The Direct Relevance of Accounting Information for Credit Default Swap Pricing

Forthcoming, Journal of Business Finance and Accounting, Vol. 38, Issue 9/10

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Abstract

This paper examines the direct relevance of accounting information for credit default swap (CDS) pricing. Prior research on the impact of accounting information for CDS pricing has neglected to include either the output of theoretical CDS pricing models or credit ratings, both of which should impound credit relevant accounting information. Both in- and out-of-sample testing results suggest that accounting information's explanatory power for CDS prices is significantly diminished when this additional information is included in regression models. Empirical findings suggest a larger indirect role for accounting information in pricing CDS', which play an important role in credit risk price discovery.

Keywords: credit default swaps, credit risk, capital markets, value relevance

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This article is based in part on my doctoral thesis at Harvard Business School. I would like to thank members of my thesis committee, Paul Healy, Krishna Palepu, and George Chacko, for their invaluable advice and support. This paper has also benefitted from seminar participants' comments at Claremont McKenna College, Harvard Business School, the University of Southern California, NERA Economic Consulting, Charles River Associates, Analysis Group, Moody's KMV, and the 2007 FARS Mid-year Meeting. I would also like to thank one of the editors, Peter F. Pope, as well as an anonymous referee for their highly insightful comments and suggestions.

I. Introduction

The purpose of this paper is to examine the *direct* relevance of accounting information for credit default swap (CDS) pricing. The CDS is a type of financial instrument that allows banks, insurance companies, and institutional investors to more effectively manage, price, and speculate on corporate credit risk[1]. Although still a relatively new instrument, many academics and practitioners now consider the CDS market to be an important arena for credit risk price discovery[2]. Given the well-established importance of financial information in predicting credit risk, as documented in numerous studies on bond pricing and default prediction, the direct usefulness of accounting information for CDS pricing would appear self-evident. Callen et al. (2009), in particular, find evidence that CDS prices react to credit-relevant information contained in quarterly earnings announcements, while Das et al. (2009) find that adding accounting information to a set of market information improves their model's predictive power for CDS pricing.

However, there is reason to question the extent to which CDS markets *directly* incorporate information in accounting reports, vs. incorporating this information *indirectly* through debt and equity security prices and credit ratings. With the important exception of information on the face value firm's debt, which is critical for determining default proximity in structural, equity-based pricing models based on Merton (1974), many extant CDS pricing

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[1] In a typical CDS contract, a bank or insurance company will purchase credit protection on a company in its credit portfolio from a protection seller, who receives quarterly premiums up until the derivative contract matures or until a firm defaults on its debt obligations. Upon default, the seller compensates the buyer at the difference between the face and market value of the company's debt.

[2] Hull et al. (2004) find that the market for corporate-level CDS' anticipates much, though not all, of the information in Moody's negative credit rating changes and that spreads on CDS' can be used to predict the occurrence of credit rating events. They attribute their findings to the stability objective of ratings agencies, who endeavor to avoid rating changes that have to be subsequently reversed. Blanco et al. (2005) find that CDS markets tend to lead bond markets in incorporating new information on default and recovery prospects of investment-grade bonds, which they attribute to the bond market's relative illiquidity and high barriers to shorting corporate bonds, both of which impede the price discovery process in that market.

models leave no direct role for accounting information, relying instead on information on equity market capitalization, equity return volatility, and debt prices, all of which may already impound information contained in firms' accounting reports.

Supporting this, numerous research papers have documented that equity markets lead CDS markets in credit risk price discovery (Norden and Weber 2009; Forte and Pena 2009; Forte and Lovreta 2009). Additionally, contemporaneous credit ratings already incorporate accounting information to a large extent (Kaplan and Urwitz 1979; Kraft 2011) and can serve as a lower cost, albeit less timely, means of extracting and synthesizing credit-relevant information from accounting reports. Aunon-Nerin et al. (2002), in their study of the determinants of CDS price levels, verify that ratings are the single most important source of information on credit risk overall, while Micu et al. (2006) note that a variety of rating agency announcements have a significant effect on CDS prices. Finally, although evidence suggests that the CDS market leads the corporate bond market in credit risk price discovery, traders often reference corporate bond prices, which appear to be affected by accounting earnings (Easton et al. 2009), as a baseline for CDS valuation[3].

Of course, theoretical pricing models may be misspecified (Bharath and Shumway 2008), agency ratings may be slow to incorporate new, credit-relevant information (Keiber and Löffler 2004; Hull et al. 2004), and the securities prices that serve as model inputs may not reflect fundamental value (Baberis and Thaler 1993). This leave space for accounting information to retain greater *direct* relevance for CDS pricing, a proposition I subject to empirical testing in this study.

[3]A discussion with a credit derivatives salesman at a major investment bank confirmed this. When bonds for the firm are difficult to find, practitioners will examine comparable firms to make baseline price assessments and then make additional judgmental adjustments.

Understanding whether accounting information has more of an indirect, rather than direct role in CDS pricing has implications for how researchers should interpret the burgeoning accounting literature on these instruments[4]. Many researchers in accounting have taken to examining CDS prices to assess credit and debt contracting-relevant research questions, as they are seen as measuring credit risk more precisely than corporate bond yield spreads. However, researchers should be cautious about interpreting this evidence as showing the extent to which CDS market participants explicitly incorporate accounting information into pricing decisions: Prices may appear to directly incorporate accounting information only because market participants are relying either on the information aggregation function of equity and debt markets or on the information processing function of rating agencies. Unless information from equity and bond market based valuation models and rating agencies is included, the *direct* information share of accounting for this novel and important financial instrument may be overstated.

A review of existing research suggests that many studies do not comprehensively incorporate security price and credit rating information in empirical credit derivative pricing models. Examining CDS pricing in levels tests, Das, et al. (2009) find that accounting information provides explanatory power incremental to that of an equity-based "distance-to-default" measure, equity returns, and other firm-specific and macroeconomic covariates. However, their model does not incorporate bond prices or disaggregated credit rating information[5]. Similarly, Callen et al. (2009) do not incorporate bond prices in their levels and changes models[6]. Moreover, while Callen et al. employ equity returns in some of their regression

[4] Recent papers in this literature include Chakravarty (2010), Andrade et al. (2010), Gallagher (2010), and Bhat et al. (2011)
[5] Das et al. (2009) incorporate only an investment-grade dummy variable.
[6] Callen et al. (2009) also only include credit ratings for short-term instruments in their regression model, when the typical CDS contract maturity is greater than one year. While long-term and short-term ratings are likely correlated, Standard & Poor's short-term ratings (with 10 separate rating categories) are far less fine-grained than long-term ratings (with 23 separate rating categories).

tests, results in Das et al. (2009) suggest that more theoretically-grounded, nonlinear models of credit risk, which use equity prices and return volatilities as inputs, have significant incremental explanatory power over equity returns. Finally, short-window event study tests in Callen et al. suggest that contemporaneous equity returns subsume much of the information in earnings surprises in explaining event period credit spread changes.

This paper attempts to fill these gaps left open in prior research. This is important given the current, early state of the literature on accounting information's effect on credit derivative pricing: As Bamber et al. (2001) note, overgeneralization of subjective research design choices from seminal papers may profoundly affect the direction of subsequent research. Including CDS prices as purer measures of credit risk is certainly advisable, but researchers should exercise caution in evaluating the extent to which derivative counterparties directly incorporate the valuation impact of accounting numbers, which, theoretically, should only have a role in determining the default boundary in CDS pricing models.

This paper is also complements papers in the finance literature on the contribution to price discovery of equity, CDS, and corporate bond markets. The literature broadly suggests that the equity market leads the CDS market in credit risk price discovery, while the CDS market tends to lead the bond market. Longstaff et al. (2005), in an early contribution to the CDS pricing literature, use a vector autoregressive model (VAR) to conclude that information flows first to the CDS market and stock markets, and then to the bond market. Norden and Weber (2009) employ daily data and an international sample in a VAR model; in contrast to Longstaff, et al. they find that equity markets tend to lead both CDS and bond markets in credit risk price discovery. Forte and Pena (2009) and Forte and Lovreta (2009) also find evidence that stock markets lead CDS markets, and that both lead cash bond markets, though Acharya and Johnson

(2007) find some limited circumstances in which the CDS market leads the stock market. Finally, Zhu (2004) finds the CDS market leading the cash bond market in price discovery. In this paper, we employ a complementary research design, exploring the importance of incorporating market and rating information in explaining CDS levels and changes.

Initial, in-sample empirical tests of the relevance of accounting information in pricing credit instruments reveal that accounting ratios do have significant explanatory power for CDS price levels and quarterly changes, incremental to the information contained in bond credit spreads, equity returns, and equity price-based credit risk models. However, the economic significance of accounting numbers is significantly muted when this additional information is included in the model, especially in levels tests. Moreover, evidence of accounting information's incremental explanatory power—over and above its role in determining the default boundary in equity price-based structural models—is wholly diminished in out-of-sample testing. Results are robust to the inclusion of additional accounting variables, the exclusion of speculative-grade firms, and to varying the out-of-sample holdout period. The results suggest a larger indirect, rather than direct role for accounting information in CDS pricing than might be inferred from prior literature, given accounting's established role in equity valuation, corporate bond valuation, and credit rating assessment.

A closely related paper is Correia et al. (2011). Correia et al. develop a comprehensive framework for incorporating accounting and market information in bond and CDS spread models, in which credit pricing is anchored to a default forecasting model. They find that a structural, distance-to-default-based model outperforms less theoretically-grounded models—based on combinations of accounting and market data—for credit pricing. In this paper, I add accounting information, in a reduced form CDS pricing model, to predicted spreads from theoretically-grounded equity and bond price-based models, as well as ratings. My finding of weak incremental explanatory power of an accounting ratio-based model (which persists even when ratings are excluded) supports Correia's et al.'s (2011) conclusion that theoretically-grounded credit pricing models are superior to models relying on *ad hoc* combinations of predictor variables. Consistent with Correia et al., I also find that residuals from a structural, equity-based CDS pricing model—representing possible deviations from a fundamentals-based model—outperform accounting ratio residuals for predicting future CDS spread changes, with residuals negatively associated with future changes. This suggests that CDS markets are slow to react to credit relevant information, and also suggests a role for fundamental value investing in credit markets.

The layout of this paper is as follows. In the next section, I outline prior literature on accounting's use in credit risk assessment and bankruptcy prediction and describe the market for credit derivatives, of which the CDS is an important component. Section III describes the research design, including descriptive statistics, selection of particular accounting variables, and details of my testing strategy. Section IV presents testing results, while Section V presents various robustness checks and additional tests. Finally, Section VI provides a summary of my results and concluding remarks.

II. Prior Literature & Background

Accounting's use in credit analysis, bankruptcy, and credit rating assessment

Previous studies have linked various sorts of accounting information and disclosures to measures of credit risk, using banks' internal default risk classifications (Dietrich and Kaplan 1982), bond returns (Bhojraj and Swaminathan 2009), bond yields (Ziebart et al.1992; Sengupta

1998; Khurana and Ramesh 2003; Yu 2005), or bankruptcy prediction (Altman 1968; Ohlson 1980; Zmijewski 1984; Shumway 2001; Beaver et al. 2005; Beaver et al. 2011). These studies generally find significant associations between measures of credit risk and the information contained in financial reports and disclosures and find that the cost of debt capital is decreasing in the quality and conservatism of financial disclosure and reporting.

Additionally, accounting information has been found to play a key role in the credit rating assessment process (Kaplan and Urwitz 1979; Ahmed et al. 2002). Recent research has also highlighted the rating agencies' sophisticated use of financial disclosures and press releases to modify (or "recast") firms' financials in order to represent firms' ongoing earnings power and to impute debt from off-balance-sheet financings (Batta et al. 2010; Kraft 2011). Models linking accounting information to CDS pricing that fail to account for credit ratings thus miss a crucial channel for interpreting and disseminating credit-relevant information derived from firms' financial reports.

Credit derivatives

A brief description of the credit derivative market follows. Investment banks developed credit derivatives to allow both hedging and speculation on the credit risk of corporate bonds, sovereign bonds, and bank debt without requiring actual ownership of the underlying "cash" asset. Commercial banks have utilized them to avoid concentration of credit risk in certain clients or industries while still maintaining existing lending relationships or avoiding selling off loans prior to maturity; rather than having to withhold credit or liquidate loans at a discount, banks can instead extend or retain credit while simultaneously purchasing protection in the derivative market. By doing so, they receive compensation from credit protection sellers, should a lending customer's credit quality decline.

Those willing to sell protection include commercial banks, insurers, and reinsurers. Other banks and insurance companies have sold protection in order to diversify their loan and bond portfolios, ultimately by offering protection on loans whose credit risk is imperfectly or negatively correlated with the credit risk of their existing portfolios. Those willing to both buy and sell protection include hedge funds and other institutional investors, who have used credit derivatives as a way to take positions in firms' credit risk that are relatively more liquid and considerably less cash-intensive than positions in firms' bonds, and as a way to avoid often prohibitive short-selling costs in corporate bonds[7]. Hedge funds in particular have utilized credit derivatives heavily to hedge away credit risk in corporate bond arbitrage strategies.

While credit derivatives come in a variety of forms, the most popular version is the credit default swap (or CDS). CDS' are essentially dealer-intermediated insurance contracts, whereby one party offers quarterly premiums to a counterparty in exchange for a payout in the event a reference entity defaults on some or all of its debt obligations. Upon the occurrence of a credit event, credit protection sellers settle through either a) cash settlement in the amount of a reference debt obligation's shortfall from face value or at a pre-specified portion of face value or b) physical settlement, whereby the protection buyer transfers underlying corporate bonds to the protection seller, who then pays out the face value of the security in cash to the buyer.

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[7] Longstaff et al. (2005) find that, relative to their credit derivative counterparts, bond credit spreads—the yield-to-maturity on a bond less an appropriate risk-free rate—carry a heavy liquidity risk premium, which relates to the ability to liquidate the bond at a price close to fundamentals. Consistent with this, discussions with a credit structuring professional at a major investment bank suggested that it is generally quite easy to unwind a credit derivative position, which is most commonly done by simply terminating the transaction at mark-to-market value with the original counterparty, though parties will occasionally unwind positions by entering into an offsetting long or short position in the firm's credit risk through a CDS. Also, financing costs are considerably smaller for CDS contracts than bond investments, as CDS positions require no upfront cash payments (except in the case of firms

Key contributors to the development of the CDS market have been developments in the technology of credit derivative valuation. Valuation models generally come in two forms. First, reduced form models, which include Duffie and Singleton (1999) and Duffie (1999), imply an approximate arbitrage relationship between credit default swap prices and bond credit spreads for bonds of the same maturity as the CDS, which can be modified to account for bond liquidity premia and mismatches between payment dates on reference bonds and payment dates on CDS contracts.

The second type of model is the so-called "structural" model, including Das (1995), Longstaff and Schwartz (1995), and Leland and Toft (1996), which uses the Merton (1974) model of risky debt pricing as a starting point. These models start by modeling equity as a call option on the value of the firm—evolving as a lognormally distributed process--with a strike price at the face value of debt (the only financial statement variable used) and with the risk-free rate and volatility serving as key model inputs. A distance-to-default can then be computed, which essentially measures the ratio of the market value of assets to the face value of debt, relative to the volatility of asset value returns. By using the option pricing formula, the models derive an implied total firm value, from which equity market value can be subtracted to arrive at an implied debt market value. By comparing the face value of debt to its implied market value, one can derive and implied yield to maturity on the debt, from which the risk-free rate can be subtracted to arrive at a credit spread, which represents the cost of insuring against default. Correia et al. (2011), following Kealhofer (2003), dispense with the lognormality assumption for asset value evolution. Instead, they incorporate a mapping between the distance-to-default and

with very high default risk). Finally, costs to adopting short positions in the bond tend to be rather high due to the relative illiquidity of the corporate bond lending market.

actual default data. Arora et al. (2005) find that models incorporating both this mapping, as well as other modifications, outperform the basic Merton (1974) model in explaining CDS prices.

A third type of hybrid model was introduced by Duffie and Lando (2001), who develop a structural model that can accommodate uncertainty over the firm value. In this model, noisily observed enterprise values allow information in addition to return volatility, debt face value, and equity market capitalization to enter into a model of default likelihoods at different maturities. Yu (2005) and Arora et al. (2011) find evidence consistent with this model, in that poorer financial disclosures and asset measurement uncertainty are significant determinants of short-term corporate bond and CDS spreads.

Accounting literature on the CDS market

The literature on empirical models of CDS pricing in accounting is growing. Chakravarty (2010) finds that CDS prices are negatively associated with the degree of conditional accounting conservatism. Andrade et al. (2010) find that the price impact of constructively-capitalized operating leases is equivalent to the price impact of balance sheet debt both before and after SEC’s FR-67 rule, which mandated more salient disclosures of operating lease obligations. Gallagher (2010) finds that unfunded pension obligations are priced in the CDS market. Finally, Bhat et al. (2011) use CDS prices to assess the transparency of IFRS accounting rules.

Additional studies attempt to tie accounting information to CDS prices. Callen et al. (2009) find evidence that credit default swap levels, changes, and event-window returns around earnings announcements are related to information in earnings, though they do not include any of the aforementioned models of CDS pricing, instead choosing to “borrow” from the structural approach to identify credit risk determinants for inclusion in their linear regression model. Das et al. (2009) find that a regression model including an equity-price-based structural model, equity returns, and additional firm-specific and macroeconomic information is enhanced when they include accounting information; they do not, however, include information from bond markets in their model, and only include an investment-grade dummy variable for credit rating information.

A key aspect of much of this research in accounting is that at least some of the information in equity prices, bond prices, or credit ratings is missing. High information acquisition and processing costs should prompt market participants to seek out the lowest cost information source. Information from security markets and rating agencies may already assimilate credit-relevant information from accounting reports and should therefore necessarily be included in models that purport to link together accounting information and CDS prices. I therefore include these, along with accounting information, in subsequent empirical tests of the incremental explanatory power of accounting information for CDS price levels and quarterly changes.

III. Research Design

Data

CDS price data from June 1997 to May 2004 were available from Credittrade (now part of Creditex), a major broker-dealer in the CDS market. Credittrade served as an intermediary between financial institutions and institutional investors wishing to take different sides of default swap contracts. The dataset consists of 260,103 bid quotes, ask quotes, and actual trades on around 700 reference firms. Swaps are quoted in terms of hundreds of basis points, and I deflate all spreads by 100 in subsequent testing. Over 90 percent of swaps are for maturities close to five years, and over 98 percent are written on firms' senior unsecured debt. To ensure consistency across data points, I focus on five-year, senior unsecured debt contracts in my study. To match prices to financial statement data, I find all trades, bid quotes, and offer quotes that fall within the third month after a firm's fiscal quarter-end, given the results of Easton and Zmijewski (1993), who find that most firms' quarterly financial reports have been released to the public by that point. For the earliest day in which both a bid and an offer quote are present in the third month after fiscal quarter end, I use the midpoint of the bid and offer as a measure of the CDS' market price of credit risk, which I substitute with actual trade prices when available.

The data are then matched to the Compustat industrial quarterly database for financial data, to the CRSP files for information on stock returns, and to the Datastream database for corporate bond yields. To simplify the analysis, I only use firms that have a December 31st year-end. For subsequent analysis, I also gather data on government bond rates from Datastream and the Federal Reserve Bank. The resulting dataset for firms meeting all data criteria consists of 861 firm-quarters, representing 242 distinct firms

Financial Statement Variables

Altman's and Zmijewski's models of bankruptcy prediction, containing variables relating to liquid capital reserves, solvency, and current earnings performance, have proved popular in forecasting financial distress. Shumway (2001), using a hazard rate model framework, finds that among Altman's and Zmijewski's variables, only net income and leverage remain significant when combined with recent excess stock returns and stock volatility. Beaver et al. (2005) and Beaver et al. (2011) additionally include a measure of cash flow to liabilities in their bankruptcy prediction models. However, in untabulated tests, Beaver et al. (2005) find very similar results to

Altman’s, Zmijewski’s, and Shumway’s model, and Beaver et al.’s (2011) addition of interactive loss terms does not appear to significantly affect their model’s predictive power[8]. In the interest of parsimony, I adopt the Shumway model, which includes net income and leverage as key accounting variables. I also test the sensitivity of the model to the inclusion of additional accounting variables and alternative earnings specifications in later robustness checks.

The structural modeling framework uses a distance-to-default measure based on the ratio of enterprise value to the face value of debt, relative to a given level of asset volatility. Accounting ratios that at least partially give heed to this framework should use financial statement variables that measure value available to all stakeholders, relative to a measure of debt obligations. The particular net income variable I therefore use is earnings before interest and taxes, deflated by interest expense (COVERAGE). The structural framework also demands that the effect of distance-to-default on default risk vary based on default proximity. To account for nonlinearities in the relationship between COVERAGE and credit risk, I include a term equal to COVERAGE when COVERAGE is less than or equal to zero and equal to zero when COVERAGE is greater than zero (COVERAGE≤0). 0<COVERAGE≤5, 5<COVERAGE≤10, 10<COVERAGE≤20, and COVERAGE>20 are defined similarly[9]. The measure of leverage I use is the firm’s long-term debt divided by its total book assets (LEVERAGE) as of the most recent balance sheet date, again measuring obligations relative to an accounting measure of assets available to all stakeholders. In later robustness checks, I assess the sensitivity of results to

[8] In Beaver et al. (2005), 82% (90%) of the firms in their top 2 (3) bankruptcy risk deciles go bankrupt within a year, relative to 81% (90%) in Beaver et al.’s (2011) model that includes interactive loss dummies.

[9] This is similar to Campbell and Taksler (2003), though I include an extra partition for COVERAGE below zero, given the ambiguous relationship between changes in negative coverage and credit risk: If a negative coverage ratio becomes more negative, it is unclear whether this arises mainly from a smaller denominator (suggesting a smaller interest burden, and thus lessened credit risk) or a more negative denominator (suggesting higher losses, and thus greater credit risk).

combining net income and leverage into a measure of distance-to-default, scaled by the volatility of return on assets, in keeping with the structural framework.

Because the partitioned COVERAGE variable is not amenable for use in a change specification, and because changes in COVERAGE may be ambiguous for negative coverage levels, I use the quarterly change in each firm's return on assets (ROA) in changes tests. I calculate ROA as each firm's pretax income plus interest expense, divided by beginning total assets.

Testing Strategy

I utilize the following regression specification for levels tests:

(1) $$\text{PRICE} = \alpha + \beta_1\text{COVERAGE} + \beta_2\text{LEVERAGE} + \beta_3\text{BOND} + \beta_4\text{EQUITY} + \beta_5\text{RATINGS} + \beta_6\text{RETURNS} + \beta_7\text{SIZE} + \varepsilon$$

PRICE is the first CDS price observed two-months after firms' quarter-end, while COVERAGE and LEVERAGE are defined as above. EQUITY is the output of the equity-based, structural CDS pricing model used in Hillegeist et al. (2004), as described in the Appendix. In this model, equity is treated as a call option on total firm value, with a strike price at the face value of total liabilities. Using the Black-Scholes option pricing model, I derive an implied total firm value, from which I subtract the observed market value of equity to derive an implied market value of debt; from this, I derive an implied yield to maturity based on the book value of total liabilities, and from this I subtract the current Treasury bill rate to arrive at a spread. There do exist competing structural models that may better explain variation in CDS prices[10]. The

[10] Variants of the model used in this paper have been used in several recent papers to measure default risk, including Vassalou and Xing (2004) and Bharath and Shumway (2008). The model utilized in this paper most closely

results I obtain using this more basic model may then serve as an upper bound on the direct relevance of accounting information for CDS pricing.

BOND is the spread on firms' senior unsecured corporate bonds with five-years left to maturity, in order to match the five-year maturity of CDS contracts. The spread is calculated as a bond's yield-to-maturity less the most recent available five-year constant maturity U.S. Treasury bond rate, obtainable from Datastream. Similar to the procedure outlined in Blanco et al. (2005), I interpolate five-year bond yields by finding a bond with 3.5 to 5 years left to maturity and another bond with more than 5 years to maturity left, and linearly interpolate to find an appropriate five-year yield to maturity[11]. Where multiple bonds of the firm meet this criterion, I choose the bond whose value lies closest to par value.

When bonds available for interpolation are missing, I take the simple average of credit spreads on bonds for firms in the same two-digit SIC code and S&P rating category[12] as the CDS sample firm, as of the last day of the second month after quarter-end. To provide greater confidence that differences in spreads between bonds are due to differences in credit risk rather than other factors, I exclude floating-rate bonds and all bonds that have embedded options, step-up coupons, or sinking fund features.

RATING is the S&P long-term corporate issuer-level debt rating from Compustat. In my main regression tests, I convert the rating to a number between 1 and 18, with rating categories

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resembles that utilized by Hillegeist et al. (2004). Eom et al. (2004) examine several structural models of corporate bond pricing, finding that none emerges as clearly superior for predicting credit spreads. Models differ based on assumptions about the stochastic evolution of firms' leverage ratios and interest rates, assumptions about recovery values upon default, and assumptions of whether equityholders have the option to issue new equity to make promised interest and principal payments. On the other hand, Arora et al. (2005) find that a model which explicitly maps a firm's distance-to-default to actual default data (as per Correia et al. 2011, and as utilized by commercial credit pricing providers like Moody's KMV) outperforms my simpler model, which relies on the Merton (1974) assumption that the market value of assets evolves according to a lognormal process.

[11] Similar to Blanco et al. (2005), I exclude bonds with less than 3.5 years left to maturity, due to the fact that the sensitivity of credit spread changes to increases in yield to maturity tends to fall considerably after this point, ensuring that the linear interpolation will result in a reasonable approximation of five-year yields.

converted to a number between one and 18 and lower ratings assigned lower numbers. However, in robustness checks, I allow each rating category to have its own dummy variable, which may capture nonlinear pricing effects of different ratings levels.

I also include two control variables suggested both by prior literature in accounting and finance on determinants of credit risk and CDS spreads. First, I include firm size (SIZE), measured as the log of total book assets. I also include recent stock price performance, for the twelve months ending two months after each fiscal quarter-end (RETURN), given that EQUITY may not fully capture credit relevant information emanating from equity markets.

Given the panel nature of the data, I adjust standard errors for heteroskedasticity and possible within-firm serial correlation using the robust panel data standard error estimator of Rogers (1993), and all variables are winsorized at the 1% level.

For tests of changes, I adopt the following model:

(2) $$\Delta PRICE = \alpha + \gamma_1 \Delta ROA + \gamma_2 \Delta LEVERAGE + \gamma_3 \Delta BOND + \gamma_4 \Delta EQUITY + \gamma_5 \Delta RATINGS + \gamma_6 RETURNS + \gamma_7 \Delta SIZE + \varepsilon$$

Δ represents the quarterly difference operator. Quarterly price differences are measured as of two months after each fiscal quarter-end. I also include the level of RETURNS, because these already represent changes in the value of shareholders' stake in the firm.

I also employ out-of-sample tests of accounting information's incremental usefulness for CDS pricing. The first test estimates parameters for alternatives model for fiscal periods up to and including the second quarter of 2002, the first half of the data in my sample period. I then assess the explanatory power for CDS price levels and changes for models including and excluding accounting variables in the latter half of the sample period by comparing differences in

[12] I use five long-term debt rating categories for this purpose: AAA, AA, A, BBB, and speculative grade.

means and medians of absolute model prediction errors (Section V includes robustness checks using a different holdout period).

Finally, since CDS prices may incorporate accounting information or other information with a delay, I also assess the explanatory power of alternative models for period-ahead CDS price changes. I do so by again comparing means and medians of absolute model prediction errors, from a regression of the period-ahead price change on the previous quarter's change in independent variables as per equation (2) above, but with lagged independent variables. I also assess whether levels model residuals—representing the difference between actual and model-predicted CDS spreads—predict future negative CDS price changes. This would suggest, as in Correia et al. (2010), that actual CDS spreads revert to model-predicted CDS spreads, highlighting potential informational inefficiency in the CDS market.

I also use this test to assess the comparability of my reduced form CDS pricing model results to Correia et al.'s (2011). Using a model in which credit pricing is anchored to default forecasting models, Correia et al. examine the relative usefulness of structural, distance-to-default-based credit pricing models to models relying on *ad hoc* combinations of accounting and market variables for predicting future credit spread changes. I assess the relative explanatory power of residuals from EQUITY, which is most comparable to the Moody's KMV, Expected Default Frequency-based model Correia et al. use, to residuals from COVERAGE and LEVERAGE. While this allows me to better assess the comparability of my results, note that I use accounting ratios to predict CDS prices in a reduced-form, ordinary least squares-based model, rather than a more theoretically-grounded model such Correia et al's. A caveat to interpreting these results is that, relative to a more theoretically-grounded model, where the economic drivers of default are explicitly modeled, there is less assurance that the model I estimate will have similar predictive power for a sample of debt instruments with a different composition of credit quality.

Descriptive Statistics

Tables 1 and 2 offer descriptive statistics for CDS sample firm-quarters and for all firm-quarters in the Compustat universe (for December year-end firms) with data available from 1999-2003. Table 1 lists the distribution of Standard and Poors' long-term debt rating categories. While the percentage of firm-quarters rated AA and above are similar between the sample firms and Compustat firms with available ratings, the most striking difference between the two is the much smaller percentage of speculative-grade firm-quarters in the CDS sample and the higher frequency of BBB ratings; fully 41.2 percent of the Compustat sample is speculative-grade, compared to 7.7 percent for the CDS sample,[13] whereas the CDS sample comprises 59.5 percent of BBB-rated firm quarters, versus 32.9 percent for the Compustat sample.

Insert Table 1

Table 2 lists descriptive statistics for sample firm-quarters, those for all December year-end Compustat firms, and those for Compustat firms with ratings available from 1999-2003. Overall, CDS sample firms are larger than Compustat firms with available ratings, and considerably larger than the average Compustat firm; they have larger levels of total book assets ($27.0 billion versus $10.7 for rated Compustat firms and $3.5 billion for all Compustat firms) and larger market capitalizations ($19.4 billion versus $5.2 and $1.7 billion for rated and unrated

[13] This smaller percentage of speculative-grade firms is driven by the fact that the cost of insuring against default for firms in this category is prohibitively expensive, dampening the demand for dealers to issue quotes. Also, the majority of corporate bond holders are institutional investors and insurance companies who face restrictions on investing in speculative grade issuers, which reduces demand for dealers to deliver quotes on these sorts of firms.

firms, respectively)[14]. CDS sample firms are on average better performing than both rated and unrated Compustat firms; with an average earnings before extraordinary items and discontinued operations (deflated by average total assets) of 0.007, versus 0.003 and -0.018 for rated and unrated firms; t-tests of means between samples reveal these differences to be significant at the one percent level.

Insert Table 2

Average leverage ratios are not significantly different between CDS and rated Compustat firms, though they are larger than ratios of unrated Compustat firms. Finally, market-to-book ratios are significantly larger for CDS firms, relative to rated Compustat firms; the ratio is 2.57 for CDS firms, versus 2.13 for rated Compustat firms. Differences appear to be due to the far greater proportion speculative-grade firms among rated Compustat firms: The ratio for investment-grade firms in the CDS (rated Compustat) sample equals 2.61 (2.35), while the ratio for speculative-grade firms is 2.13 (1.80).

Table 3 lists a correlation matrix for CDS spreads, accounting variables, bond spreads, CDS structural model output, ratings, and control variables. Panel A lists correlations for levels of these variables. As expected, CDS spreads are positively correlated with leverage ratios, bond spreads, and structural model spreads, and negatively correlated with earnings, firm size, excess stock returns, and bond ratings. Also as expected, the more comprehensive sources of information about credit risk, such as bond credit spreads, equity-based structural models, and

[14] Part of the size difference can be attributed to the fact that the demand for credit insurance will be greater for larger firms with greater amounts of debt outstanding. Additionally, information asymmetry between the buyers and sellers of credit protection may play a part. Anson et al. (2004, 19) note that when banks buy protection based on firms in their loan portfolio, they often have access to information about those firms that is not readily available to the public, which raises the fear among protection sellers that they may be underprice the cost of insuring these firms based on inadequate information. In this context, given the relationship between firm size and the quality of a firm's information environment established by Bhushan (1989), the concentration of credit derivative contracts among larger, more visible firms is understandable.

bond ratings have the strongest univariate correlations with CDS spreads. BOND and EQUITY are also well-correlated with COVERAGE and LEVERAGE, as they both should be incorporated in bond and equity prices. I obtain similar results in Panel B, which includes quarterly variable differences. The change in return on assets is well-correlated with the change in price, though the change in BOND and EQUITY are more strongly correlated. However, the change in BOND and EQUITY are more weakly correlated with the change in accounting variables, relative to levels models.

Insert Table 3

IV. Results

In-sample tests

Table 4 lists results of tests for accounting information's incremental explanatory power over bond- and equity-based CDS pricing models. Column 1 reveals that accounting information alone explains 19.4 percent of the variation in CDS price levels (in terms of R^2). All predictors are statistically significant and have the expected sign. The coefficient estimate on COVERAGE is also more negative the closer COVERAGE is to zero, which is expected, given that variation in COVERAGE should have a greater impact when it is closer to zero.

Column 2 shows that market-based variables bond credit spreads (BOND) and the output of equity-based structural models (EQUITY) alone explain 62.3% percent of the variation. Both BOND and EQUITY are statistically significant and have the expected positive sign. Column 3 includes RATING; ratings explain less of the variation in CDS prices than BOND or EQUITY, but they are still significant, and higher ratings indeed translate into lower CDS prices. In column 4, I include RETURNS and SIZE in a regression with accounting variables; these control variables' contribution to the model's explanatory power is relatively modest, with an increase in adjusted-R^2 of around six percent (24.8-18.8).

Finally, column 5 includes all predictor variables in one model. The statistical significance of individual COVERAGE partitioning variables is reduced considerably, with only Coverage≤0, 0<COVERAGE≤5, and LEVERAGE remaining significant. However, an F-test of the joint significance of COVERAGE and LEVERAGE reveals that these variables retain their joint significance. All other variables retain their statistical significance. In-sample tests thus suggest that accounting variables still have incremental explanatory power when market variables and ratings are included in pricing models. However, the economic significance of the remaining significant accounting variables is curtailed significantly: The coefficient on 0<COVERAGE≤5 goes from -0.230 in column 4 (excluding market-based models and ratings) to -0.052 in column 5 (the model including all variables). For a firm to increase COVERAGE by one in this range, column 4 suggests that would produce a 23 basis point decrease in the cost of credit insurance; column 5 suggests that this would only produce a 5 basis point decrease.

Insert Table 4

Table 5 shows regressions of CDS price changes on quarterly differences of independent variables. Column 1 includes only ΔROA, ΔLEVERAGE, time period dummies, and a constant. ΔROA is highly statistically significant. Columns 2 and 3 include changes in market-based CDS valuation models and the change in RATING; both market-based models retain their statistical significance in the changes specification. In column 5, I include all predictors. Similar to the levels specification, accounting variables retain their statistical significance. The economic significance of accounting is also diminished, though not to the same extent, as the coefficient on ΔROA falls to -2.368, from -2.971.

Insert Table 5

Out-of-sample tests

Out-of-sample tests provide more robust evidence on the importance of accounting information for CDS spreads. Within levels-based tests, Model 1 is run by regressing CDS spread levels in the first half of the sample period on (partitioned) COVERAGE and LEVERAGE, without time period dummies. Model 2 uses the market-based model output of BOND and EQUITY. Model 3 uses RATING, while Model 4 uses all but accounting variables: BOND, EQUITY, RATING, RETURNS, and SIZE. Finally, Model 5 includes all covariates. Table 5, Panel A, reports the mean and median absolute value of model residuals, which can also be considered model pricing errors, from the second half of the sample period. Absolute pricing errors are in hundredths of basis points.

Table 6 shows the results of levels-based out-of-sample tests. The average pricing error of accounting-based models (Model 1) is quite high, equal to 102 basis points. Market-based models pricing errors (Model 2) are considerably lower, however, equal to only 66 basis points, with a median of 38. Ratings-based models are roughly comparable to that of accounting-based models. Finally, the model including all variables has an average pricing error of 62 basis points, with a median of 45.

Insert Table 6

Most strikingly, there is minimal reduction in pricing errors from including COVERAGE and LEVERAGE in the model. Untabulated tests of differences in mean absolute pricing residuals confirm that accounting models do not significantly reduce pricing errors; moreover, median absolute residual actually are *higher* when accounting variables are included. In additional untabulated tests, when I add COVERAGE and LEVERAGE to a model only including EQUITY and BOND (the theoretically-derived market-based models), mean pricing errors drop by only 2 basis points. This suggests that, consistent with Correia et al. (2011), theoretically-grounded credit pricing models are superior to models relying on *ad hoc* combinations of predictor variables.

Table 7 includes results for out-of-sample regressions for contemporaneous and period-ahead CDS spread changes. For each out-of-sample model, I estimate the changes model (described in Section III above) in the first half of the sample period. I then compute model residuals in the second half of the sample, and use these to compute the mean and median absolute value of residuals.

Insert Table 7

Panel A shows a mean and median absolute prediction error for contemporaneous changes equal to 23 and 13 basis points, respectively, for Model 1, which only includes the change in accounting variables. Model 2 includes the change in the output of bond and equity-based pricing models; they offer a slight improvement in predictive accuracy, with mean absolute errors equal to 19 basis points. Model 3 only includes ratings, which have mean absolute pricing errors of 23 basis points.

Model 5 includes all variables. Relative to Model 4, which includes all variables but for COVERAGE and LEVERAGE, there is again no difference in absolute pricing errors, which average 19 basis points in both models, which I confirm through (untabulated) tests of means. In additional untabulated tests, when I add COVERAGE and LEVERAGE to a model only including EQUITY and BOND, mean pricing errors are unchanged.

Table 7, Panel B, shows absolute prediction errors for models predicting period-ahead changes. Model 1 (only the change in accounting variables) generates mean absolute pricing errors of 20 basis points, with a median of 13. Model 2, which only includes ΔBOND and ΔEQUITY, and Model 3, which only includes ΔRATING, produce only a slight improvement in pricing error reduction, with average absolute pricing errors equal to 20 and 19, respectively. Model 4, which includes ΔBOND, ΔEQUITY, ΔRATING, and controls, produces similarly sized average and median pricing errors, equal to 21 and 14 basis points, respectively. When accounting variables are added (Model 5), however, there is no significant difference in mean and median absolute pricing errors.

Examining period ahead price changes implies some degree of informational inefficiency in CDS markets. Table 8 shows results of a regression of residuals from price levels models, estimated in the first half of the sample, on period-ahead changes in the second half. Should period-ahead changes be negatively associated with residuals, it suggests, as in Correia et al. (2011), a degree of informational inefficiency in the CDS market, as CDS prices revert to model-implied fundamental values. I define residuals as in Correia et al.'s (2011) "credit relative value" formulation: Ln(actual spread/predicted spread). RESIDUALS in column 1—derived from a model including accounting variables, but excluding EQUITY, BOND, and RATING—are not statistically significant predictors of period ahead price changes. In contrast, residuals from columns 2, 3, 4, 5, and 6, which contain EQUITY, BOND, or RATING, all are significant predictors of period ahead price changes. Moreover, adding (partitioned) COVERAGE and LEVERAGE to all other variables does not significantly improve the fit of the model (the difference in R^2 between columns 5 and 6 is minimal). The results are suggestive of informational inefficiency in the market for credit protection and further confirm the diminished direct importance of accounting information for CDS pricing, incremental to EQUITY, BOND, or RATING.

Insert Table 8

To assess the comparability of my reduced form CDS pricing results to Correia et al. (2011), I also, in untabulated tests, assess the relative explanatory power of residuals form EQUITY vs. COVERAGE and LEVERAGE for period-ahead CDS price changes. In a model that anchors credit pricing to default prediction, Correia et al. find that a model like EQUITY outperforms *ad hoc* combinations of accounting and market predictor variables for CDS pricing. Using Davidson and MacKinnon's (1981) J-test for model selection, I similarly find that residuals from EQUITY have superior explanatory power for future CDS price changes relative to the accounting ratios. The result is robust to the adding both SIZE and RETURNS to COVERAGE and LEVERAGE in the initial levels model.

In contrast to in-sample tests, out-of-sample testing results suggest accounting ratios do not contribute significantly to a model attempting to explain CDS price levels, contemporaneous changes, or period-ahead changes, at least incremental to the role accounting plays role in determining the default boundary in EQUITY.

V. Robustness Checks and Additional Tests

Varying estimation period in out-of-sample tests

To assess whether out-of-sample results are robust to using a different estimation period, I run estimation models using the second half of the sample, that is, starting in the third quarter of 2002. I then compute the absolute value of residuals in the first half of the sample. Results are qualitatively similar using this variation of the estimation period[15].

Alternative earnings and volatility measures

In levels tests, I also use ROA, rather than COVERAGE, to see if results are altered using this measure. Results are qualitatively similar when I employ this earnings definition. For changes models, results are also similar when I use seasonally differenced earnings (i.e., current earnings less earnings from the same fiscal quarter in the prior year) or a seasonal random walk model with drift, estimated as per Bernard and Thomas (1990). In both levels and changes tests, I also use an accounting-based variable that more closely maps into a distance-to-default measure from structural models of CDS pricing. Similar to the model described in the Appendix, I use $(\ln[V_A/X] + (r - \delta + (\sigma_A/2))T)/(\sigma_A\sqrt{T})$, with V_A equal to total book assets, X equal to long-term debt, r equal to the one-year T-bill rate, δ equal to the annualized, trailing twelve-quarter mean of ROA (using r as a floor for this measure of expected asset returns), σ_A equal to the annualized, trailing twelve-quarter standard deviation of ROA, and T equal to one. This essentially represents an accounting-based leverage ratio, relative to an accounting-based measure of asset return volatility. Results are robust to using this accounting-based distance-to-default measure.

[15] Mean absolute pricing errors from a levels model including all variables are 56 basis points, compared with 57 basis points in a model excluding accounting variables. This economically insignificant difference is statistically significant, but only on a one-sided basis at below the 10% level.

Finally, I test whether results are robust to using 150-trading day equity volatility as and input into EQUITY, rather than the 60-trading day estimate used. Results are robust to using this longer estimation window.

Additional accounting variables

To test whether additional financial variables may also explanatory power for CDS prices over and above earnings and leverage, I include a sales divided by average total assets and the ratio of firms' current assets to current liabilities (the current ratio) in all regressions. The coefficient on sales and the current ratio are significant and in the expected directions in levels models including only COVERAGE and LEVERAGE; however, when all other covariates are included, they no longer retain their statistical significance. Neither variable is significant in the changes specification or in any out-of-sample tests.

Bond rating dummies

Variation in bond rating categories may have a nonlinear impact on CDS pricing, so I also replace RATING by dummy variables for all ratings categories, but for one excluded category. Results are qualitatively similar.

Using swap rate as the risk-free rate

Houweling and Vorst (2005) and Blanco et al. (2005) find that average differences between CDS rates and credit spreads computed using 5-year swap rates for dollars and euros are smaller than the average difference between CDS rates and bond spreads computed using 5-year government bond rates. The authors attribute this to the fact that taxation treatment, repo specials, and scarcity premia affect the government bond's role as an ideal proxy for the unobservable risk-free rate. I test the sensitivity of my results to the use of 5-year dollar swap rates as the risk-free rate for computing bond yield spreads. The results are qualitatively similar, which perhaps is not surprising, given that financial numbers are unlikely to be strongly correlated with any of these factors.

VI. Summary and Conclusion

In this paper, I assess the *direct* importance of accounting information for the valuation of credit default swaps. In-sample tests of levels and changes of CDS prices suggest that accounting variables retain their incremental explanatory power when market-based CDS valuation model outputs and ratings are included in models; however, especially in levels tests, the economic significance of earnings and leverage are greatly diminished. In contrast, out-of-sample testing results show a greatly diminished incremental explanatory power of earnings and leverage for CDS price levels and changes, as they appear to add no explanatory power to models already including bond- and equity-based CDS valuation model outputs, stock returns, and credit ratings. I subject these results to a battery of robustness checks, and all results hold qualitatively.

CDS prices may serve a very useful role in credit-based accounting research: They represent a purer measure of credit risk than corporate bond yield spreads and a more timely measure than credit ratings. My results only suggest caution in interpreting recent studies on the impact of accounting information on CDS prices: Prices may appear to incorporate accounting information directly only because market participants are relying either on the information aggregation function of equity and debt markets or on the information processing function of rating agencies to value these instruments.

Appendix

Hillegeist et al. (2004) implement a version of the Merton (1974) model of risky debt pricing. Equity is deemed a call option on the value of the firm, with the strike price of the option equal to the face value of the firm's liabilities and the option maturing at the bond's maturity. At time T, equityholders will let their call option expire when the value of assets is not sufficient to fully repay the firm's debts.

The Merton equation for valuing equity as a European call option on the value of the firm's assets, modified to accounting for dividends accruing to equityholders, is given by equation (1) below:

$$(1) \quad V_E = V_A e^{-\delta T} N(d_1) - X e^{-rT} N(d_2) + (1 - e^{-\delta T}) V_A$$

Where $N(d_1)$ and $N(d_2)$ are the standard cumulative normal of d_1 and d_2, respectively, and

$$d_1 = (\ln[V_A/X] + (r - \delta + (\sigma_A/2))T)/(\sigma_A \sqrt{T})$$

$$d_2 = d_1 - \sigma_A \sqrt{T}$$

V_E is the current market value of equity; V_A is the current market value of assets; X is the face value of debt; r is the continuously compounded risk-free rate; δ is the continuous dividend rate expressed in terms of V_A; and σ_A is the standard deviation of firm asset (not equity) returns. The dividend rate, δ, appears twice in the RHS of equation (1). The $V_A e^{-\delta T}$ term accounts for the reduction in the value of assets due to the dividends that are distributed before time T. The addition of the $(1 - e^{-\delta T})V_A$ is necessary because equity holders receive the dividends.

As a first step, I estimate the value of V_A and σ_A by simultaneously solving equation (1) and the optimal hedge equation, $[\sigma_E = (V_A N(d_1)\ \sigma_A)/V_E]$. V_E is equal to the total market value of equity and r the one year t-bill rate as of the last day of the second month after each fiscal quarter-end. X the book value of total liabilities at each fiscal quarter. In a slight departure from the Hillegeist, et al. formulation, rather than using one year's trading data, I use the standard deviation of equity returns for the 60 trading days ending two months after each fiscal quarter end as an intial value of σ_E. I set T equal to one year, consistent with Berndt et al. (2004), who use the output of structural models at a one-year horizon to estimate the systematic default risk component of five-year CDS spreads. They argue that measurement error in five-year-horizon CDS pricing models outweighs using a model horizon that reflects the typical (i.e., five-year) maturity of CDS spreads. Hull et al. (2004) also find that one- and five-year credit spreads implied from Merton's model to be highly correlated. They find Spearmen (Kendall) rank order correlations of 0.954 (0.826) between one- and five-year horizon estimates.

I set the dividend rate (δ) equal to the sum of common and preferred dividends, scaled by an estimate of the total asset value of the firm, which I approximate by the sum of equity market value plus the book value of total liabilities. Because equation (1) and the optimal hedge equation have no closed-form solutions for V_A and σ_A, I approximate each simultaneously using the Newton-Raphson search algorithm; the search ends when the difference between estimated and actual values of V_E and σ_E falls below 10e-4.

I then use the estimated value of V_A to estimate the market value of debt

$$V_D=V_A - V_E$$

and then solve for the yield to maturity (y) on debt through the following equation (with T equal to one):

$$V_D= Xe^{-yT}$$

Finally, I solve for the spread by subtracted the one-year t-bill rate (r), available from Datastream, from y.

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Table 1. Rating category distribution

Table 1 reports the distribution of credit rating categories for firm-quarters in the CDS sample, Compustat firm-quarters with Standard and Poors' long-term debt rating data available, and all Compustat firm-quarters (for December year-end firms with asset, equity market value, earnings and debt value available) from 1999-2003.

	CDS sample		*Compustat firm-quarters with ratings available*		*All Compustat firm-quarters*	
AA and above	42	4.9%	1,095	4.8%	1,095	1.2%
A	241	28.0%	4,869	21.2%	4,869	5.5%
BBB	512	59.5%	7,567	32.9%	7,567	8.6%
Speculative-grade	66	7.7%	9,469	41.2%	9,469	10.7%
No rating					65,201	73.9%
Total	861	100.0%	23,000	100.0%	88,201	100.0%

Table 2. Descriptive statistics

Table 2 reports summary statistics for the book value of total assets, equity market values, earnings (earnings before extraordinary items and discontinued operations deflated by average total assets), market to book ratios, and leverage ratios (Total long-term debt divided by total long-term debt plus equity market value) for firm-quarters in the CDS sample and Compustat firm-quarters with and without Standard and Poors' long-term debt ratings (for December year-end firms) in 1999-2003. For the market-to-book ratio, the book value of common stockholders' equity is computed as the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), less the book value of preferred stock (consistent with Fama and French [1996]). Depending on availability, I use redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. All numbers are winsorized at the one percent level.

	Mean	St.dev.	Lower Quartile	Median	Upper quartile
CDS Sample (N=861,with 242 distinct firms)					
Assets ($M)	27,004	37,516	7,570	15,063	30,499
Equity market value ($M)	19,452	30,748	4,401	9,016	18,579
Earnings	0.007	0.015	0.002	0.007	0.014
Leverage ratio	0.296	0.139	0.203	0.274	0.379
Market to book	2.57	2.53	1.14	1.83	2.96
Compustat sample, issuer ratings available (N =23,000, with 1,713 distinct firms)					
Assets ($M)	10,653	19,233	1,157	2,900	9,706
Equity market value ($M)	5,159	9,593	460	1,451	4,543
Earnings	0.003	0.035	0.0004	0.006	0.014
Leverage ratio	0.32	0.21	0.17	0.30	0.45
Market to book	2.13	3.69	0.81	1.43	2.43
All Compustat firms (N =88,201, with 6,529 distinct firms)					
Assets ($ million)	3,450	11,477	76	337	1,496
Equity market value ($M)	1,721	5,679	40	175	795
Earnings	-0.018	0.076	-0.149	0.003	0.013
Leverage ratio	0.19	0.21	0.01	0.11	0.38
Market to book	2.42	4.24	0.76	1.44	2.65

Table 3. Correlation Matrix, CDS prices, accounting variables, bond spreads, equity-based pricing models, and controls

Table 3 shows correlations for CDS prices, earnings, leverage, bond spreads, equity-based structural models and control variables. PRICE is the midpoint of the bid-ask spread for the first price available two months after fiscal quarter-end. COVERAGE is pretax income (Compustat Quarterly Industrial File Item #22), plus income statement interest expense (#22), deflated by interest expense. LEVERAGE is the firm's long-term debt (#51) divided by the firm's total assets. BOND is the actual or estimated five-year bond spread for the reference entity (its precise calculation is described in Section III). EQUITY is the output of an equity-based model of CDS pricing (its precise calculation is described in the Appendix). SIZE is the logarithm of total assets (#44). RETURNS is the firm's monthly-compounded buy-and-hold stock return for the twelve months ending two months after quarter end, less monthly-compounded buy-and-hold returns to the value-weighted NYSE, Nasdaq, and AMEX portfolio over the same period. RATING is the firm's Standard and Poors' long-term debt rating, with rating categories converted to a number between one and 18 and lower ratings assigned lower numbers. ROA is pretax income (Compustat Quarterly Industrial File Item #22), plus income statement interest expense (#22), deflated by beginning total assets (#44). The Δ operator represents the quarterly difference in each item.

Panel A: Levels

N=861	PRICE	COVERAGE	LEVERAGE	BOND	EQUITY	SIZE	RETURNS	RATING
PRICE	1.00							
COVERAGE	(0.26)	1.00						
LEVERAGE	0.34	(0.27)	1.00					
BOND	0.48	(0.13)	0.18	1.00				
EQUITY	0.60	(0.10)	0.14	0.25	1.00			
SIZE	(0.09)	0.09	(0.14)	(0.16)	0.00	1.00		
RETURNS	(0.30)	0.10	(0.03)	(0.09)	(0.27)	(0.07)	1.00	
RATING	(0.56)	0.40	(0.42)	(0.40)	(0.23)	0.36	(0.06)	1.00

Panel B: Changes

N=562	ΔPRICE	ΔROA	ΔLEVERAGE	ΔBOND	ΔEQUITY	ΔRATING	RETURNS	ΔSIZE
ΔPRICE	1.00							
ΔROA	(0.14)	1.00						
ΔLEVERAGE	0.05	(0.19)	1.00					
ΔBOND	0.35	(0.10)	(0.04)	1.00				
ΔEQUITY	0.31	0.05	(0.05)	0.31	1.00			
ΔRATING	(0.01)	0.08	(0.10)	0.02	0.10	1.00		
RETURNS	(0.14)	0.12	(0.08)	(0.01)	0.02	0.20	1.00	
ΔSIZE	(0.05)	0.19	(0.08)	(0.00)	0.05	0.03	0.06	1.00

Table 4. Regressions of CDS prices on accounting information, bond spreads, equity-based structural models, and control variables

Table 4 shows regressions of CDS prices on earnings, leverage, bond spreads, equity-based structural models and control variables. CDS prices are defined as the midpoint of the bid-ask spread for the first price available two months after fiscal quarter-end. COVERAGE is pretax income (Compustat Quarterly Industrial File Item #22), plus income statement interest expense (#22), deflated by interest expense. COVERAGE≤0 is equal to COVERAGE if COVERAGE is less than or equal to zero, and equal to zero if COVERAGE is greater than zero (0<COVERAGE≤5, 5<COVERAGE≤10, 10<COVERAGE≤20, and COVERAGE>20 are defined similarly). LEVERAGE is the firm's long-term debt (#51) divided by the firm's total assets. BOND is the actual or estimated five-year bond spread for the reference entity (its precise calculation is described in Section III). EQUITY is the output of an equity-based model of CDS pricing (its precise calculation is described in the Appendix). SIZE is the logarithm of total assets (#44). RETURNS is the firm's monthly-compounded buy-and-hold stock return for the twelve months ending two months after quarter end, less monthly-compounded buy-and-hold returns to the value-weighted NYSE, Nasdaq, and AMEX portfolio over the same period. RATING is the firm's Standard and Poors' long-term debt rating, with rating categories converted to a number between one and 18 and lower ratings assigned lower numbers. All t-statistics (reported below each coefficient estimate) are adjusted for heteroskedasticity and within-firm error dependence using the Rogers (1993) robust panel data standard error estimator. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

		(1)	**(2)**	**(3)**	**(4)**	**(5)**
N=861	**pred. sign**			**coef. est./t-stat**		
CONSTANT	?	1.433***	0.302***	5.589***	2.610***	0.954*
		(5.642)	(4.050)	(14.49)	(3.861)	(1.918)
COVERAGE≤0	?	-0.051*			-0.040	-0.050***
		(-1.872)			(-1.412)	(-2.792)
0<COVERAGE≤5	-	-0.251***			-0.230***	-0.052*
		(-4.544)			(-4.446)	(-1.769)
5<COVERAGE≤10	-	-0.143***			-0.138***	-0.015
		(-5.014)			(-5.110)	(-0.961)
10<COVERAGE≤20	-	-0.082***			-0.072***	-0.008
		(-5.077)			(-4.460)	(-0.737)
COVERAGE>20	-	-0.031***			-0.028***	0.002
		(-5.576)			(-5.433)	(0.450)
LEVERAGE	+	2.462***			2.478***	1.197***
		(4.190)			(4.104)	(3.690)
BOND	+		0.526***			0.403***
			(13.22)			(9.230)
EQUITY	+		0.840***			0.662***
			(10.66)			(7.816)
RATING	-			-0.376***		-0.161***
				(-11.51)		(-6.198)
RETURNS	-				-1.045***	-0.604***
					(-6.610)	(-6.422)
SIZE	-				-0.126**	0.114***
					(-2.161)	(2.889)

F-statistic on joint significance of COVERAGE & LEVERAGE	18.05***	n/a	n/a	17.34***	5.21***
R^2	0.194	0.623	0.323	0.255	0.703
Adjusted R^2	0.188	0.622	0.323	0.248	0.699

Table 5. Regressions of CDS prices changes on changes in accounting information, bond spreads, equity-based structural models, ratings, and control variables

Table 5 shows regressions of CDS price changes on changes in earnings, leverage, bond spreads, equity-based structural models, ratings, and control variables. Price changes are measured as the difference between the CDS price two months after each fiscal quarter end and the CDS price two months after the previous fiscal quarter end. ROA is pretax income (Compustat Quarterly Industrial File Item #22), plus income statement interest expense (#22), deflated by beginning total assets (#44). LEVERAGE is the firm's long-term debt (#51) divided by the firm's total assets. BOND is the actual or estimated five-year bond spread for the reference entity (its precise calculation is described in Section III). EQUITY is the output of an equity-based model of CDS pricing (its precise calculation is described in the Appendix).SIZE is the logarithm of total assets (#44). RETURNS is the firm's monthly-compounded buy-and-hold stock return for the twelve months ending two months after quarter end, less monthly-compounded buy-and-hold returns to the value-weighted NYSE, Nasdaq, and AMEX portfolio over the same period. RATING is the firm's Standard and Poors' long-term debt rating, with rating categories converted to a number between one and 18 and lower ratings assigned lower numbers. The Δ operator represents the quarterly difference in each item. All t-statistics (reported below each coefficient estimate) are adjusted for heteroskedasticity and within-firm error dependence using the Rogers (1993) robust panel data standard error estimator. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

		(1)	**(2)**	**(3)**	**(4)**	**(5)**
N=562	**pred. sign**			**coef. est./t-stat**		
CONSTANT	?	0.027**	0.049***	0.026*	0.030**	0.051***
		(2.130)	(3.652)	(1.929)	(2.342)	(3.618)
ΔROA	-	-3.403***			-2.971**	-2.368**
		(-2.714)			(-2.384)	(-2.231)
ΔLEVERAGE	+	0.353			0.231	0.594
		(0.684)			(0.435)	(1.006)
ΔBOND	+		0.114***			0.108***
			(4.408)			(4.411)
ΔEQUITY	+		0.178**			0.191**
			(2.129)			(2.231)
ΔRATING	-			-0.013		-0.003
				(-0.427)		(-0.0840)
RETURNS	-				-0.141***	-0.145***
					(-2.894)	(-3.033)
ΔSIZE	-				-0.139	-0.228
					(-0.802)	(-1.346)
F-statistic on joint significance of ΔROA & ΔLEVERAGE		4.16**	n/a	n/a	3.06*	3.80**
R^2		0.020	0.172	0.000	0.035	0.207
Adjusted R^2		0.016	0.169	-0.002	0.028	0.196

Table 6. Out-of-sample regressions of CDS spreads on alternative CDS spread prediction models

Table 6 shows results of regressions of CDS prices on alternative CDS spread prediction models. CDS prices are defined as the midpoint of the bid-ask spread for the first price available two months after fiscal quarter-end. Models are estimated using firm-fiscal quarters up to the second quarter of 2002. Covariates used in estimating each model are listed below the table. COVERAGE is pretax income (Compustat Quarterly Industrial File Item #22), plus income statement interest expense (#22), deflated by interest expense. COVERAGE is partitioned into five regions: COVERAGE≤0 is equal to COVERAGE if COVERAGE is less than or equal to zero, and equal to zero if COVERAGE is greater than zero (0<COVERAGE≤5, 5<COVERAGE≤10, 10<COVERAGE≤20, and COVERAGE>20 are defined similarly). LEVERAGE is the firm's long-term debt (#51) divided by the firm's total assets. BOND is the actual or estimated five-year bond spread for the reference entity (its precise calculation is described in Section III). EQUITY is the output of an equity-based model of CDS pricing (its precise calculation is described in the Appendix).SIZE is the logarithm of total assets (#44). RETURNS is the firm's monthly-compounded buy-and-hold stock return for the twelve months ending two months after quarter end, less monthly-compounded buy-and-hold returns to the value-weighted NYSE, Nasdaq, and AMEX portfolio over the same period. RATING is the firm's Standard and Poors' long-term debt rating, with rating categories converted to a number between one and 18 and lower ratings assigned lower numbers. Absolute prediction errors are reported in thousandths of basis points.

N=465	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Model pricing errors in levels model					
Mean absolute error	1.02	0.66	0.98	0.63	0.62
Median absolute error	0.77	0.38	0.89	0.40	0.45
Prediction Model Covariates					
COVERAGE	X				X
LEVERAGE	X				X
BOND		X		X	X
EQUITY		X		X	X
RETURNS				X	X
SIZE				X	X
RATING			X	X	X

Table 7. Out-of-sample regressions of CDS price changes on alternative price change prediction models

Table 7, Panels A and B, shows absolute and median residuals of regressions of CDS price changes on alternative change prediction models. Models are estimated on quarterly changes using firm-fiscal quarters up to the second quarter of 2002, and residuals are calculated for all subsequent quarters with available data in the sample. CDS spreads are defined as the midpoint of the bid-ask spread for the first price available two months after fiscal quarter-end. Period-ahead spread changes are measured as the difference between the CDS spread two months after the next fiscal quarter end and the CDS spread two months after the current fiscal quarter end. Covariates used in estimating each model are listed below the table. ROA is pretax income (Compustat Quarterly Industrial File Item #22), plus income statement interest expense (#22), deflated by beginning total assets (#44). LEVERAGE is the firm's long-term debt (#51) divided by the firm's total assets. BOND is the actual or estimated five-year bond spread for the reference entity (its precise calculation is described in Section III). EQUITY is the output of an equity-based model of CDS pricing (its precise calculation is described in the Appendix). SIZE is the logarithm of total assets (#44). RETURNS is the firm's monthly-compounded buy-and-hold stock return for the twelve months ending two months after quarter end, less monthly-compounded buy-and-hold returns to the value-weighted NYSE, Nasdaq, and AMEX portfolio over the same period. RATING is the firm's Standard and Poors' long-term debt rating, with rating categories converted to a number between one and 18 and lower ratings assigned lower numbers. The Δ operator represents the quarterly difference in each item.

N=344	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Panel A: Model pricing errors using contemporaneous spread changes					
Mean absolute residual	0.23	0.19	0.23	0.19	0.19
Median absolute residual	0.13	0.09	0.12	0.09	0.10

N=185					
Panel B: Model pricing errors using period-ahead spread changes					
Mean absolute residual	0.20	0.20	0.19.	0.21	0.22
Median absolute residual	0.13	0.12	0.11	0.14	0.14
<u>Prediction Model Covariates</u>					
ΔROA	X				X
ΔLEVERAGE	X				X
ΔBOND		X		X	X
ΔEQUITY		X		X	X
RETURNS				X	X
ΔSIZE				X	X
ΔRATING			X	X	X

Table 8. Out-of-sample regressions of CDS price residuals on period-ahead spread changes

Table 8 shows regression results of residuals from CDS price level models on period-ahead spread changes. Levels models are estimated using firm-fiscal quarters up to the second quarter of 2002. RESIDUALS are calculated for all subsequent quarters with available data in the sample, and are formulated as per Correia et al. (2011) as ln(actual spread/predicted spread). CDS spreads are defined as the midpoint of the bid-ask spread for the first price available two months after fiscal quarter-end. Period-ahead spread changes are measured as the difference between the CDS spread two months after the next fiscal quarter end and the CDS spread two months after the current fiscal quarter end. Covariates used in estimating each model are listed below the table. COVERAGE is pretax income (Compustat Quarterly Industrial File Item #22), plus income statement interest expense (#22), deflated by interest expense. COVERAGE is partitioned into five regions: COVERAGE≤0 is equal to COVERAGE if COVERAGE is less than or equal to zero, and equal to zero if COVERAGE is greater than zero (0<COVERAGE≤5, 5<COVERAGE≤10, 10<COVERAGE≤20, and COVERAGE>20 are defined similarly). LEVERAGE is the firm's long-term debt (#51) divided by the firm's total assets. BOND is the actual or estimated five-year bond spread for the reference entity (its precise calculation is described in Section III). EQUITY is the output of an equity-based model of CDS pricing (its precise calculation is described in the Appendix). SIZE is the logarithm of total assets (#44). RETURNS is the firm's monthly-compounded buy-and-hold stock return for the twelve months ending two months after quarter end, less monthly-compounded buy-and-hold returns to the value-weighted NYSE, Nasdaq, and AMEX portfolio over the same period. RETURNS is the firm's monthly-compounded buy-and-hold stock return for the twelve months ending two months after quarter end, less monthly-compounded buy-and-hold returns to the value-weighted NYSE, Nasdaq, and AMEX portfolio over the same period. RATING is the firm's Standard and Poors' long-term debt rating, with rating categories converted to a number between one and 18 and lower ratings assigned lower numbers. All t-statistics (reported below each coefficient estimate) are adjusted for heteroskedasticity and within-firm error dependence using the Rogers (1993) robust panel data standard error estimator. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)
N=205	**pred. sign**	**coef. est./t-stat**					
CONSTANT	?	-0.076**	-0.088***	-0.066***	-0.091***	-0.070***	-0.072***
		(-2.51)	(-2.93)	(-3.38)	(-2.73)	(-3.26)	(-3.27)
RESIDUALS	-	-0.048	-0.072**	-0.049*	-0.076*	-0.054*	-0.060**
		(-1.17)	(-2.10)	(-1.92)	(-1.84)	(-1.97)	(-2.08)
R^2		0.020	0.044	0.014	0.043	0.014	0.015
<u>Prediction Model Covariates</u>							
COVERAGE		X					X
LEVERAGE		X					X
BOND				X		X	X
EQUITY			X	X		X	X
RETURNS						X	X
SIZE						X	X
RATING					X	X	X