# Credit Default Swap Market Determinants

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JP Morgan [2002b] defines a credit derivative as "a bilateral financial contract that isolates specific aspects of credit risk from an underlying instrument and transfers risk between two parties" (p. 4). Market participants include banks, hedge funds, corporations, pension funds, insurance, and reinsurance companies. Credit derivatives have been widely praised as risk management tools that mitigate risk by spreading it throughout the system. However, they have recently come under attack as the credit crisis has shown how this very same dispersion of risk can amplify systemic risk to financial markets.

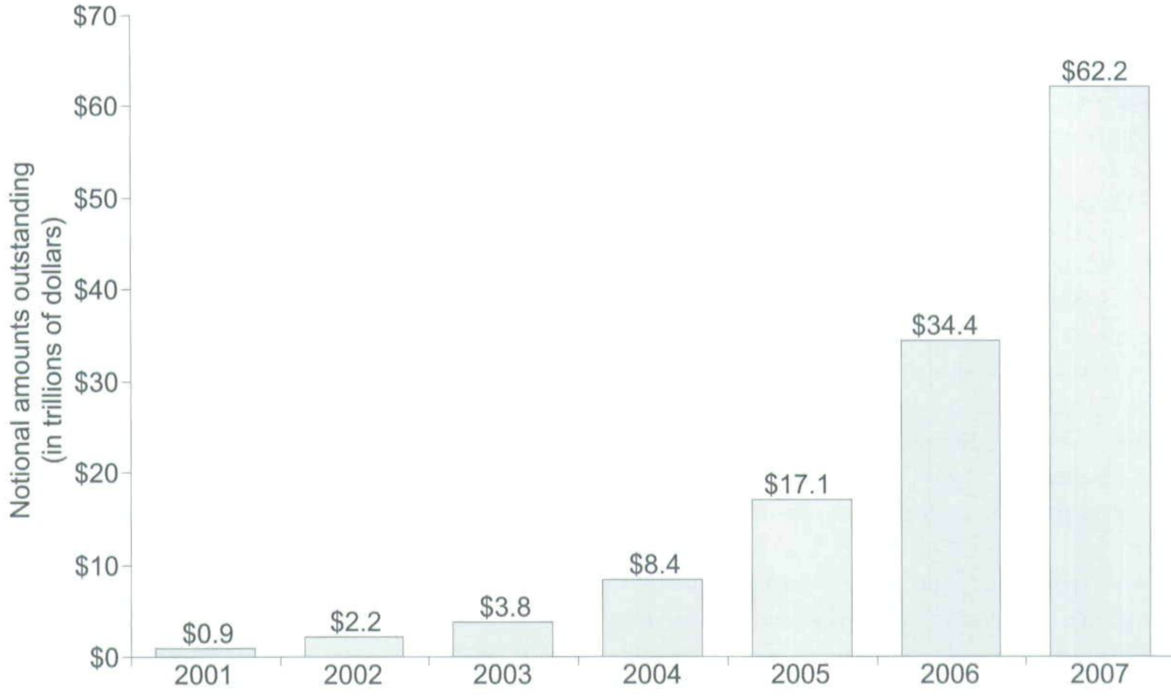
The most common credit derivative is the credit default swap (CDS). Since inception in the mid-1990s, the CDS market has experienced tremendous growth (see Exhibit 1). At year-end 2007, the total notional amount of credit default swaps was estimated to be \$62.2 trillion (ISDA [2008]). In a single-name credit default swap, one party buys credit protection on a reference obligation (i.e., a bond or loan) by a specified issuer from a protection seller. The party buying protection pays the seller a fixed premium each period until a credit event occurs or the swap contract matures. Credit events include bankruptcy, failure to make a payment on a debt obligation, restructuring, obligation acceleration or default, repudiation, and moratorium. If the underlying firm experiences a credit event such as default, the protection seller is obligated to buy the defaulted bond or loan back from the buyer at its par value.

The premium reflects both the probability of default and the loss given default and "equates the present value of premium payments to the present value of expected losses" (Morgan Stanley [2006, p. 11]). The price of the credit default swap, also called the *spread*, is quoted in basis points, as the percentage of the notional value that is to be paid annually. A credit default swap is similar to an insurance contract compensating the buyer for losses arising from default. The premium, or spread, isolates credit risk and is, in itself, a measure of risk. Wider spreads indicate that the market perceives higher credit risk associated with the underlying reference entity.

There has been a growing debate over the ability of variables implied by structural models to explain corporate bond credit spreads (CS) and credit default swap spreads. The key variables implied by the structural approach to pricing credit risk are leverage, volatility, and the risk-free rate. Many articles (e.g., Collins-Dufresne, Goldstein, and Martin [2001]; Avramov, Jostova, and Philipov [2007]; Blanco, Brennan, and Marsh [2005]; Abid and Naifar [2006]; Ericsson, Jacobs, and Oviedo-Helfenberger [2004]; and Aunon-Nerin, Cossin, and Hricko [2002]), motivated by the structural approach, have empirically tested the ability of variables to explain variation in CDS spreads and corporate bond credit

EXHIBIT 1

**Credit Default Swap Notional Amounts in Trillions of Dollars**




*Source: ISDA.*

spreads. Empirical results vary greatly. Some authors have concluded that variables implied by structural models only explain approximately 25% of the variation in CS/CDS spreads (e.g., Collins-Dufresne, Goldstein, and Martin [2001] and Blanco, Brennan, and Marsh [2005]). Other authors have asserted that these variables can explain more than 50% of the variation in credit and CDS spreads (e.g., Avramov, Jostova, and Philipov [2007]). This article seeks to add to this debate using one of the more comprehensive CDS datasets, provided by Markit, spanning over five years and 333 firms.

Specifically, this study employs regression analysis to explore the ability of structural variables to explain the variation in monthly CDS spread changes. This approach is similar to that of Collins-Dufresne, Goldstein, and Martin [2001] and Avramov, Jostova, and Philipov [2007]; however, the focus of the research presented here is on CDS spread changes as opposed to corporate bond credit spreads. While previous studies have explored the determinants of credit default swaps, some have used levels rather than changes in spreads, while others have analyzed a shorter time period due to the limited availability of good CDS pricing data.[1] The focus of this study is on changes in CDS spreads as opposed to levels because stationarity tests find CDS spread levels to be nonstationary, while CDS spread changes are stationary. Thus, focusing on spread changes is important from a statistical point of view to avoid spurious regression inferences. Furthermore, as noted in Avramov, Jostova, and Philipov [2007], credit spread changes are analogous to excess bond returns and "like expected equity returns in equity analysis, are the key to characterizing the risk-return trade-off in ... credit-derivatives pricing" (p. 90). Most importantly, while other studies have used equity market returns and the slope of the term structure to proxy for general business conditions, this study is the first to use a CDS rating-based index to account for general market movements in this context. This index was found to be the single best predictor of changes in individual CDS spreads.

Following is an overview of the CDS data, the variables employed in the regression model, and their hypothesized relationship to changes in CDS spreads. Each variable's individual relationship to CDS spread changes is then analyzed in a univariate setting before the full multivariate regression model is estimated at the individual firm-level and results are compared to previous empirical work.

## CDS DATA AND EXPLANATORY VARIABLES USED IN THE STUDY

### CDS Dataset

CDS spread levels from January 2001 to March 2006 were supplied by Markit, an aggregator of data from the leading CDS market broker/dealers. For inclusion in the study, only senior debt, U.S. dollar contracts on underlying U.S. entities was selected. Only contracts having a modified restructuring document clause or excluding restructuring were selected because they are the more common document types traded in the U.S. market.

To avoid redundancy, only one contract type was chosen per entity. If the firm was investment grade, the modified restructuring contract was used. If the firm was non-investment grade, contracts that excluded restructuring were used. If the firm vacillated between the two grades, the one with more data points was used. Although the dataset included numerous subcompanies under a parent company in the energy sector, only the primary company was used to avoid redundancy and an overconcentration in the energy industry. The five-year maturity contract price was used in the analysis because it is by far the most commonly traded maturity.

A total of 476 firms met the initial criteria. However, in estimating monthly regressions, 18 firms were excluded for lack of COMPUSTAT data and an additional 125 firms were excluded for having less than 30 monthly observations. This left 333 firms with a total of 16,748 monthly observations for the analysis. The average number of monthly observations per firm was 49. A monthly frequency was used for four reasons: 1) to be consistent with Collins-Dufresne, Goldstein, and Martin [2001] and Avramov, Jostova, and Philipov [2007]; 2) to minimize the effects of noise in the data; 3) to better capture variation over time if certain CDS spreads do not vary on a daily basis and still allow enough observations to analyze at the firm level; and 4) to mitigate the issue of autocorrelation in the data.

### Theoretically Motivated Variables and their Relationship to CDS Spreads

Merton [1974] stated that "[f]or a given maturity, the risk premium is a function of two variables: 1) the variance (or volatility) of the firm's operations, $\sigma^2$, and 2) the ratio of the present value (at the riskless rate) of the promised payment to the current value of the firm" (pp. 454–455). Key variables implied by the structural approach—and therefore considered in this analysis—include leverage, volatility or business risk, and the risk-free rate. These variables' hypothesized relationships and empirical specifications are outlined as follows.

***Leverage***. In the structural framework, default is a function of the firm's capital structure, triggered when the leverage ratio reaches unity. As such, a positive relationship between changes in a firm's leverage ratio and changes in CDS spreads is hypothesized. In this study, leverage is measured as the book value of debt divided by the book value of debt plus the market value of equity,

$$LEV_{it} = \frac{BVD_{it}}{BVD_{it} + MVE_{it}}$$

The book value of debt was obtained from COMPUSTAT as the sum of long-term debt plus debt in current liabilities. The market value of equity was obtained by multiplying the number of shares outstanding times the price per share as listed in the monthly CRSP file. Because COMPUSTAT figures are only available on a quarterly basis, linear interpolation was used to obtain monthly estimates as in Collins-Dufresne, Goldstein, and Martin [2001].

Welch [2004] found that stock returns explain a significant portion of debt ratio dynamics. Therefore, in addition to the leverage ratio, and consistent with prior studies (e.g., Collins-Dufresne, Goldstein, and Martin [2001]; Blanco, Brennan, and Marsh [2005]; and Avramov, Jostova, and Philipov [2007]), monthly stock returns were also considered as a proxy for leverage. Blanco, Brennan, and Marsh, in rationalizing the use of equity returns as a measure of leverage, stated that

> [l]everage enters the determination of the default barrier in structural models. However, at a weekly frequency and over a relatively short horizon, it is not practical to include a clean measure of firm leverage. Instead we proxy changes in the firm's health with the firm's equity return (p. 2274).

***Volatility***. In the Merton [1974] structural framework, equity is a call option on the underlying firm, while debt is similar to a put option. Thus, an increase in volatility should decrease the value of risky debt and increase credit default swap spreads. Therefore, both firm-specific and market-wide volatility were estimated. Firm-specific volatility, $VOL_{it}$, is estimated as the 250-day rolling variance of the individual stock returns for firm $i$ at date $t$. Daily stock return data was obtained from CRSP. In addition, the CBOE volatility index, $VIX_t$, was included to proxy for overall market volatility, as in Collins-Dufresne, Goldstein, and Martin [2001]. It was also hypothesized that firm-specific volatility will be a better predictor of CDS spreads than market-wide volatility.

***Business climate***. Merton [1974] made the point that the volatility of a firm's value is a function of its business risk, which is, in turn, dependent on overall market conditions. Both Collins-Dufresne, Goldstein, and Martin [2001] and Avramov, Jostova, and Philipov [2007] noted that changes in the overall business climate affect the expected recovery rate given default. A weakening economy leads to decreased expected recovery rates and, hence, an increase in CDS spread changes. These studies used aggregate equity market returns to proxy for the state of the overall economy and found a strong negative relationship between aggregate equity returns and credit spread changes.

This study differs, in that, in addition to using equity market returns, a rating-based index of CDS spreads was used to proxy for the overall business climate. A rating-based index was used in the CDS event studies of Hull, Predescu, and White [2004], Norden and Weber [2004], and Jorion and Zhang [2007]. These prior studies subtracted the index from raw CDS spread changes to account for macroeconomic effects in analyzing abnormal performance around credit events, such as rating changes or bankruptcies. However, as can best be determined, this variable has not been considered in an analysis of the determinants of CDS spreads.[2]

This variable is similar in spirit to the inclusion of an equity market factor, such as the CAPM beta or the market model parameter in equity research. The hypothesis in this study was that a CDS market factor will better explain variation in CDS spread changes than a stock market factor. Furthermore, the extent to which these markets provide separate and distinct information to credit markets (as suggested in Longstaff, Mithal, and Neis [2003]) was considered by examining the relative explanatory power of a CDS factor and a stock market aggregate factor.

The rating-based index, $INDX_{it}$, is calculated as the mean spread on date $t$ for all firms in the same rating category as firm $i$. The rating categories are AAA/AA, A, BBB, and non-investment grade (NIG). The AAA/AA category includes all firms rated AAA, AA+, AA, or AA– by Standard and Poor's (S&P). The A category includes all firms rated A+, A, or A– by S&P. The BBB category includes all firms rated BBB+, BBB, or BBB– by S&P. And the NIG category incorporates all firms with ratings below BBB–. There is an average of 118 observations per rating category per day. $INDX_{it}$ is included not only to account for overall changes in business climate, but also to allow for variation among various rating categories as numerous empirical articles have shown that credit rating is a key determinant of CDS spreads. A positive relationship was expected between the index and individual CDS spreads because improving market conditions should improve individual spreads. For comparison purposes, the CRSP equal-weighted index and S&P 500 returns were also included to proxy for business risk.

***Interest rates***. The structural approach to valuing risky claims predicts a negative relationship between the interest rate and credit spreads. Collins-Dufresne, Goldstein, and Martin [2001] noted that a higher spot rate should increase the risk-neutral drift of the value process, an increase that reduces the probability of default and decreases spreads. Using the 10-year Treasury rate as a benchmark for the risk-free rate, they found a strong statistically significant relationship between the risk-free rate and credit spreads. To be consistent with the five-year maturity of the CDS contracts used in the sample, five-year swap rates obtained from Bloomberg were used as the estimate of the risk-free rate, $SPOT_t$.

In addition to the spot rate, others have reasoned that an increase in the slope of the yield curve should increase expected future short rates and can also be considered as a proxy for future business conditions in that an increasing slope signifies improving overall economic health and a decreasing slope signifies an increased probability of recession (e.g., Aunon-Nerin, Cossin, and Hricko [2002] and Collins-Dufresne, Goldstein, and Martin [2001]). For both reasons, an inverse relationship between CDS spreads and the slope of the yield curve should be observed. The slope of the yield curve was, thus, measured as the difference between the 10-year and 2-year swap rates. The variables considered in the factor model and their predicted signs are summarized in Exhibit 2.

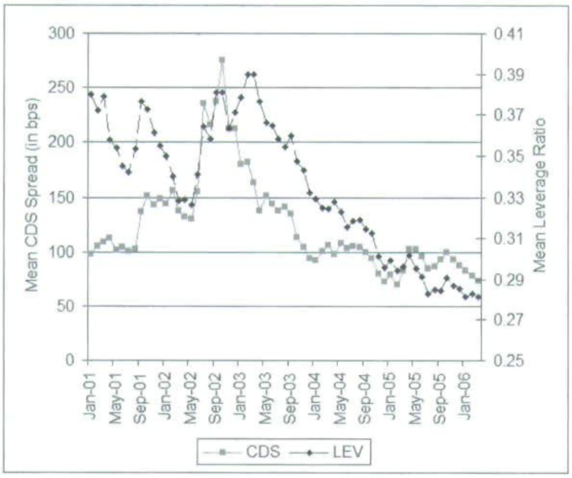
Exhibit 3 presents the time-series plots of monthly mean CDS spreads versus the various independent variables. The relationships observed in the figures largely conform to the study's hypotheses. Exhibit 3, Panel A, plots mean CDS spreads and corresponding mean leverage ratios. In 2001, it appears that leverage ratios were falling as CDS spreads rose, but, in 2002, both rose sharply and then steadily declined in tandem from 2003 onward. Exhibit 3, Panel B, plots the relationship between mean CDS spreads and firm-specific equity volatility and Exhibit 3, Panel C, plots the relationship between mean CDS spreads and the CBOE VIX series. Both series depict a strong co-movement between volatility and CDS spreads. Exhibit 3, Panel D, seems to depict the five-year swap rate generally moving inversely to CDS spread levels. However, whereas CDS spreads reached a maximum in 4Q 2002 and then reverted back to more modest levels from 2004 onward, the spot rate did not reach its minimum until May 2003, and then rose throughout the remainder of the sample. Although it was hypothesized that the slope of the yield curve would vary inversely with CDS spreads, Exhibit 3, Panel E, depicts a more positive relationship. Both seem to have risen in the first part of the sample and then to have declined in the latter part; however, the rise and fall of

## EXHIBIT 2
**Variables Included in Factor Model and Predicted Sign**

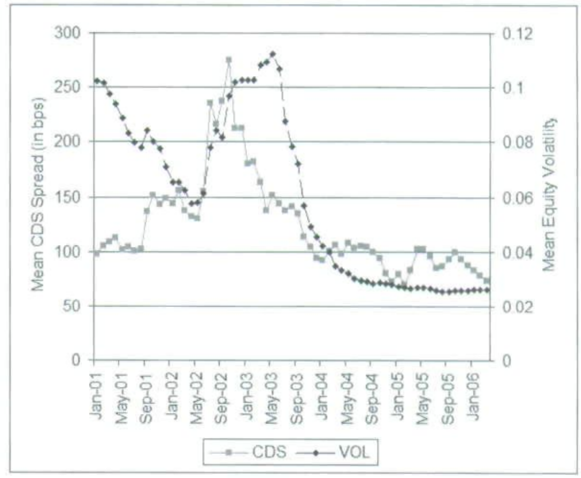
| Variable | Description | Data Source | Predicted Sign |
|---|---|---|---|
| $LEV_{it}$ | Debt/Value ratio = Book Value of Debt/(Book Value of Debt + Market Value of Equity) = BVD = long-term debt + debt in current liabilities MVE = # of shares outstanding ∗ price per share | COMPUSTAT/ CRSP | + |
| $RET_{it}$ | Monthly stock returns | CRSP | – |
| $VOL_{it}$ | 250-day rolling variance of individual stock returns | CRSP | + |
| $VIX_t$ | CBOE volatility index | CBOE | + |
| $INDX_{it}$ | An equal-weighted index of all firms in firm *i*'s rating category as of day *t*. Credit ratings are Standard & Poor's and the four rating categories include: AAA/AA, A, BBB, and non-investment grade. An average of 118 firms is in each rating category per day. | Markit<br>Credit ratings obtained from S&P | + |
| $CRSP_t$ | The return on the CRSP equal-weighted market index | CRSP | – |
| $S\&P_t$ | The return on the S&P 500 Index | CRSP | – |
| $SPOT_t$ | 5-yr swap rate | Bloomberg | – |
| $SLOPE_t$ | Slope = (10yr – 2yr): 10-yr swap rate – 2-yr swap rate | Bloomberg | – |

## Exhibit 3
### Time-Series Graphs

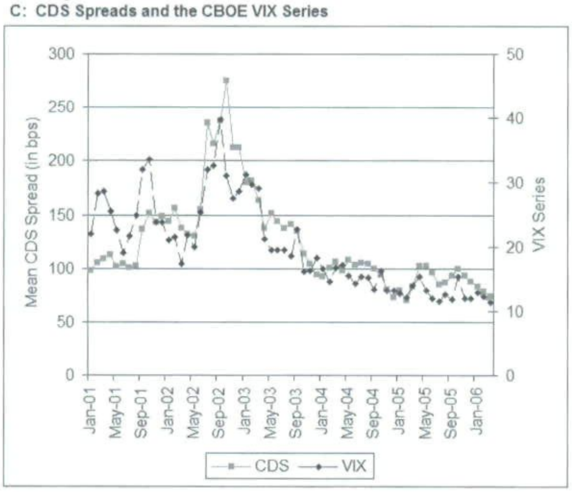
*Leverage*
**A: CDS Spreads and Leverage Ratios**



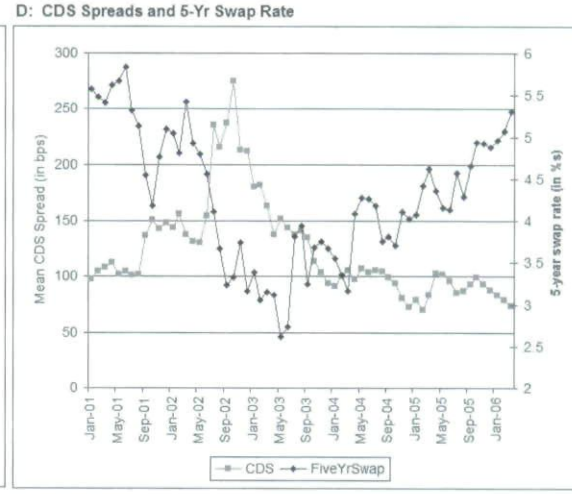

*Volatility*
**B: CDS Spreads and Equity Volatility**



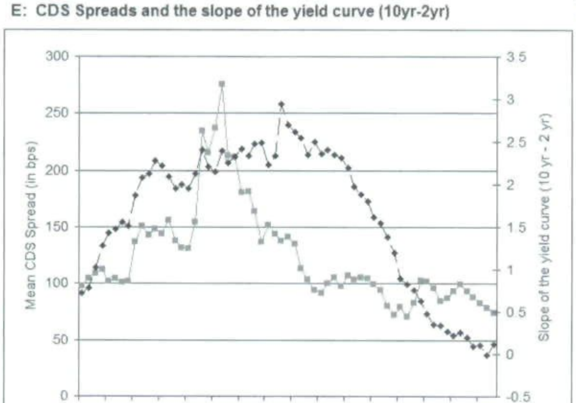

*Volatility*
**C: CDS Spreads and the CBOE VIX Series**




*Risk-free rate*
**D: CDS Spreads and 5-Yr Swap Rate**




*Risk-free rate*
**E: CDS Spreads and the slope of the yield curve (10yr-2yr)**




*Business climate*
**F: CDS spreads and the S&P500 Index**

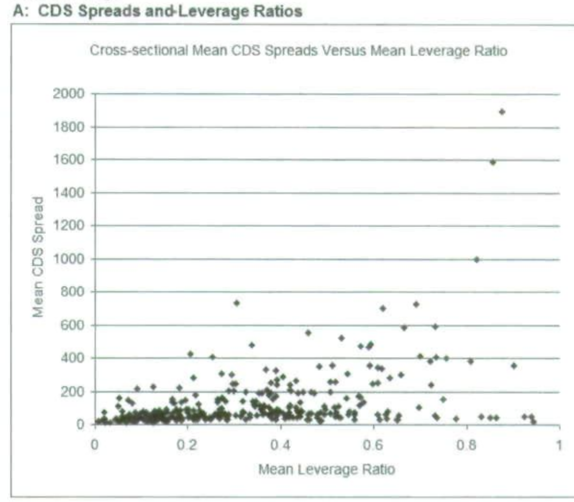
the term structure seems to lag behind that of CDS spreads. Exhibit 3, Panel F, shows that spreads do vary with macroeconomic movements, as measured by S&P 500 returns. It also shows a strong negative co-movement between the CDS and equity markets. The CDS spreads reached their maximum in the fall of 2002, just as the S&P 500 reached its lowest levels for the time period.

Panels A and B of Exhibit 4 portray cross-sectional, as opposed to time-series, graphs of the firm-specific independent variables and CDS spreads. Again, a positive relationship is observed between both leverage and volatility and CDS spreads. Exhibit 4, Panel C, clearly shows a positive relationship between CDS spreads and a corresponding index of similarly rated entities supporting the inclusion of a rating-based CDS index in the regression model. In addition to highlighting the relationship between CDS spreads and the theoretically motivated variables, the cross-sectional graphs reveal two potential econometric issues pertinent to the estimation of the regression model. One issue is the presence of heteroscedasticity, and the second is the presence of outliers in the dataset. These outliers appear to be the lowest credit-quality firms with very high mean CDS spreads. In light of these issues, the estimation of individual firm-level regressions seems more appropriate than pooling the data.

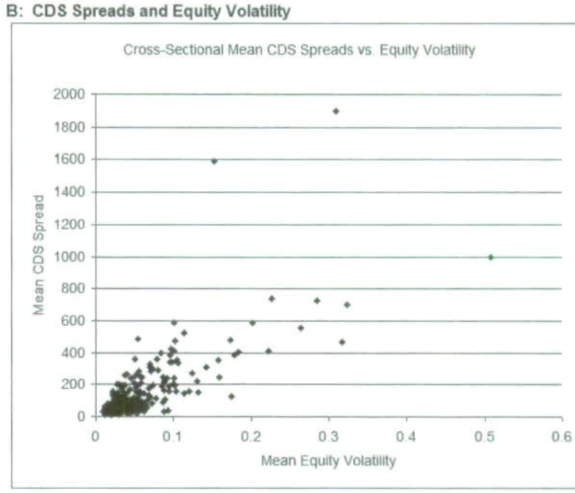
While the time-series plots display a strong co-movement between CDS spreads and leverage, volatility, and overall business climate, they also bring to light the issue of stationarity. A stationary series is one in which the mean and variance are constant over time and the covariance, $\gamma(h) = \mathrm{Cov}(Y_t, Y_{t+h})$, is a function of $h$ only (Dickey [2007]). As is common with financial data, the time-series plots show that many of these variables do not seem to have a constant mean or variance and thus are potentially nonstationary. As Granger and Newbold [1974] cautioned, regression analysis using nonstationary variables can lead to spurious regression in which invalid inferences are drawn. If the variables are I(1), that is, nonstationary in levels, but stationary in first differences, the model should be estimated in first differences. Stationarity tests were conducted for all variables considered in the regression analysis.[3] With the exception of the VIX series, stationarity tests confirmed that the variables in the analysis were, by and large, nonstationary in levels, but stationary in first differences. Based on these findings, the regression analysis was conducted using first differences to avoid spurious regression inferences.

## EXHIBIT 4
### Cross-Sectional Diagrams

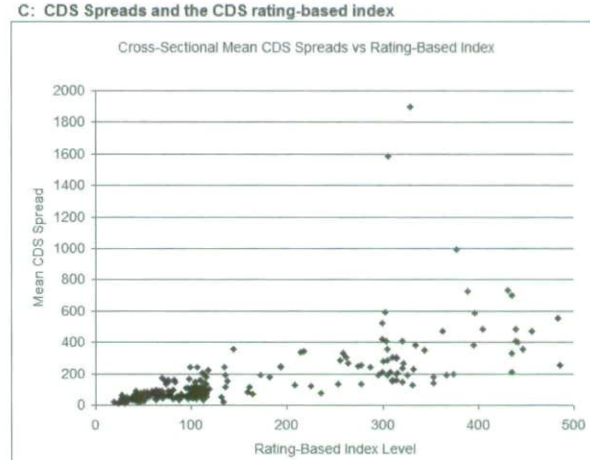
*Firm Leverage*
**A: CDS Spreads and Leverage Ratios**




*Volatility*
**B: CDS Spreads and Equity Volatility**




**C: CDS Spreads and the CDS rating-based index**



## UNIVARIATE ANALYSIS

Before estimating the multivariate regression models, each independent variable's relationship to CDS spreads was explored by calculating correlation coefficients and estimating univariate regressions. Exhibit 5 gives the ordinary Pearson correlation coefficients between monthly changes in CDS spreads and each of the independent variables. The correlation coefficients between the changes in CDS spreads and the dependent variables all have the expected sign with the exception of the slope of the yield curve. The variables with the strongest correlation with monthly CDS spread changes are firm-specific monthly stock returns ($\rho = -0.36$), changes in the CDS index ($\rho = +0.34$), and changes in a firm's leverage ratio ($\rho = +0.30$), followed by changes in volatility and CRSP returns ($\rho = +0.16$ and $\rho = -0.15$, respectively). Because leverage is a key input into the structural framework, the relatively strong correlation of stock returns and leverage with CDS spread changes supports the Merton [1974] model. The relatively strong correlation with an overall index of similarly rated entities is evidence that this variable is an important addition to the regression model. By construction, stock returns and leverage should be correlated with each other because monthly changes in leverage are primarily driven by changes in equity prices. The strong correlation coefficient of −0.83 between these two independent variables confirms this notion.

Exhibit 6 provides univariate regression results that are consistent with the correlation coefficients reported in Exhibit 5. All coefficient estimates are the hypothesized sign and are statistically significant with the exception of the coefficient for changes in the slope of the yield curve, which is neither. $\Delta INDX_{it}$, by far, has the largest explanatory power in the univariate setting with an adjusted $R^2$ value of 0.201, followed by monthly equity returns and leverage with an adjusted $R^2$ of 0.115 and 0.107, respectively. Comparing the explanatory power of changes in the CDS index with that of an equity market index, the univariate analysis supports the hypothesis that CDS spread changes are more sensitive to aggregate movements in their own market than to those of the stock market. The interest rate variables have the least explanatory power with changes in the slope of the yield curve explaining only 1.2% of the variation in CDS spread changes, while changes in the spot rate explain 3.1% of the variation in CDS spread changes.[4]

## THE MULTIVARIATE REGRESSION MODEL

The multivariate regression model was estimated as

$$\Delta CDS_{it} = \alpha_0 + \beta_1 \Delta LEV_{it} + \beta_2 \Delta VOL_{it} + \beta_3 \Delta INDX_{it} + \beta_4 \Delta SPOT_t + \beta_5 \Delta SLOPE_t + \varepsilon_t$$

with two lags of CDS spread changes included to control for autocorrelation in the data. Variations of the model were estimated using

- equity returns as a proxy for leverage,
- the VIX index as opposed to firm-specific equity volatility, and
- CRSP and S&P 500 returns to measure the overall business climate, rather than a CDS rating-based index.

### EXHIBIT 5
**Pearson Correlation Coefficients**

| Variable | ΔCDS | ΔLEV | RET | ΔVOL | ΔVIX | ΔSPOT | ΔSLOPE | ΔINDX | CRSP | S&P |
|---|---|---|---|---|---|---|---|---|---|---|
| ΔCDS | 1.00 | 0.30 | −0.36 | 0.16 | 0.11 | −0.09 | 0.04 | 0.34 | −0.15 | −0.13 |
| ΔLEV | 0.30 | 1.00 | −0.83 | 0.10 | 0.29 | −0.14 | 0.10 | 0.18 | −0.35 | −0.36 |
| RET | −0.36 | −0.83 | 1.00 | −0.06 | −0.34 | 0.16 | −0.09 | −0.19 | 0.41 | 0.42 |
| ΔVOL | 0.16 | 0.10 | −0.06 | 1.00 | 0.03 | −0.09 | −0.02 | 0.16 | −0.09 | −0.04 |
| ΔVIX | 0.11 | 0.29 | −0.34 | 0.03 | 1.00 | −0.40 | 0.17 | 0.18 | −0.65 | −0.79 |
| ΔSPOT | −0.09 | −0.14 | 0.16 | −0.09 | −0.40 | 1.00 | 0.19 | −0.16 | 0.32 | 0.38 |
| ΔSLOPE | 0.04 | 0.10 | −0.09 | −0.02 | 0.17 | 0.19 | 1.00 | 0.10 | −0.14 | −0.11 |
| ΔINDX | 0.34 | 0.18 | −0.19 | 0.16 | 0.18 | −0.16 | 0.10 | 1.00 | −0.27 | −0.21 |
| CRSP | −0.15 | −0.35 | 0.41 | −0.09 | −0.65 | 0.32 | −0.14 | −0.27 | 1.00 | 0.84 |
| S&P | −0.13 | −0.36 | 0.42 | −0.04 | −0.79 | 0.38 | −0.11 | −0.21 | 0.84 | 1.00 |

## Exhibit 6
**Univariate Regression Results**

| | RET | ΔLEV | ΔVOL | ΔVIX | ΔSPOT | ΔSLOPE | ΔINDX | CRSP | S&P |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | –1.517 | –2.427 | –2.551 | –2.465 | –2.815 | –3.296 | –1.457 | 0.810 | –1.808 |
| | (–5.36) | (–6.53) | (–4.38) | (–5.13) | (–6.38) | (–4.50) | (–3.29) | (1.55) | (–4.11) |
| Coefficient | –1.066 | 524.308 | 621.066 | 2.407 | –16.607 | 9.338 | 0.683 | –2.146 | –2.577 |
| | (–10.31) | (10.05) | (10.54) | (7.44) | (–7.70) | (1.41) | (14.33) | (–8.61) | (–7.60) |
| Adj $R^2$ | 0.115 | 0.107 | 0.049 | 0.068 | 0.031 | 0.012 | 0.201 | 0.089 | 0.073 |

*Note: Exhibit 6 reports average coefficient estimates across all 333 firms with associated test statistics calculated by dividing the coefficient estimate by the standard deviation of the $N_j$ estimates and scaling by $\sqrt{N_j}$, as in Collins-Dufresne, Goldstein, and Martin [2001].*

Debt figures are only available on a quarterly frequency and often do not vary from quarter to quarter. Recalling the Pearson correlation coefficient of $\rho = -0.83$, equity returns should be a fairly good proxy for leverage. It was also expected that the influence of market-wide volatility (as estimated by the VIX) would be weaker at the individual firm-level than the firm-specific equity volatility measure. To test this hypothesis, the regression model was estimated first using the $\Delta VOL_{it}$ measure and subsequently using changes in the VIX ($\Delta VIX_t$); the results of the two estimations were compared. It was hypothesized that firm-specific equity market information and changes in the CDS rating-based index will account for the majority of the model's predictive power. In effect, these variables should overpower the influence of interest rate variables in the CDS market.

Previous research, as well as the graphical, correlation, and univariate analyses conducted in this article, has documented an inverse relationship between the CDS and stock markets. The two markets are not perfectly correlated, however, and there are occasions when that relation may not hold.[5] Acknowledging that these are two separate and distinct markets, it was further hypothesized that a CDS rating-based index is a better systemic risk factor than aggregate equity returns. Finally, it was hypothesized that the explanatory power of the model should increase as credit quality deteriorates. This hypothesis is consistent both with Kwan [1996], who found that lower credit-quality bonds more closely resemble equities, and with Avramov, Jostova, and Philipov [2007], who were able to account for significantly more of the variation in credit spread changes for high-risk bonds than for low-risk bonds. To explore the sensitivity of the results to creditworthiness, results were stratified by credit quality.

Panel A of Exhibit 7 reports the results of estimating 333 individual firm-level time-series regressions. Overall, the model explains 35% of the variation in CDS spread changes. As expected, the coefficient for leverage is positive and statistically significant. Furthermore, although leverage is perhaps the most critical variable in the structural approach, firm-specific equity returns seem to be as good a proxy for leverage as the leverage ratio itself. Replacing the leverage ratio with equity returns (as in M2), the explanatory power remains unchanged; the adjusted $R^2$ for the base model (M1) is 0.350 compared to 0.352 for M2. Furthermore, the coefficient on equity returns is negative and statistically significant with a *t*-statistic comparable in magnitude to that of the leverage ratio. The strong statistical relationship between the leverage ratio and CDS spread changes provides support for the structural approach to pricing credit risk. Providing further evidence in favor of the structural models, the coefficient on $\Delta VOL_{it}$ is both positive and statistically significant. However, when volatility is measured at the aggregate level—using changes in the VIX in lieu of a firm-specific volatility measure as in M3—the coefficient is no longer statistically significant.

In contrast to the strong statistical significance of firm-specific equity market information, the macroeconomic interest rate variables were found to add little to the explanatory power of the model. The coefficient estimates for both $\Delta SPOT_t$ and $\Delta SLOPE_t$ are not statistically significant;[6] the coefficient on $\Delta SLOPE_t$ remains insignificant throughout all variations of the regression model. However, when the CDS rating-based index is replaced by an equity market index, as in M4 and M5, the coefficient on $\Delta SPOT_t$ is negative and statistically significant, as predicted. This would imply that the rating-based index, as a common market factor, subsumes the influence of the risk-free interest rate. The rating-based index is positive and statistically significant in every variation of the regression model with a coefficient estimate of 0.62 for M1 indicating that for every basis point increase in a swap's rating-based index, the CDS spread can be expected to increase by 0.62 basis point. As an indicator of overall credit market conditions, the rating-based index appears to be a far superior proxy than the slope of the yield curve. This is not surprising because little empirical evidence of a strong relationship between credit spreads and CDS spreads and the slope of the yield curve is documented in the literature.

Furthermore, when aggregate equity market returns are used to proxy for general market conditions (M4 and M5), the coefficients for both CRSP equal-weighted returns and S&P 500 returns are negative and statistically significant, indicating that these are important variables to be considered. However, the explanatory power falls substantially from 35% to 22% when the CDS rating-based index is replaced by these alternative proxies. Hence, there is strong support that a change in the CDS rating-based index is the single most important predictor of a change in individual CDS spreads, and that the CDS market is more sensitive to its own market common factor than to a common equity market factor. As hypothesized, this would imply that these two markets, although correlated,

**EXHIBIT 7**
**Multivariate Regression Results**

Panel A: Summary Results for Firm-Level Estimations

| | Model Specification | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Intercept | −1.252 | −0.720 | −0.937 | −0.806 | −1.697 | −0.794 | −2.021 | −1.008 |
| | (−3.25) | (−1.84) | (−3.14) | (−1.16) | (−2.37) | (−2.85) | (−4.90) | (−4.35) |
| ΔLEV | 352.867 | | 381.403 | 357.133 | 387.956 | 354.532 | 472.245 | |
| | (8.73) | | (8.78) | (7.94) | (8.09) | (9.19) | (9.81) | |
| RET | | −0.718 | | | | | | |
| | | (−8.85) | | | | | | |
| ΔVOL | 299.312 | 309.355 | | 380.568 | 472.623 | 294.587 | 506.234 | |
| | (4.51) | (4.74) | | (5.74) | (6.95) | (4.72) | (7.68) | |
| ΔVIX | | | 0.235 | | | | | |
| | | | (0.87) | | | | | |
| ΔINDX | 0.621 | 0.605 | 0.635 | | | 0.624 | | 0.731 |
| | (14.52) | (14.82) | (14.18) | | | (14.00) | | (14.30) |
| CRSP | | | | −1.037 | | | | |
| | | | | (−5.89) | | | | |
| S&P | | | | | −0.951 | | | |
| | | | | | (−3.53) | | | |
| ΔSPOT | −0.322 | −0.523 | −0.430 | −5.452 | −5.903 | | | |
| | (−0.32) | (−0.55) | (−0.40) | (−4.40) | (−4.66) | | | |
| ΔSLOPE | −6.307 | −5.679 | −5.530 | −0.835 | 1.416 | | | |
| | (−1.65) | (−1.42) | (−1.41) | (−0.15) | (0.25) | | | |
| $\Delta CDS_{t-1}$ | −0.047 | −0.039 | −0.024 | −0.040 | −0.023 | −0.050 | −0.031 | −0.036 |
| | (−4.31) | (−3.60) | (−2.18) | (−3.46) | (−1.95) | (−4.61) | (−2.78) | (−3.36) |
| $\Delta CDS_{t-2}$ | −0.045 | −0.043 | −0.040 | −0.032 | −0.028 | −0.049 | −0.035 | −0.048 |
| | (−4.22) | (−4.11) | (−3.68) | (−3.10) | (−2.69) | (−4.63) | (−3.42) | (−4.61) |
| Adj $R^2$ | 0.350 | 0.352 | 0.348 | 0.225 | 0.220 | 0.344 | 0.179 | 0.256 |

## EXHIBIT 7 *(continued)*

Results broken out by credit rating category for Model 1:

$$\Delta CDS_{it} = \alpha_0 + \beta_1 \Delta LEV_{it} + \beta_2 \Delta VOL_{it} + \beta_3 \Delta INDX_{it} + \beta_4 \Delta SPOT_t + \beta_5 \Delta SLOPE_t + \varepsilon_t$$

Panel B: Results by Credit Rating Category

| | Credit Rating Category | | | |
|---|---|---|---|---|
| | AAA/AA | A | BBB | <BBB− |
| Intercept t | −0.327 | −0.142 | −0.390 | −5.648 |
| | (−2.52) | (−1.04) | (−0.93) | (−3.15) |
| ΔLEV | 85.584 | 143.102 | 344.019 | 853.884 |
| | (4.00) | (4.39) | (5.57) | (6.00) |
| ΔVOL | 38.065 | 223.822 | 308.893 | 510.865 |
| | (1.14) | (3.35) | (2.56) | (2.53) |
| ΔINDX | 0.634 | 0.597 | 0.542 | 0.858 |
| | (4.30) | (11.77) | (9.41) | (5.30) |
| ΔSPOT | 0.129 | −0.355 | −0.943 | 0.983 |
| | (0.30) | (−0.79) | (−0.87) | (0.20) |
| ΔSLOPE | −1.552 | 0.598 | −1.759 | −31.408 |
| | (−1.54) | (0.67) | (−0.59) | (−1.59) |
| $\Delta CDS_{t-1}$ | −0.053 | −0.089 | −0.012 | −0.050 |
| | (−1.08) | (−4.39) | (−0.73) | (−2.23) |
| $\Delta CDS_{t-2}$ | −0.031 | −0.059 | −0.011 | −0.102 |
| | (−0.78) | (−3.31) | (−0.64) | (−4.67) |
| Adj. $R^2$ | 0.232 | 0.333 | 0.353 | 0.417 |
| No. of firms | 21 | 111 | 140 | 60 |

*Note: Exhibit 7, Panel A, reports average coefficient estimates across all 333 firms with associated test statistics calculated by dividing the coefficient estimate by the standard deviation of the $N_j$ estimates and scaling by $\sqrt{N_j}$, as in Collins-Dufresne, Goldstein, and Martin [2001]. Adjusted R-squared values are averages for the $N_j$ regressions. Panel B provides results for estimation of M1 from Panel A broken out by a firm's average credit rating. Note that one firm had no S&P credit rating information and, therefore, is not included in Panel B.*

do provide separate and distinct information to CDS market participants.

Because it appears that virtually all of the model's explanatory power is coming from two firm-specific variables—equity returns and equity volatility—and the common CDS market factor, M6 regresses CDS spread changes on these three variables alone. The explanatory power of the model is virtually unchanged with an adjusted R-squared value of 0.344. When the regression is estimated using firm-specific equity returns and volatility (as well as two lagged CDS values), the explanatory power falls to 18% (M7). When CDS spread changes are regressed on the CDS index alone and the lagged CDS values, the explanatory power is 26% (M8). Thus, although half of the model's explanatory power can be attributed to firm-specific equity market information and the lagged values of CDS spread changes, the rating-based index is, by far, the single best predictor of CDS spread changes.

Throughout all these specifications, two lags of CDS spread changes were included to control for autocorrelation. Although the use of monthly (as opposed to daily or weekly) data reduces the presence of autocorrelation, the statistical significance of the lagged values shows that the monthly series is still autocorrelated. The regressions were also run without the lagged values and the explanatory power was somewhat lower; the adjusted $R^2$ for M1 was equal to 0.30 versus 0.35. Importantly, the percentage of the firm-level regressions for which the residuals were not white noise, as evidenced by the number of Ljung-Box test statistic $p$-values less than 0.05, was twice as high in the regressions without the two lags—49 of 333 firm-level regressions rejected the null hypothesis of white noise residuals when no lags were included versus 25 firms that rejected the null of white noise when the two lags were included for M1. Hence, although autocorrelation is not entirely eliminated for every firm in the sample, it is substantially reduced using this specification.

Panel B of Exhibit 7 reports the estimation of M1 with results broken out by the four credit-rating categories: AAA/AA, A, BBB, and non-investment grade. As hypothesized, the explanatory power of the model increases as credit quality declines with adjusted $R^2$ values ranging from 23% for AAA/AA-rated entities to 42% for non-investment grade firms. Both a standard $t$-test and the Wilcoxon rank-sum test confirm that the difference between the two groupings is significant at the 1% level. Furthermore, the magnitude of the coefficient on equity returns and volatility increases considerably as credit quality declines. These findings support previous work by Kwan [1996], Avramov, Jostova, and Philipov [2007], and Norden and Weber [2004], who affirmed a closer relationship between credit and equity markets as credit quality deteriorates.

The results of this analysis are compared to previous research findings in Exhibit 8. The results of this study are comparable to those of previous studies, which analyzed changes in either corporate bond credit spreads or changes in CDS spreads. These studies (i.e., Collins-Dufresne, Goldstein, and Martin [2001], Blanco, Brennan, and Marsh [2005], and Ericsson, Jacobs, and Oviedo-Helfenberger [2004]) explained approximately 25% of the variation in credit spread and CDS spread changes, whereas this study explains approximately 35% of the variation in CDS spread changes. Yet Avramov, Jostova, and Philipov [2007] were able to explain approximately 54% of the variation in corporate bond credit spread changes. Although admittedly weaker, the findings reported in this article are not inconsistent with those of Avramov, Jostova, and Philipov in that these findings explain significantly more of the variation in CDS spread changes for low-grade firms (42%) than for more highly rated firms (23%). The study's findings are also consistent with those of Blanco, Brennan, and Marsh [2005] who found that CDS spreads are more sensitive to firm-specific information than corporate bond credit spreads, whereas credit spreads are more sensitive to macroeconomic interest rate and equity market variables than CDS spreads.

Abid and Naifar [2006] and Aunon-Nerin, Cossin, and Hricko [2002] were able to explain up to 66% and 82%, respectively, of the variation in CDS spreads by focusing on spread levels (as opposed to spread changes) in a cross-sectional setting. Therefore, to determine if the results of this study are comparable, the model was estimated in levels. The mean adjusted $R^2$ was 0.87.[7] With the exception of the increased explanatory power, the conclusions based on this study remain qualitatively unchanged. Regardless of whether the equation was estimated in levels or changes, the coefficient on a CDS rating-based index was consistently positive and statistically significant throughout, and firm-specific equity variables and the CDS index continued to explain the vast majority of the variation in CDS spreads.

## CONCLUSION

This article explores the ability of variables suggested by structural models to explain variation in credit default swap spread changes. Using monthly changes in CDS spreads for 333 firms from January 2001 to March 2006, these variables were found to explain 35% of the variation in CDS spread changes. It was also found that 87% of the variation in CDS spreads can be accounted for when regressions are estimated in levels. These findings, however, are subject to spurious regression due to the fact that CDS spreads are I(1).

Leverage and volatility are key determinants of CDS spread changes, because these two variables account for approximately half of the explained variation in monthly CDS spread changes. As suggested by Blanco, Brennan, and Marsh [2005], equity returns and leverage are comparable proxies for a firm's health when using monthly data over a relatively short time horizon. Macroeconomic interest rate variables do not perform as well as firm-specific equity market variables because they seem to contribute little to the predictive power of the regression model. However, a CDS rating-based index that accounts for both credit risk and overall market conditions is the single best predictor of CDS spread changes, which suggests that a systemic component to CDS pricing exists. This aggregate CDS factor is a better proxy for overall credit conditions than either macroeconomic interest rates or aggregate equity returns. The superiority of this factor versus aggregate equity index returns suggests that, although the two

# EXHIBIT 8
**Comparison of Related Research**

| Study | Dependent variable/Data | Independent Variables | Findings |
|---|---|---|---|
| Collins-Dufresne, Goldstein, and Martin [2001] *Journal of Finance* | Monthly Δs in corporate bond credit spreads, July 1988–Dec. 1997, 688 bonds (261 issuers) | Δs in the spot rate (10yr)<br>Δs in the slope of the yield curve<br>Δs in leverage, Δs in the VIX<br>Δs in the slope of the smirk<br>S&P 500 index returns | - Explain 25% of variation in Δs in corporate bond spreads.<br>- Common omitted factor is identified via principal components analysis. |
| Avramov, Jostova, and Philipov [2007] *Financial Analysts Journal* | Monthly Δs in corporate bond credit spreads, Sept. 1990–Jan. 2003 (extended to Aug. 2006), 2,375 corporate bonds | Market and firm-specific<br>- Equity returns<br>- Δs in equity volatility<br>- Δs in P/B<br>Δs in spot rate (5-yr)<br>Δs in the slope of the yield curve<br>Fama-French Factors<br>Fed cycle dummy | - Explain 54% of variation in Δs in corporate bond spreads.<br>- Results vary by credit quality: adj $R^2$ range from 30−36% for low risk to 68−70% for high risk. |
| Abid and Naifar [2006] *International Journal of Theoretical and Applied Finance* | CDS spreads, May 2000–May 2001, 207 trades | Credit rating<br>Maturity<br>Risk-free rate<br>Slope of the yield curve<br>Equity volatility | - Explain up to 66% of the variation in CDS spread levels. |
| Ericsson, Jacobs, and Oviedo-Helfenberger [2004] CIRANO | CDS spreads and Δs in CDS spreads, 1999–2002, 4,813 bid and 5,436 offer quotes | Leverage<br>Volatility<br>Risk-free rate [10yr, 2-yr, $(2yr)^2$]<br>Slope of the yield curve<br>S&P500 returns<br>Slope of the smirk<br>*Variables estimated in both levels and differences | - Leverage, volatility and the riskless rate explain approximately 60% of variation in spread levels and 23% in Δs in spreads.<br>- Including more variables increases explanatory power to 72% for levels and 32% for first differences. |
| Aunon-Nerin, Cossin, and Hricko [2002] FAME | CDS spreads, Jan. 1998–Feb. 2002, 392 trades | Credit rating<br>Interest rates<br>Slope of the yield curve<br>Time-to-maturity<br>Stock price changes<br>Equity volatility<br>Leverage<br>Market cap | - Explain up to 82% of the variation in CDS spreads.<br>- Credit rating is single most important determinant followed by equity market information. |
| Blanco, Brennan, and Marsh [2005] *Journal of Finance* | Weekly CDS spreads and corporate bond credit spreads, Jan. 2001–June 2002, 33 reference entities ≥350 daily CDS mid-market quotes and bond yields per firm | Δs in the spot rate (10yr)<br>Δs in the slope of the yield curve<br>Equity returns (firm-specific and market)<br>Δs in implied volatility (firm-specific and market)<br>Δs in the slope of the smirk<br>S&P 500 Index returns | - Explain approximately 25% of variation in CDS and corporate bond spread changes. |
| Greatrex [2008] | Monthly Δs in CDS spreads, Jan. 2001–Mar. 2006, 16,748 monthly observations, 333 firms* | Δs in leverage/equity returns<br>Δs in equity volatility/Δs in the VIX<br>Δs in the spot rate (5-yr)<br>Δs in the slope of the yield curve<br>Δs in a CDS rating-based index<br>CRSP returns/S&P500 returns | - Explain up to 35% of the variation in Δs in CDS spreads.<br>- Results vary by credit quality: adj. $R^2$ range from 23% for AAA/AAs to 42% for <BBBs.<br>- A CDS rating-based index is the single most important determinant followed by firm-specific equity market information. |

**Monthly data is extracted from a larger set of 413,844 daily observations for 476 firms.*

markets are correlated, the CDS market and the stock market provide separate and distinct information to the credit markets. Furthermore, the fact that a rating-based index, firm-specific equity returns, and equity volatility account for virtually all of the model's predictive power provides practitioners with a parsimonious model with only three factors to consider in modeling CDS spread changes.

## ENDNOTES

I would like to thank Duncan James, Erick Rengifo, Hrishikesh D. Vinod, and an anonymous reader for their helpful comments. I would also like to thank Nishul Saperia of Markit and Christie Mullery and Margaret Cannella of JP Morgan Chase for enabling access to Markit's data. Any errors and omissions are my own.

[1]Abid and Naifar [2006] and Aunon-Nerin, Cossin, and Hricko [2002] studied the determinants of CDS spreads in levels. Blanco, Brennan, and Marsh [2005] analyzed changes in CDS and credit spreads, while Ericsson, Jacobs, and Oviedo-Helfenberger [2004] analyzed CDS levels and differences; the time periods of these latter two studies are from January 2001 to June 2002 and from 1999 to 2002, respectively. The time period of the study presented in this article is January 2001 to March 2006.

[2]A numeric rating level has been considered as an explanatory variable. For example, Aunon-Nerin, Cossin, and Hricko [2002] and Abid and Naifar [2006] regressed CDS spread levels on credit rating alone and were able to explain 47% and 42%, respectively, of the variation in spread levels.

[3]Both augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) stationary tests were conducted for all variables. Results are available upon request.

[4]Alternative measures were used to calculate interest rate variables including the 5-yr constant maturity Treasury rate as a proxy for the risk-free rate, the 10-yr–2-yr Treasury rate for the slope of the yield curve, and various combinations of long and short swap rates to calculate the slope of the yield curve. These alternative proxies all had a similar weak explanatory power in the univariate setting.

[5]For example, if a firm announces a stock buyback funded with debt, this will benefit shareholders by increasing equity returns, while simultaneously increasing the probability of default and, thus, increasing credit spreads.

[6]Results, available upon request, were qualitatively unchanged using constant maturity Treasury rates obtained from FRED to proxy for the risk-free rate and the slope of the yield curve.

[7]Results available upon request. Once again, due to the time-series nature of the data, the differenced regressions reported in Exhibit 7 are the more appropriate ones from which to draw inferences.

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