.410	0.397	0.414	0.423	0.421

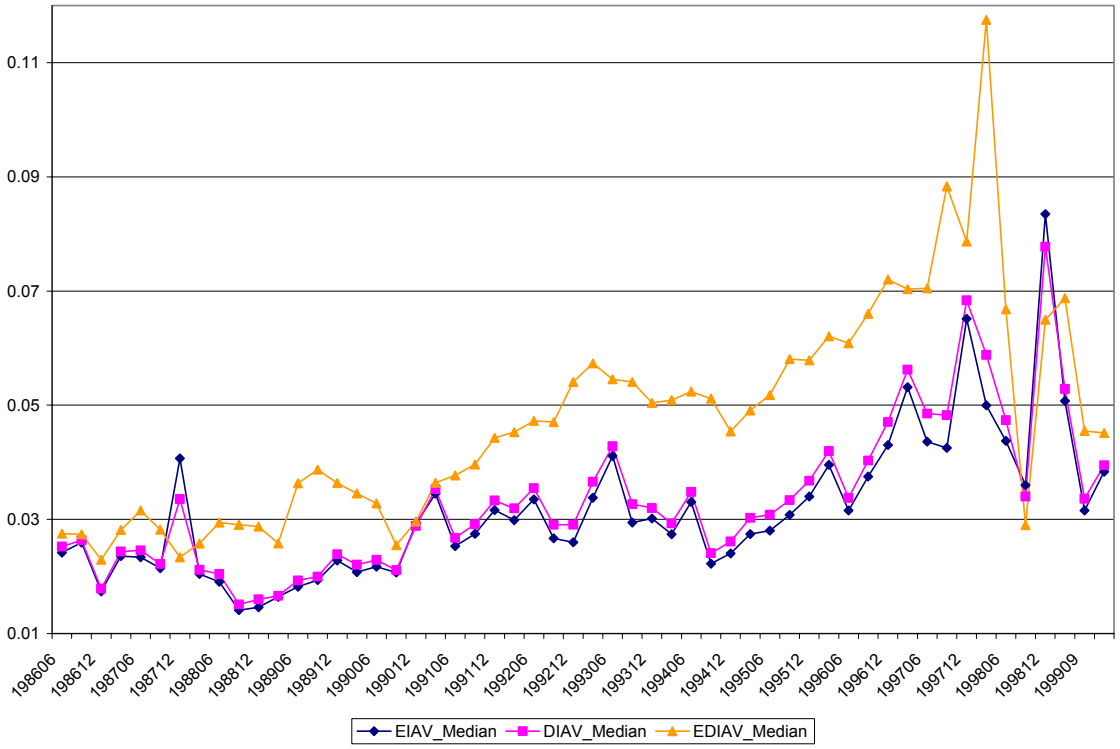

Figure 3-1. Median implied asset volatility (IAV) through time for 1986-1999

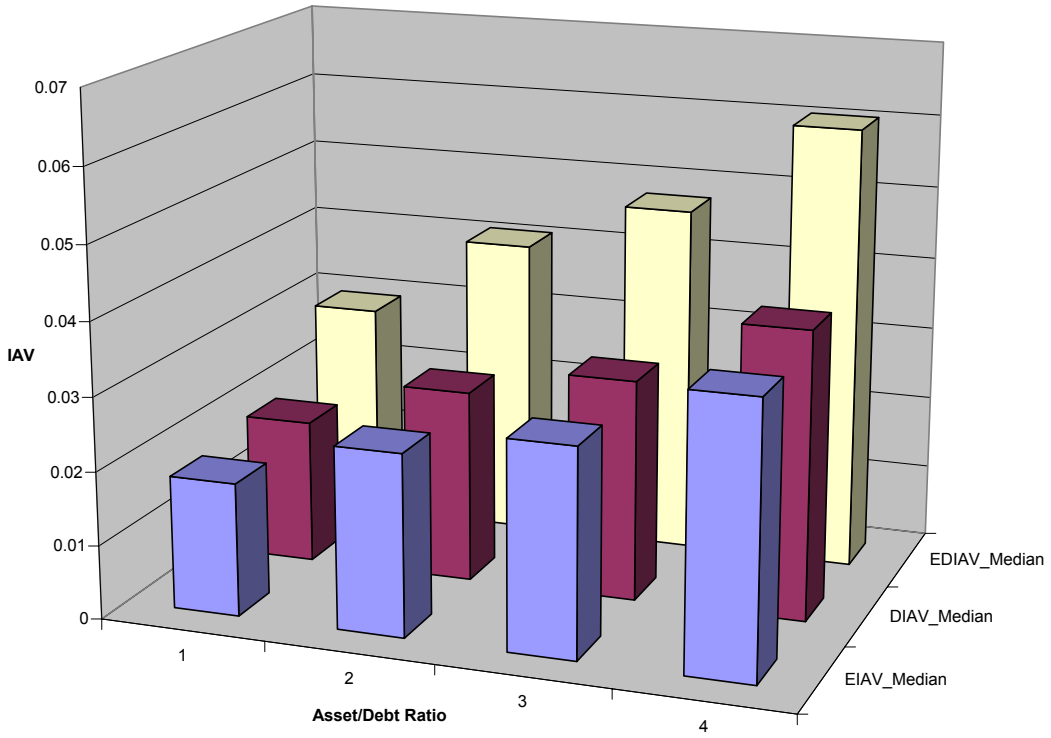

Figure 3-2. Median implied asset volatility (IAV) by asset-to-debt ratio quartile

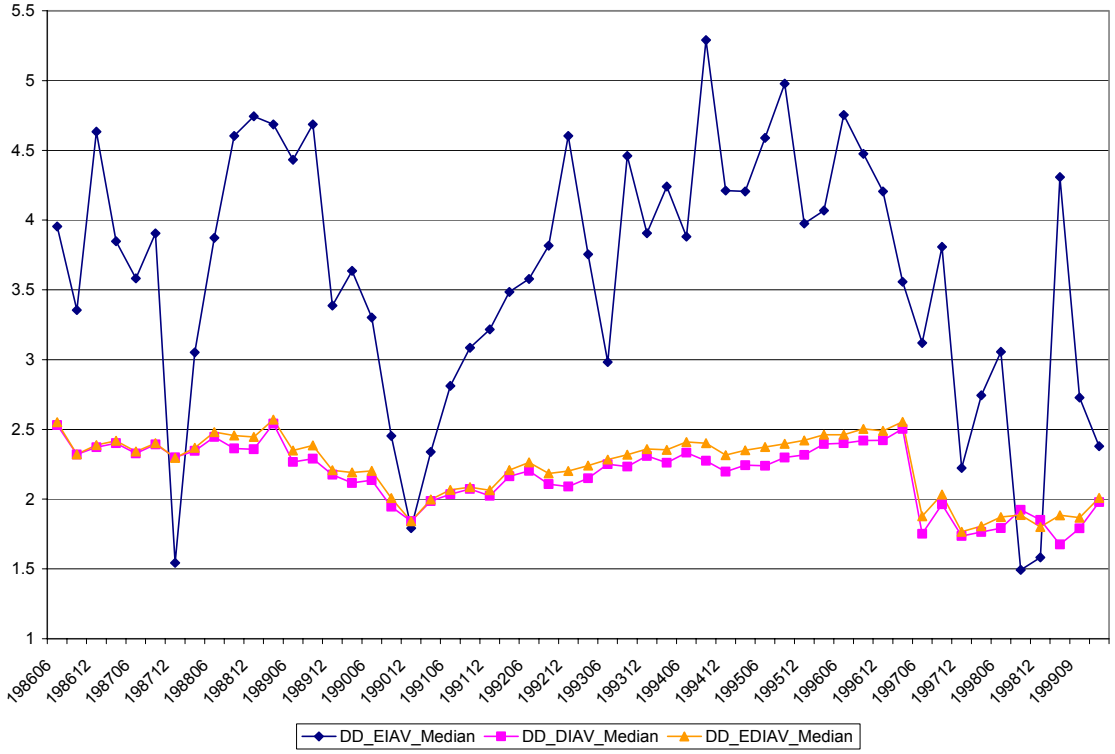

Figure 3-3. Median distance to default (DD) through time 1986-1999

CHAPTER 4
CONCLUSION

In chapters 2 and 3 we examine the ability to extract risk information from the prices of a firm's equity and debt claims. In each case we use contingent claim models for firm valuation to construct risk measures from equity prices, debt prices, and a combination of both. We provide empirical evidence on the relative accuracy and forecasting ability of these measures for industrial firms (chapter 2) and financial firms (chapter 3). We now conclude by reviewing the main results from each chapter.

In chapter 2, we compare a number of methodologies for constructing implied asset volatility estimates for industrial firms. We review the empirical properties of these estimates, assess their value as measures of firm risk, and document two important findings. First, while different methodologies produce different estimates of implied asset volatility, the analysis in the chapter suggests that these differences are not crucial in explaining realized asset volatility, Moody's credit ratings, Altman's (1968) Z scores, and default occurrences. Within each test, some estimates outperform others. But no estimate is consistently "best". This implies that firm risk can be extracted from equity and debt prices equally accurately, thus suggesting that researchers and practitioners can use high-frequency and high-quality equity prices without losing much important information.

The second important finding in chapter 2 concerns the impact of alternative model assumptions on estimates of implied asset volatility for industrial firms. While the choice of using equity or debt prices to extract firm risk information appears to be inconsequential, we find that the choice of model parameters is quite important. We show

that the manner in which we adjust yield spreads to account for embedded call options, and tax differences between corporate and Treasury securities has a significant effect on the level and rank ordering of firm risk measures. In addition, assumptions about the maturity of debt and debt priority structure seem to affect the forecasting ability of both implied-volatility and distance-to-default estimates. In contrast, using alternative assumptions about each firm's default point and alternative approaches to aggregating issue yields into issuer yields appear immaterial. This finding underscores the importance of robustness checks whenever equity and debt valuation is based on contingent-claim pricing models. It also provides researcher and practitioners with some direction as to the model parameters most likely to influence results.

The analysis in chapter 3 offers valuable contribution to the literature on market discipline of banks and BHCs. While previous studies have successfully argued that government oversight should be supplemented with risk information from bank equity and debt prices, they have offered little guidance as to which set of prices to use and how to use it. Chapter 3 addresses both questions. First, we compare bank risk information extracted from equity prices to that extracted from debt prices in explaining bank credit ratings, asset portfolio quality, and overall financial health. We observe that default risk measures constructed from debt prices generally outperform those constructed from equity prices. This finding is in contrast to the commonly held belief that debt prices are too noisy for the information in them to be useful. We further document that models using information from <u>both</u> equity and debt prices improve on the explanatory power of equity-only or debt-only models and that the magnitude of the improvement depends on how similar the information in equity and debt prices is.

A second dimension of the analysis in chapter 3 evaluates whether regulators should use market information as contemporaneous affirmation, or as a forecasting tool of a BHC's financial condition. We conclude that market information can be valuable in as both. The contemporaneous analysis suggests that risk measures constructed from equity and/or debt prices are related to indicators of BHC risk. This implies that regulators can use market information to reinforce their assessment of a BHC's current state. In that sense, it can also be used as a tripwire for supervisory actions, which might help reduce regulatory forbearance (Evanoff and Wall 2000). Our forecasting analysis indicates that market indicators can also be used to predict material changes in the firm's default probability and quarter-to-quarter changes in the firm's asset-portfolio quality and overall condition. Thus, market information can be used as an early warning signal of changes in a BHC's condition.

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