Fundamentals-Based versus Market-Based Cross-Sectional Models of CDS Spreads

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Abstract

Whereas much of the empirical work on credit default swap spreads has looked at time-series dynamics, in this paper, we examine cross-sectional regularities in CDS pricing. Using data over the period 2001 to 2005, we estimate econometric models explaining the cross-section of credit default swap spreads. We assess models based on market variables with those based on firm financials, and find that the latter perform comparably, if not better. Combining both models into a comprehensive hybrid one slightly improves fit suggesting that there is information contained in the financial statements not captured by market models in explaining the cross-section of CDS spreads. We examine the model out-of-sample to explore spread forecasts, the accuracy with which spread rankings may be forecast, so as to analyze the quality of directional signals of spread movements. We find evidence that the model supports profitable convergence trades.

JEL Classification: G12

1 Introduction

The growth of the credit derivatives market since the turn of the century has been astounding. The Office of the Comptroller of the Currency (OCC) reported credit derivative volumes of $287 billion at the end of 1999. Various estimates now put this volume at over $15 trillion. The credit derivatives instrument with the greatest volume by far is the credit default swap (CDS). This market has grown rapidly and is very liquid. Hence, the quantity and quality of data now supports extensive empirical work. Whereas much of the empirical work on credit default swap spreads has looked at time-series dynamics [see Chen, Cheng and Wu (2005) for example], in this paper, we examine cross-sectional regularities in CDS pricing. We use 2,860 firm-quarter observations of the spreads on CDS contracts (of non-financial firms) to develop models that explain these spreads. These quarterly CDS spreads are from 506 CDS securities representing 230 unique firms. Our models are able to explain two-thirds of the cross-sectional variation in CDS spreads.

Section 2 provides a description of these contracts. In brief, a CDS is a default insurance contract - the buyer pays the seller a periodic premium in return for compensation in the event that a reference firm defaults. The periodic payment or spread, taken as a percentage of the notional value of the CDS contract, is a metric of the credit risk of the reference firm. It is also a forecast of the expected loss on a reference bond issued by the reference issuer. The expected loss is, of course, a function of the probability of default of the issuer and the recovery obtained in the event of default.

Extracting information from credit spreads is an important activity for various market participants such as corporate bond fund managers (especially for high-yield portfolios), rating agencies, credit market data vendors, speculators on credit quality, relative value traders, and regulators. For example, a hedge fund might be interested in long-short trades using two corporate bonds. To this purpose, a spread prediction model needs only to be accurate in forecasting the relative rankings of the spreads. This demands a coarser level of accuracy than forecasts of spread point estimates. In our empirical work, we will examine both the model fit to spreads, as well as the model's ability to predict relative value rankings of spreads.

Most CDS contracts today are written on reference issuers that are large firms, and hence have traded equity, debt and options. Therefore, market prices may be used in models that explain spreads. Our goal in this paper is to examine the extent to which non-market information may be used to explain CDS spreads, so that the model may also be applicable to private firms. Another facet of the empirical model we develop is that it does not rely on time-series dynamics, so that using the model to examine less frequently traded names is possible. Many credit derivative structures, in particular collateralized default obligations (CDOs) embed issuers that are private firms, especially in the case of collateralized loan obligations (CLOs). A model that is not predicated on using market data would therefore be useful. Indeed, we find that we can explain a substantial amount of spread variation without requiring market variables.

Modeling the bond spreads of private firms has been explored by Moody's in their private firm model (see Falkenstein, Boral and Carty (2000)). They use financial data to predict defaults. In contrast, we use firm financial data augmented by economy-wide variables to model CDS spreads. Starting from a baseline model that exploits no firm-specific market data or time-series dynamics also enables us to analyze the improvement in the model when market data is injected into it. We find that there is a statistically significant improvement in the model, but the explanatory power only increases by about 7%.

One view of the existing research that examines credit data comes from dividing it into two streams: One, that extracts and analyzes the probability of default, and the other that examines the determinants of credit spreads. In the past, default likelihood was modeled primarily by credit ratings, but this has been supplemented recently by structural and reduced-form models that use different types of market information to determine default probabilities. Indeed, in both strands of modeling, credit spreads become the input to determining default probabilities, at least under the risk-neutral measure.

Credit spreads on any issuer are now available from two broad sources, bonds and credit default swaps (CDS). The literature has begun to focus on the latter, given that the CDS market is usually more liquid than that of corporate bonds, and has smaller tax effects as well (see Elton, Gruber, Agrawal and Mann (2001) for a look at factors other than default risk that determine bond spreads). Longstaff, Mithal and Neis (2003) and Ericsson, Reneby and Wang (2004) examine the difference in spreads between bonds and CDS, and are able to attribute it to the liquidity and tax characteristics of bonds. CDS spreads are now used to extract default probabilities in the framework of structural models, as in the `CreditGrades` model of Finkelstein, Pan, Lardy, Ta, and Tierney (2002). Likewise, CDS spreads may be used in reduced-form models in the Duffie-Singleton class (see Duffie and Singleton (1999)). For example, Berndt, Douglas, Duffie, Ferguson, and Schranz (2003) extract default intensities in this modeling framework from an extensive data set on CDS spreads. Lando and Mortensen (2005) also find that they can explain the slope of the credit curve better when using CDS data. In another paper similar to ours, Arora, Bohn and Zhu (2005) use CDS data to compare structural models and reduced-form ones, finding that structural models do better except when there are many bonds trading in addition to CDS. In contrast, we compare models that use market data versus ones that use only firm financials, fand find that both models do comparably well, with the latter slightly better.

Explaining credit spreads implicitly involves an understanding of the factors that drive spreads dynamically over time, as well as explain the cross-sectional difference amongst spreads of various issuers. Longstaff and Rajan (2006) present a framework in which the variation in spreads is decomposed into firm-level variations in credit risk, industry variations and economy-wide factors (or even international factors, as in Favero, Pagano and von Thadden (2005)). Longstaff and Rajan (2006) examine the spreads of tranches of the Dow Jones CDX Index, which is an index of credit default swaps. They find that almost two-thirds of the variation in spreads may be attributed to firm-level factors, and about one-fourth to industry factors. The model we develop in this paper will use primarily firm-level and macroeconomic variables as determinants of spreads, and the results are consistent with the findings of Longstaff and Rajan (2006).

Wu and Zhang (2004) model bond spreads as a function of macroeconomic factors, specifically inflation pressure, real output growth, and financial market volatility. Huang and Kong (2005) find that macroeconomic news releases dramatically impact high-yield bond spreads. As we will see, using economy-wide variables, namely the level of the term structure and past stock market returns, will enable us to achieve high levels of explanatory power. The economy-wide variables we use are based directly on the default probability model of Duffie, Saita and Wang (2005), and our results confirm their choice of explanatory variables; whereas their aim was to explain defaults, ours is to explain CDS spreads. Also in support of factors other than pure firm-level ones, is the paper of King and Khang (2005), who find that simple structural models may be improved by incorporating systematic factors. Similar results have been developed in the realm of hybrid models for explaining bond yield spreads, as in Sobehart, Stein, Mikityanskaya, and Li (2000).

Within the set of models that focus on firm-level variables, a debate exists as to which variables are better. On the one hand, purists believe that the market values of a firm's equity and its volatility of returns contain sufficient information to determine a firm's likelihood of default [see Crosbie (1999) for a delineation of this philosophy, embodied in the KMV model, which is based on the model of Merton (1974)]. These models do not admit the need to use balance-sheet variables. Indeed, Duffie, Saita and Wang (2005) corroborate this idea, showing extremely high predictive power (in terms of out-of-sample default rankings and ROC-curve based accuracy rations). However, they also use economy-wide variables. Hybrid models, such as the previously mentioned one of Sobehart, Stein, Mikityanskaya, and Li (2000) claim better performance than models that use only firm-level market variables. Whereas these comparisons have been made in the realm of default prediction, no such analysis has been made towards understanding which approach is better in explaining CDS spreads. The analysis in this paper seeks to shed light on this issue. The results of Collin-Dufresne, Goldstein and Martin (2001), Wu and Zhang (2004), Blanco, Brennan and Marsh (2005) and Longstaff and Rajan (2006) certainly suggest that more than just firm-level variables are required to explain spreads.

Whether a pure market based indicator of a firm's default such as KMV's distance to default measure is sufficient to explain default is an open issue. distance to default is essentially a volatility-adjusted measure of leverage. Bharath and Shumway (2005) have recently shown that not only is the Merton (1974) model based KMV approach inferior to a naive measure of distance to default, but the model can be improved significantly using other variables. They also find that there is only a very weak connection between implied default probabilities from CDS spreads and the distance to default measure from the Merton-KMV model. Hence, it is very likely that even if the KMV approach provides adequate explanation of defaults, it may not be sufficient for explaining spreads. As we will show, we achieve high levels of explanatory power ($R^2 = 65\%$) without using distance to default or other market variables for the firm, and the subsequent inclusion of these variables enhances the explanatory power of the model by another 7%. The results of Bharath and Shumway (2005) also explain bond spreads using various market and balance-sheet variables and attain levels of explanatory power similar to ours, that are based on CDS spreads. Interestingly, the analysis may be run the other way, i.e. estimate the model using market variables, and then assess whether the inclusion of firm financials adds explanatory power. When we do so, we obtain an increase of 8% in explanatory power. Whereas this is significant, it is small. A related result appears in Chava and Jarrow (2004) who explain defaults (not spreads).

Other variables that might explain spreads better are ratings and equity volatility. Even though ratings are known to be delayed measures of a change in a firm's credit quality, nevertheless, they are firm-specific, and given the results of Longstaff and Rajan (2006), may have explanatory power. Das, Freed, Geng and Kapadia (2001) find that the time-series variation of default likelihood is explained significantly by volatility, as is shown also in the paper by Aunon-Nerin, Cossin, Hricko and Huang (2002) for CDS markets in Europe. Zhang, Zhou and Zhu (2005) confirm this result and decompose volatility into diffusion and jump components, explaining most of credit spreads using the diffusion component. They use a comprehensive model and obtain explanatory levels of about 77%, higher than we achieve in this paper. However, they do not provide the performance of a model that ignores firm-specific market variables. Campbell and Taksler (2003) find that the usual balance-sheet variables fail to displace ratings in explaining bond spreads; however, idiosyncratic volatility is significant, even in the presence of ratings. They achieve R^2s ranging from 40-60%, depending on the model used. In contrast, we find that we are able to explain CDS spreads to higher levels of fit, with fewer variables.

Brown (2001) finds that spreads of bonds issued by different firms with similar maturities behave as if they have a common factor separate from credit risk variables. It is therefore interesting to ask whether the same is true of CDS spreads. As it turns out, we find maturity of the CDS to be a significant explanatory variable.

We provide a brief synopsis of the results of the paper:

1. There are three levels of data one might use to explain CDS spreads: (a) firm-level market prices of equity and options, (b) firm-level financial data, and (c) industry and economy-wide data. Our goal in this paper is to exploit the latter two types of data. We find that we can explain two-thirds of the cross-sectional variation in spreads with our model. We also undertake a comparison of the financials-based specification (which we will denote Model 1 subsequently) versus the market based one (denoted Model 2). Finally we explore a comprehensive hybrid model, combining the other two, and denote it as Model 3.

2. Our results are consistent with the work of Duffie, Saita and Wang (2005) - we use their firm-financial and economy-wide variables and find that these are significant in our model. The ability to explain a large proportion of spread variation follows from the fact that a firm's default probability is a component of spreads.

3. Using cumulative accuracy profiles (CAP curves) and accuracy ratios therefrom, we are able to predict relative value CDS spread rankings. We obtain accuracy ratios of 58-62% for spread rankings. These compare with reported accuracy rations for defaults (not spreads) of public firms with one-year forecast horizons of 53-76% (in-sample) and 53-73% out-of-sample (Sobehart, Stein, Mikityanskaya, and Li (2000)). Similar levels of accuracy for public and private firms are reported by Chava and Jarrow (2004). The improved model of Duffie, Saita and Wang (2005) attains accuracy ratios of 88% over default rankings. Similar levels are achieved by Chava and Jarrow (2004) when accounting for industry effects, which they show are important. Reported private firm accuracy ratios of defaults are around 45% (Falkenstein, Boral and Carty (2000)). We do not expect to achieve the same accuracy levels in predicting spread rankings as we do in defaults, since there are many components in the spread over and above default probability. We believe that the use of CAP curves and accuracy ratios in the realm of CDS spread prediction is a novel use of the statistic, one which has not been attempted before. However, given the widespread popularity of relative value spread trades undertaken by hedge funds, this is precisely the analysis that informs practitioners of the efficacy of such trading strategies.

4. We find that the incremental value of market variables such as distance to default over and above firm-financial and economy-wide variables is of the order of 7%. This suggests that models using primarily non-equity market data (such as Altman (1968), Altman (2000)) may be as good as those keying off distance to default in predicting spreads.

5. We examine whether the divergence of our model spreads from the actual market values is indicative of profitable convergence trading. Our analyses show that all three models (financials-based, market-based and comprehensive) might have been successfully employed towards profitable convergence trades.

The rest of the paper proceeds as follows. In Section 2, we provide a brief description of credit default swaps. In Section 3, we describe our data set. Section 4 describes our results, and Section 5 provides concluding comments.

2 Credit Default Swaps

Credit Default Swaps are contingent claims with payoffs that are linked to the credit risk of a given entity. The entity can be a public or private firm, the subsidiary of either type of firm, a sovereign government or governmental agency. The buyer of the CDS receives protection from default risk in exchange for periodic payments (usually quarterly but sometimes semi-annually) until the expiration of the contract or until a predefined credit event occurs which, for our data, is default by the given entity. In the event of default, the buyer of the CDS spread receives a payoff equal to the difference between the face value and the market value of the underlying debt minus the CDS premium which has accrued between the default date and the last periodic payment date. In practice, buying a CDS contract is tantamount to buying insurance against default where the quarterly premium payments are determined from the CDS spreads. The CDS spreads are the annualized premium rate (using an actual-360 day convention) quoted as a fraction of the notional value of the underlying debt. In case of default, there are two settlement procedures: physical settlement which is the most widely used, and cash settlement. In a physical settlement, the buyer of protection delivers the notional value of deliverable obligations of the reference entity to the protection seller in return for the notional amount paid in cash. The acceptable set of deliverable obligations include restrictions based on maturity and need to be *pari passu*, meaning they have the same priority. In a cash settlement, the seller pays the buyer the face value of debt minus the recovery rate of the reference asset (this is also known as the loss rate on default). The recovery rate is calculated by either referencing dealer quotes or by observing market prices over some period after the default occurred.

An example will illustrate how CDS securities function. Suppose that the buyer of protection purchases a 5-year CDS security with a spread of 100 basis points and that the notional value of the underlying debt on which protection is purchased is $10 million. The buyer of the CDS will make quarterly payments of 0.01 times $10 million divided by 4 (since the CDS is quoted in annualized rates), which equals $25,000. Let us further suppose that shortly after the CDS is purchased, the reference entity defaults. If the reference entity has a recovery price of 40% the settlement is as follows: the seller compensates the buyer for the loss on the face value which is $6 million and the buyer pays the accrued premium from the last premium payment date to the date of default. For example, if default occurs 2 months after the last premium was paid the accrued premium would be $25,000 times two-thirds or approximately $16,667.

CDS securities have resulted in a number of innovations in the credit markets by making it easy to trade the credit risk of debt. This has been very popular among hedge funds wishing to hedge current credit risk exposures or wishing to take a bearish credit view. An advantage of the CDS is that it is unfunded, meaning investors do not make an upfront payment enabling them to leverage positions. Of particular interest to hedge funds is the possibility of long-short CDS trading strategies.

The CDS market has grown very rapidly over the last few years. The International Swaps and Derivatives Association (ISDA) as the primary regulator of CDS markets reports that the total notional value of underlying debt for the CDS market was only about $630 million in 2001 and has grown to over $12 trillion in 2005. The impressive growth in the CDS market was accompanied by enhancements in the definitions used to determine credit defaults which we believe is reflected in most of our data.

In order to motivate the empirical specification, it is useful to examine briefly a generic model for the pricing of CDS. If the rate of default of an issuer depends on a (usually stochastic) intensity process λ_t, then the survival probability for the issuer from time zero to time τ is given by $s_\tau = \exp\left(-\int_0^\tau \lambda_t \, dt\right)$. In a fairly priced CDS contract, the expected present value of premium payments by the buyer to the seller will equal the expected present value of default loss payments from the seller to the buyer. The expected present value of payments by the seller of the CDS to the buyer will be, for a notional value of $1, given various default times τ:

$$E\left[\int_0^T \exp\left(-\int_0^\tau r_t dt\right) s_\tau \lambda_\tau (1-\phi_\tau) d\tau\right] \tag{1}$$

where r_t is the instantaneous interest rate at time t, and ϕ_τ is the recovery rate at default time τ. The expectation $E[.]$ is taken over all interest rate, intensity and recovery paths, and all default times. The exposition here is presented in continuous time, and may just as easily be undertaken using a discrete time analog, as is done later to facilitate estimation. The expression above has terms for discounting, as well as the *conditional* probability of default, given no prior failure, i.e. $s_\tau \lambda_\tau$, and the loss on default, $(1-\phi_\tau)$.

The expected present value of premium payments at rate CS per annum from the buyer to the seller are as follows:

$$E\left[\int_0^T \exp\left(-\int_0^\tau r_t dt\right) s_\tau \; CS \; d\tau\right] \tag{2}$$

Since the payments in expected present value terms between buyer and seller should be equal for the CDS to be fairly priced, equating (1) and (2) and re-arranging, results in the formula for the CDS spread

$$CS = \frac{E\left[\int_0^T \exp\left(-\int_0^\tau r_t dt\right) s_\tau \lambda_\tau (1-\phi_\tau) d\tau\right]}{E\left[\int_0^T \exp\left(-\int_0^\tau r_t dt\right) s_\tau \; d\tau\right]} \tag{3}$$

It is clear that the spread CS must depend on the factors that determine interest rates (r_t), default intensities (λ_t) and recovery rates (ϕ_t), comprising both firm variables as well as economy-wide factors. Firm-level variables might be either market prices of debt and equity and financials, and economy-wide variables would be from equity and interest rate markets. For details of the valuation of CDS contracts, see the article by Duffie (1999). We may write the following functional form for the default intensity (suppressing the time subscript on these forward intensities):

$$\lambda = \exp[\mathbf{B}' \, \mathbf{X}] \tag{4}$$

where $\mathbf{B} = [\beta_0, \ldots, \beta_k]'$ is a vector of coefficients in the non-linear specification above, and $\mathbf{X} = [1, X_1, \ldots, X_k]'$ is a vector of explanatory variables, which may include both market variables and firm financials. (Both vectors are dimension $(k+1)$, where k depends on the specifics of the model). Given that the default intensity lies in the range $[0, \infty)$, this specification maintains the required bounds as well. We substitute this specification into a discrete form of equation (3), presented below, and estimate this non-linear model for all three of the models described earlier, the financials-based one, the market-based one, and the comprehensive one.

We assume that the discrete periods in the model are based on time interval h, and that defaults and premium payments occur at the end of the period. Given the CDS maturity, the number of periods n is determined. The periods are indexed by $j = 1, 2, \ldots n$. The discrete-time equivalent of equation (3) is as follows:

$$CS[\lambda(\mathbf{B})] = \frac{E\left[\sum_{j=1}^{n} e^{-z_j jh}\ (1-\phi_j)\ e^{-\lambda_j (j-1)h}\left(1-e^{-\lambda_j h}\right)\right]}{h\ E\left[\sum_{j=1}^{n} e^{-z_j jh}\ e^{-\lambda_j (j-1)h}\right]} \tag{5}$$

where z_j is the zero-coupon discount rate for period j. Of course, λ_j is the default intensity in period j. Noting that λ is a function of $\mathbf{B}$ and $\mathbf{X}$ from equation (4), we may undertake a least-squares fit of the CDS spread c as follows, across all observations:

$$\mathbf{B}^* = \text{argmin}_{\mathbf{B}} \sum_i \sum_t \left[CS_{it} - \widehat{CS}_{it}\right]^2 \tag{6}$$

where CS_{it} is the actual observed value of the CDS spread and $\widehat{CS}_{it}$ is the fitted value for firm i at time t. Thus, $\mathbf{B}^*$ is the best fit value of the parameters. In the special case where $\lambda_j = \lambda$, i.e. constant conditional on the given state vector $\mathbf{X}$, and the recovery rate is constant, i.e. $\phi_j = \phi$, we obtain a simplified expression of equation (5), i.e.

$$CS[\lambda] = \frac{(1-\phi)\left(1-e^{-\lambda(\mathbf{B})h}\right)}{h} \tag{7}$$

Taking logarithms, we obtain an approximate linear estimation equation:

$$\begin{aligned}
\log\{CS[\lambda]\} &= \log\left[\frac{(1-\phi)}{h}\right] + \log\left[\left(1-e^{-\lambda(\mathbf{B})h}\right)\right] \\
&\approx \log\left[\frac{(1-\phi)}{h}\right] + \log\left[\lambda(\mathbf{B})h\right] \ = \ \log\left[\frac{(1-\phi)}{h}\right] + \mathbf{B}'\mathbf{X}\ h
\end{aligned}$$

where we have exploited the fact that $\lambda = \exp[\mathbf{B}'\ \mathbf{X}]$. The expression highlights the fact that it is natural to regress the natural logarithm of CDS spreads on explanatory variables. Indeed, as may be noticed in the work of Aunon-Nerin, Cossin, Hricko and Huang (2002), regressions in the logarithm of spreads do fit better than in levels directly.

This simplified expression intentionally downplays the role of the dynamics of spread processes (see Pan and Singleton (2005) for a model of spread dynamics with sovereign CDS). Our primary goal in this paper is to develop models that explain the cross-sectional variation in spreads, with a view to extending CDS pricing to private firms. For this purpose the simple specification is ideally suited. Further, by setting the default intensities to be functions of the state variables $\mathbf{X}$, we latently model their movement over time without explicitly modeling the dynamics of the state variables. As a consequence of the nascent stage of the CDS market, the lack of contiguity in the time series record on spreads for most issuers in the sample would result in the loss of a large proportion of the sample were the dynamics to be explicitly modeled. Nevertheless, as the results will show, we are able to attain high levels of explanatory power in all the model specifications we take to the data.

3 Data

3.1 Sample collection and description

Our data collection was initiated by obtaining a list of all the CDS securities with spreads available on Bloomberg. Bloomberg lists 10,503 CDS securities covering 1,563 unique debtor entities. From this list we eliminated all CDS securities where the notional value is not dollar denominated reducing the sample to 4,168 CDS securities covering 960 unique debtor entities. On this sample, we collected the CDS constant-maturity spreads on the last trade that occurred at the end of each quarter over the period 2001-2005 from Bloomberg with Morgan Stanley data as a source. Cossin and Lu (2005) argue that this CDS quote represents the market price for the credit risks of the borrower and is thus adequate for our purposes. We are able to obtain spread information on 790 CDS securities on 340 unique debtor entities. The sample is then merged with the COMPUSTAT Quarterly Industrial database and the CRSP daily stock file. This last procedure eliminates from the sample all non-publicly traded entities and non-US firms. Eventually, to determine our final sample, we further require that each firm possess at least 50 trading days of stock price returns prior to the end of each quarter and that data on total assets be available. Following standard practice, we exclude financial firms from the sample identified using the Fama and French (1997) 17 industry classification. Our final sample comprises 2,860 quarterly CDS spreads on 506 CDS securities representing 230 unique firms. Table 1 presents the time profile of the sample by CDS maturity. We observe from Table 1 that 5-year CDS contracts are the most common maturity traded, representing 73% of our entire sample, followed by 1- and 3-year CDS contracts, each representing around 13% of all observations. Additionally, Table 1 shows that we are unable to obtain any CDS spread quotes before the 3rd quarter of 2001 even though our search starts at the beginning of 2001 and that the sample size increases steadily over time. Our sample size drops to 37 observations in the 1st quarter of 2005 because the 2005 COMPUSTAT quarterly updates were not complete at the time of this study.

Table 2 presents the industry profile of the sample firms. We assign a company to one of 16 industries (financials are excluded from our analysis) determined by Fama and French (1997), and located on Kenneth French's website, by using the CRSP primary SIC code (COMPUSTAT SIC codes often differ from those in CRSP). For the purpose of Table 2, we allow each company to enter the sample once per year. In 2001 we thus have only 4 unique companies whereas in 2004 we have 204. Over all years, there are 230 unique companies as reported before. We find that all industries but Fabricated Products are included in our sample and that no single industry dominates the sample. The three largest industries are Utilities, Machinery and Business Equipment and Retail Stores, all representing roughly 10% each of the data. As a basis for comparison, we report the industry profile of the COMPUSTAT universe over the same period. Notably our sample over-represents the Automobile, Chemical, Utilities and Oil industry and under-represents the Mining and Minerals industry.

We now turn our attention to the CDS spreads themselves. In Table 3 we present the mean and medians of CDS spread values by maturity and year. The 2-year maturity spreads are not presented in the interest of space since there are only 2 values for that category. The obvious relationship that emerges from Table 3 is that for a given year the CDS spreads with longer maturities have monotonically higher values (we dismiss the sole 10-year CDS spread in 2005 as not meaningful). Furthermore, CDS spreads on all maturities have decreased over the period for our sample suggesting an overall improvement in credit quality in the market.

In Table 4 we report the mean and median CDS spreads by industry. Overall, we find that there is considerable time variation in CDS spreads within a given industry group. The spreads in the Utilities industry for instance drop considerably from a median of 157 in 2002 to roughly 47 in 2004. In the cross-section, however, there appears to be an industry effect in which the Automobile industry most notably stands out as having consistently higher and more stable CDS spreads.

In Table 5 we report spreads by rating. Given the sample period, the spreads have declined from 2002 to 2005, as the general quality of issuers in the credit markets has improved. Spreads also increase with worsening credit rating, except that AAA spreads are higher than that of AA. This aberration comes from the fact that we have only a few AAA names in the sample, and they are likely to be either lower quality within AAA, or for longer maturities. There is considerable overlap in spread ranges for adjoining rating categories, known from bond data, and recently in CDS data as well. As has been well-documented in the past, there is a dramatic increase in spreads when moving from investment grade firms to those in non-investment grade.

3.2 Variable Construction

3.2.1 Financial-Based Variables

We construct our financial-based variables following the Moody's Private Debt Manual published on the Moody's-KMV website. We use 10 variables to proxy for 1- firm size, 2- profitability, 3- financial liquidity, 4- trading account activity, 5- sales growth and 6- capital structure.

1. As a measure of firm size we use the value of total assets (COMPUSTAT-Quarterly item 44) divided by the Consumer Price Index on all-urban consumers, all items (Series CUUR0000SA0) with a base of 100 in the period 1982-1984.

2. We compute three ratios that gauge profitability: return on assets (ROA), net income growth, and interest coverage. ROA is constructed as net income (item 69) divided by total assets. Net income growth is calculated as net income minus the previous quarter's net income divided by total assets. Interest coverage is calculated as pretax income (item 23) plus interest expense (item 22) divided by interest expense.

3. To assess the firm's financial liquidity we use the quick ratio and the cash to asset ratio. The quick ratio is constructed as current liabilities (item 40) minus inventories (item 38) over current assets (item 49) and the cash-to-asset ratio is cash and equivalents (item 36) over total assets.

4. We measure the firm's trading account activity by using the ratio of inventories to cost of goods sold (item 30).

5. The quarterly sales growth is calculated as sales (item 2) divided by the previous quarter sales minus one.

6. Finally, to proxy for differences in the capital structure of the firm, we calculate the ratio of total liabilities (item 54) to total assets and the ratio of retained earnings (item 58) to total assets.

In some instances of flow items, COMPUSTAT reports a missing value in the first and third quarter of the year when the data reported in the second and fourth quarters are semi-annual numbers. When this event occurs, we set the first and second quarter data to one-half the semi-annual reported value in the second quarter. We proceed similarly in the third and fourth quarter using the fourth quarter semi-annual numbers.

In order to account for seasonal effects, we take the trailing four-quarter average of ROA, sales growth, interest coverage, and inventories over cost of goods sold before including these variables in the model. The relationship between CDS spreads and interest coverage is likely to be monotonically increasing; yet when the interest coverage is very large, the effect of small changes in interest coverage should be negligible. Moreover, when the interest coverage is negative, the ratio is not meaningful since the relative magnitude of pretax income to interest expense is blurred. For these reasons, we follow Blume, Lim, and MacKinlay (1998) by transforming the interest coverage ratio in two ways. First, before taking the trailing four quarter average, we set any quarterly interest coverage ratio to zero if they are negative. Second, any trailing 4 quarter average interest coverage ratio that exceeds 100 is censored on the assumption that further increases in value convey no additional information. We also follow Blume, Lim, and MacKinlay (1998) in changing the specification of the model to allow the data to determine the shape of the nonlinearity. Specifically, let IC_{it} be the interest coverage for firm i in quarter t, we then include the interest coverage ratio in the regression model as:

$$IC_{it} = \sum_{j=1}^{4} \kappa_j c_{jit} \tag{8}$$

where c_{jit} is defined in the following table as:

	c_{1it}	c_{2it}	c_{3it}	c_{4it}
$IC_{it} \in [0, 5)$	IC_{it}	0	0	0
$IC_{it} \in [5, 10)$	5	$IC_{it} - 5$	0	0
$IC_{it} \in [10, 20)$	5	5	$IC_{it} - 10$	0
$IC_{it} \in [20, 100]$	5	5	10	$IC_{it} - 20$

This specification allows the regression model to determine different coefficient parameters on each increment of the interest coverage ratio.

3.2.2 Distance to Default

We now turn to constructing our market-based measure of default. We estimate the market value of debt using the Merton (1974) bond pricing model where the total value of the firm is assumed to follow a geometric Brownian motion,

$$dV = \mu V dt + \sigma_v V dW \tag{9}$$

where V is the total value of the firm, μ is the expected continuously compounded return on V, σ_v is the volatility of firm returns and dW is a standard Weiner process. The firm is assumed to have one discount bond maturity in T periods. Under these assumptions the equity of the firm E is a call option on the underlying value of the firm with an exercise price equal to the face value of debt F and a time to maturity of T. The value of equity is then modeled using the Black-Scholes-Merton formula,

$$E = VN(d_1) - e^{-rT} FN(d_2) \tag{10}$$

where $N(.)$ is the cumulative normal distribution function with d_1 and d_2 given by:

$$d_1 = \frac{\log(V/F) + (r + \sigma_v^2/2)T}{\sigma_v \sqrt{T}}, \quad d_2 = d_1 - \sigma_v \sqrt{T} \tag{11}$$

Under the Merton (1974) assumptions the value of equity is a function of the value and time so it follows directly from Ito's lemma that:

$$\sigma_e = \left(\frac{V}{E}\right) \frac{\partial E}{\partial V} \sigma_v \tag{12}$$

The Merton model uses equations (10) and (12) as a system of two equations and two unknowns to solve for V and σ_v where σ_e, μ, E, F, and r can all be estimated exogenously. T is assumed to be one year following standard practice. We estimate these inputs in the following manner: σ_e is the annualized standard deviation of returns and is estimated from the prior 100 trading days of stock price returns from CRSP. μ is estimated as the annualized mean equity returns on the prior 100 trading days. Similar to Bharath and Shumway (2005), we require that at least 50 trading days be available in the computations. E the market value of equity is computed from COMPUSTAT as the number of shares outstanding times the end of quarter closing stock price. Following Vassalou and Xing (2004), we take the face value of debt F to be debt in current liabilities (item 45) plus one-half of long-term debt (item 51). The risk-free rate r is obtained using the 3-month treasury constant maturity rate from the Federal Reserve Bank of Saint-Louis. The 1-year treasury constant maturity rate is often used instead to match with the maturity of the bond. We follow Duffie, Saita and Wang (2005) in choosing the 3-month rate. Using these inputs, we numerically solve the system of simultaneous equations in the Merton model to obtain the firm value V and the volatility of the firm and calculate the distance to default as:

$$DTD = \frac{\log(V/F) + (\mu - \sigma_v^2/2)T}{\sigma_v \sqrt{T}} \tag{13}$$

3.2.3 Macroeconomic Variables

We include in our models additional variables to proxy for the macroeconomic environment. We use the risk-free rate r estimated again as the 3-month treasury constant maturity rate, the prior year return on the S&P 500, and the prior year return on the Fama and French (1997) industry group that the firm belongs to. Since periods of low interest rates are usually related to economic downturns, we expect a negative relation between the risk free rate and CDS spreads. Duffee (1998), Collin-Dufresne, Goldstein and Martin (2001) and Bharath and Shumway (2005) find a negative relationship between changes in interest rates and changes in default risk. We also expect a negative coefficient on the S&P 500 and industry returns, as low market returns are associated with higher probabilities of default. Duffie, Saita and Wang (2005) find that the trailing 1-year S&P 500 returns are positively correlated to default events and explain that this relationship might be due to the trailing nature of returns and business cycles. Collin-Dufresne, Goldstein and Martin (2001), on the other hand, use the monthly S&P 500 index returns as a measure of business climate and find a negative relationship with default risk. To some extent the first two variables can be viewed as a proxy for quarterly period effects and the industry returns can be viewed as time-varying industry effects.

Table 7 presents descriptive statistics on our financial-based and market-based determinants of CDS spreads for the sample firms. In this table, every given firm is represented as many times as CDS spreads are available on that company. Notably, the average firm value V is roughly \$35 billion with a median of approximately \$14.5 billion, suggesting that a few companies have very large firm values, thereby skewing the distribution. The volatility of equity appears to be well distributed around a mean of 28%. Our sample firms tend to be smaller and less volatile than the 71 firms with available CDS quotes studied in Ericsson, Reneby and Wang (2004) who report an average firm size of \$84 billion and a mean volatility of equity of 46%. Our measure of the distance to default appears well distributed around 10. This value is much higher than the ones reported in Ericsson, Reneby and Wang (2004) suggesting that our sample firms are further from default; this result might be accounted for in part by the fact that they eliminated all firms with AAA rated debt.

4 Results

4.1 Univariate Results

We start our analysis by examining the univariate relationship of CDS spreads with our firm-level financial variables. Table 8 reports the mean and median CDS spreads for quartiles of the sample sorted on the basis of the firm-level financial variable of interest. Quartile 1 stands for the lowest values of the variable. We find strong results that suggest financial-based variables play an important role in explaining CDS spread values. Notably, we find a strong monotonic relationship in both the mean and median spreads of several variables in a direction which is consistent with theory. The mean and median spreads drop considerably as ROA, and the interest coverage ratio increase. As expected, the capital structure of the firm plays an important role in determining spreads with higher levels of book leverage associated with higher mean and median spreads and higher levels of retained earnings associated with both lower mean and median spreads. Interestingly, our measure of trading-account activity, the inventory over cost of goods sold appears to be strongly monotonic in the unexpected direction that higher levels in the ratio are associated with lower spreads. One would expect higher inventory levels to be associated with a business downturn and thus to higher credit risks. It is possible however that the market perceives inventory levels as valuable assets which can be liquidated in the event of default.

The quick ratio appears to produce mixed effects with median spreads monotonically decreasing with higher quick ratio levels and the mean spreads monotonically increasing with higher quick ratio levels.

In our univariate results, there does not appear to be a meaningful relationship between CDS spreads and our measures of size, income growth, sales growth, and the cash ratio. KMV-Moody's does find empirical evidence suggesting that measures of sales growth have a non-monotonic relationship with the probability of default but we are not able to corroborate these findings as both the mean and median of CDS spreads are virtually the same across all quartiles. These variables, and in particular firm size, are likely to be important in a multivariate setting since most of our variables are normalized using firm size.

4.2 Multivariate Results

We next examine (i) a financials-based multivariate model of the determinants of credit spreads and we compare its explanatory power to (ii) a model which uses market information and (iii) a comprehensive model which includes both financial- and market-based information.

4.2.1 Financials-Based Model

For each firm i and quarter t we estimate the following least-squares regression where $\log(CS_{it})$ is the natural log of the CDS spread at the end of quarter t for firm i.

$$\begin{aligned}\log(CS_{it}) \quad = \quad & \beta_0 + \beta_{1i}\ Size_{it} + \beta_{2i}\ ROA_{it} + \beta_{3i}\ incgrowth_{it} \\ & + \beta_{4i}\ c_{1it} + \beta_{5i}\ c_{2it} + \beta_{6i}\ c_{3it} + \beta_{7i}\ c_{4it} \\ & + \beta_{8i}\ quick_{it} + \beta_{9i}\ cash_{it} \\ & + \beta_{10i}\ trade_{it} + \beta_{11i}\ salesgrowth_{it} + \beta_{12i}\ booklev_{it} \\ & + \beta_{13i}\ retained_{it} + \beta_{14i}\ r_t^{3month} + \beta_{15i}\ S\&P_t^{-1yr} \\ & + \beta_{16i}\ indret_{it} + \beta_{17i}\ invgrade_{it} + \beta_{18i}\ maturity_{it} \\ & + \beta_{19i}\ seniority_{it} + \epsilon_{it}\end{aligned} \tag{14}$$

Table 6 provides a description of the short-hand variable names as well as their predicted signs. Table 9, column 1, presents our findings on this regression model. As a result of missing firm-level data, the number of observations in our model drops to 2,242 firm-quarters. We find a negative and statistically significant (at the 1% level) relationship between the book value of size and CDS spreads meaning that larger firms present less risk of credit default. Corroborating our univariate results, we find a strong negative relationship between accounting performance as measured by ROA and CDS spreads. Furthermore, as we hypothesized earlier the relationship between interest coverage and spreads is overall negative and non-linear. When the interest coverage is between 0 and 5 the parameter coefficient is -0.08 and is significant at more than the 1% level of statistical significance. This coefficient decreases to -0.02 when the interest coverage is between 5 and 10 and the level of significance decreases but is still below 5% level of statistical significance. Between 10 and 20 the interest coverage ratio is not significant, whereas beyond 20 the coefficient is negative but very close to zero and significant at the 5% level. The quick ratio which appeared to produce mixed results in the univariate setting is positively related to spreads in the multivariate regression with a coefficient of 0.07, which is significant at the 5% level. The cash-to-asset ratio and sales growth measure, as in our univariate results, produce no significant association with the CDS spreads.

In the regression we control for macroeconomic factors as we discussed earlier by including the risk-free rate, the prior year S&P 500 returns, and the return on the industry. We find a negative relationship between all three variables and the CDS spreads suggesting that the security is very sensitive to the current macroeconomic environment and, in particular, to stock market conditions. This is consistent with the findings of Duffie, Saita and Wang (2005). We include in the regression a dummy for whether the underlying debt is considered to be investment grade or not. We define investment grade as a debt issued by a firm with a BBB rating or higher in which case the attribute variable takes on a value of 1 and 0 otherwise. Not surprisingly, we find that investment grade firms have significantly lower spreads.

Finally, we control in our model for characteristics of the CDS contract including maturity and whether the underlying debt is senior. The explanatory power of our financial-based model is high as it is able to explain 65% of the variation in our sample of CDS spreads. Overall, the explanatory power of this model, which does not include a single firm-level market variable, compares very favorably to market-based models reported in other studies (e.g. Berndt, Douglas, Duffie, Ferguson, and Schranz (2003)). Differences in our financial-based model with those found in other studies could very easily be due to differences in the sample itself rather than the model specification. For instance, as mentioned earlier our sample includes a larger number of unique firms in many more different industries than prior studies. Our panel is cross-sectionally diverse, which suits the goals of this study, rather than long in the time-series which is better for studies that focus on dynamics. We now estimate a model based on market variables (firm-level and general market) for the benefit of comparison.

4.2.2 Market-Based Model

There is accumulating evidence that equity market information may be used to explain credit spreads, as in papers by Collin-Dufresne, Goldstein and Martin (2001), Das, Freed, Geng and Kapadia (2001), Duffie, Saita and Wang (2005), Zhang, Zhou and Zhu (2005), and Bystrom (2005). Therefore, our market-based model contains both firm and market-wide equity variables.

For each firm i and quarter t we estimate the following least-squares regression where $\log(CS_{it})$ is the natural log of the CDS spread at the end of quarter t for firm i.

$$\begin{aligned} \log(CS_{it}) &= \beta_0 + \beta_{1i}\ DTD_{it} + \beta_{2i}\ ret_{it} + \beta_{3i}\ \sigma ret_{it} \\ &\quad + \beta_{4i}\ r_t^{3month} + \beta_{5i}\ S\&P_t^{-1yr} \\ &\quad + \beta_{6i}\ indret_{it} + \beta_{7i}\ invgrade_{it} + \beta_{8i}\ maturity_{it} \qquad (15) \\ &\quad + \beta_{9i}\ seniority_{it} + \epsilon_{it} \end{aligned}$$

In Table 9, column 2, we present the results of the preceding regression model where market variables are used to determine CDS spreads. Our main variable of interest in this model is the distance to default (DTD) which is often regarded as a sufficient statistic to determine the probability of default. We also include in the model the same variables that proxy for business climate as were used previously as well an investment grade dummy. We control for the CDS contract characteristics in the same manner as model 1. Additionally, we include the last 100 trading-days average of the equity returns for firm i at quarter t, which we denote in the model as ret_{it}. This measure is used by Duffie, Saita and Wang (2005) in combination with distance to default (DTD) to measure firm default intensity. Rather than use DTD, a volatility adjusted measure of leverage, Carr and Wu (2005) employ option volatility and find this simpler variable also provides high explanatory power for the few firms they examine in their paper; similar ideas permeate the paper by Cossin and Lu (2005). Ericsson, Jacobs and Oviedo-Helfenberger (2004) show that a model with leverage and volatility variables can explain over 60% of the levels of CDS spreads. Chen, Cheng and Wu (2005) employ a similar market-based regression as the one above in a four-factor model and find that two interest rate factors, and a credit and liquidity factor are all significant in explaining CDS spreads.

Before performing the regression we ensure that the market model is estimated on the same observations as the financial based model for the sake of comparison. As expected, we find that the distance to default is strongly negatively related to CDS spreads at more than the 1% level of significance. We also find that the trailing 100-day return is highly significant. Puzzlingly, we find that the parameter loadings on that variable are positive, suggesting that trailing equity performance is associated with larger credit risks. Overall, we find that the explanatory power of the market-based model is comparable to our financial-based model with an R^2 of 64% versus 65% in the latter model. From this we may infer that firm financials are important variables to use in explaining spreads cross-sectionally, since they do as well, if not better than market-based measures. This may also indicate that market trading results in values consistent with those reported in the financial statements for the purposes of credit information. These results beg the question as to whether model improvements are possible if market-based measures are used in combination with financial-based measures.

4.2.3 Comprehensive Model

We address the question as to whether market-based measures of default add any value if they are used in combination with financial measures by performing the following regression model (which we call "comprehensive").

Our comprehensive model consists in estimating the following least-squares regression for each firm i and quarter t where $\log(CS_{it})$ is the natural logarithm of CDS spread:

$$\begin{aligned}\log(CS_{it}) \quad = \quad & \beta_0 + \beta_{1i}\ Size_{it} + \beta_{2i}\ ROA_{it} \\ & + \beta_{3i}\ incgrowth_{it} + \beta_{4i}\ c_{1it} + \beta_{5i}\ c_{2it} \\ & + \beta_{6i}\ c_{3it} + \beta_{7i}\ c_{4it} + \beta_{8i}\ quick_{it} \\ & + \beta_{9i}\ cash_{it} + \beta_{10i}\ trade_{it} + \beta_{11i}\ salesgrowth_{it} \\ & + \beta_{12i}\ booklev_{it} + \beta_{13i}\ retained_{it} + \beta_{14i}\ DTD_{it} \\ & + \beta_{15i}\ ret_{it} + \beta_{16i}\ \sigma ret_{it} + \beta_{17i}\ r_t^{3month} + \beta_{18i}\ S\&P_t^{-1yr} \\ & + \beta_{19i}\ indret_{it} + \beta_{20i}\ invgrade_{it} + \beta_{21i}\ maturity_{it} \\ & + \beta_{22i}\ seniority_{it} + \epsilon_{it}\end{aligned} \tag{16}$$

The variables that are included in the comprehensive model are simply the union of variables in model 1 and model 2. In this model, we find strong results indicating that market-based information is complementary to firm-level accounting-based data or *vice-versa*. Indeed, the variables which constituted the basis of the financial-based model are still strongly significant with the same signs (except for the quick ratio whose coefficient was pushed down to zero). The previous statement applies equally to the market-based variables which retain their signs and levels of significance except for the prior 100-day firm equity returns. The explanatory power of the comprehensive model is 72% which is a strong improvement over the previous two models. Overall these results suggest two things. First, the distance to default may not be a sufficient statistic in modeling the cross-section of credit default swap spreads. Second, accounting variables possess valuable information in determining spreads which is not captured by the traditional market-based measures of default.

4.3 Robustness

In this section, we conduct several robustness checks. Our first robustness check consists in re-estimating all three models on the subset of 5-year CDS spreads. Our second check consists in using the probability of default rather than the distance to default as our primary market-based measure of default. The third consists in re-estimating our financial-based model with only the variables that are significant at the 5% level or better.

First, we estimate the models using only the 5-year CDS spread data. The number of observations drops to 1,624 but our results are qualitatively unchanged. The financial-based model R^2 decreases to 62%, the market-based model R^2 decreases to 61%, whereas the comprehensive model R^2 stands at 69%. All coefficients and degrees of significance remain virtually identical.

Second, many studies prefer to use the probability of default (defined as $N(-DTD)$), rather than the distance to default. We re-estimate all three models with the full sample of 2,242 CDS-quarters and, overall, find weaker results for both the market based and comprehensive model which under this new specification can explain 50% and 66% of the variance in the logarithm of CDS spreads. We also re-estimate the market based model and comprehensive model with the logarithm of the probability of default and find R^2's of 58% and 68% respectively. Therefore, the models are sensitive to non-linear scaling of distance to default; our results suggest that using distance to default directly provides better results.

Third, we re-estimate the financials-based and comprehensive model with only the variables that are significant at the 5% level or higher (not reported). We find that both models do not suffer as a result. The R^2's for the financial-model and the comprehensive model remain at 65% and 72%, respectively. This suggests that the cash-to-asset ratio, the sales growth, and income growth identified by Moody's-KMV as important variables in determining credit worthiness are superfluous in a model of CDS spreads.

Finally, one concern is that financial-based data is not actually known at the end of the quarter but at some subsequent time. Sengupta (2004) finds that this delay is on average around 40 days, although it has been widespread over the period for managers to offer earnings guidance prior to the official press release [Noe, Christopher and Hansen (1998)]. This problem is not an issue in uncovering the determinants of CDS spreads *per se* but is relevant in assessing whether some trading strategies are implementable in real-time. To verify this we re-examine all three models using the next quarter CDS spreads as the dependent variable. The findings reported in table 10 are that the financial-based model retains strong explanatory power with an R^2 of 60%. The market-based model fairs relatively better at explaining the leading spreads with an R^2 of 62% and the comprehensive model is able to retain most of its explanatory power with an R^2 of 69%. These results are quite robust considering that the measurements of the independent and dependent variables are so far apart.

4.4 Rank-Order Predictability

Of central interest to hedge fund managers and CDS traders is the possibility of predicting the relative ranking of CDS spreads rather than their point estimates. We set out to investigate how the financial-based model compares to the market based model in terms of relative rankings of CDS spreads. Notice that even though we model the logarithm of CDS spreads rather than spread levels, this does not affect their relative rankings.

To assess the performance of our model in determining relative rankings we construct cumulative accuracy profile (CAP) curves and the associated accuracy ratio (AR) statistics. The cumulative accuracy profile consists in ranking the predicted values of $\log \widehat{CS}_{it}$ (log credit spreads) and the corresponding actual values $\log CS_{it}$ independently from highest to lowest. We then create 100 bins and assign the top 1% of all predicted values to the first bin, the top 2% to the second bin and so on and so forth until the 100^{th} bin is populated which, of course, would consist of the total number of observations. We then repeat this exercise for the actual values. Once our bins are populated, we compare how many predicted values in a given bin also have their actual values in that same bin.

We then plot that percentage for each bin; the resulting graphic is the cumulative accuracy profile of our model. The accuracy ratio associated with a given cumulative accuracy profile is defined in the manner of Duffie, Saita and Wang (2005) as twice the area that lies between the curve and the 45 degree line. The maximum accuracy ratio is thus by construction 100% and the minimum 0%. In general, accuracy ratios above 50% are considered acceptable for the purpose of predicting default.

Figure 1 presents the cumulative accuracy profile for all three models and their corresponding accuracy ratios. The accuracy ratio is 61.6% for our comprehensive model, 56.7% for our financial-based model and 56.5% for the market-based model. These results suggest that the relative rankings of CDS spreads are more difficult to model than actual default events where Duffie, Saita and Wang (2005) find accuracy ratios of 88% based on the distance to default measure and economy-wide level data. Hamilton and Cantor (2004) find accuracy ratios of 65% based on Moody's Credit Ratings. Also, Blochwitz, Liebig, and Nyberg (2000) find accuracy ratios of 59.7% for the KMV Private Firm Model. Credit spreads may also contain other elements like liquidity and tax effects, though our use of CDS spreads is an attempt to mitigate the influence of such factors. Also, CDS spreads contain default risk premia, which are harder to rank and explain.

4.5 Out-of-sample Tests

4.5.1 Split-Sample Forecasts

To test the out-of-sample forecast of our cross-sectional models we randomly split our pooled sample of CDS spreads into an in-sample and out-of-sample of approximately equal sizes (the in-sample and out-of-sample contain 1,124 and 1,136 observations respectively). We then re-estimate all three models in-sample and use the resulting parameters to determine the out-of-sample predicted values. If the model predicts correctly out-of-sample we would expect the actual values and predicted values to be highly correlated. Furthermore if we were to regress the actual values on the predicted values we would expect the intercept to be zero and the the slope to be one. Figures 2 through 4 show the results of those regressions for all three models. As is apparent all three models present very strong abilities to forecast out-of-sample CDS spreads. Model 1 and 2 have R^2's of 65%-67% range respectively. The coefficients on both models is statistically no different than one and the intercepts are statistically no different than zero. An F-test of the joint hypothesis that the slope is equal to one and the intercept is zero fails to be rejected at any conventional level of significance. For model 3 the fit is much stronger with an R^2 of 71% and the joint hypothesis that the slope is one and the intercept is zero also fails to be rejected. Figure 5 presents the out-of-sample CAP curves. There appears to be little loss of power in our out-of-sample predictions. This result supports the robust cross-sectional fit of the model.

4.5.2 Relative-Value Trading Strategies

Many trading strategies are based on deviations from model values. By establishing positions that bet on the convergence of market values to model values, traders, especially hedge funds, attempt to profit from temporary deviations from fundamentals.

In this section, we examine whether our spread models provide sufficient reason for their application to convergence trades. An example of such a trade would be to buy CDS contracts or to short the bond of the issuer, if model spreads are higher; and vice-versa if model spreads are lower. If a model spread is higher than that in the market, we examine if there is convergence in the direction predicted by the model over the following quarter. The model spreads are estimated out-of-sample using a rolling 4-quarter window. We present the results of these convergences by dividing the sample into quartiles, based on the deviation of actual market spreads from model spreads. More formally, the analysis is as follows:

- Let $d_{it} = CS_{it} - \widehat{CS}_{it}$ be the difference in the spread fitted by the model ($\widehat{CS}_{it}$) and the actual spread (CS_{it}) in the market for firm i in quarter t.
- Next, we sort the observations on variable d_{it}, so that we obtain the data in quartiles. This coarsely ranks the spreads by deviation from model values.
- Quartile 1 (lowest d) comprises cases where the fitted spread was higher than the actual; conditional on the model being accurate, this implies that the spread is too low in the market and should converge by rising. These are good names to sell the bonds of, as potential depreciation is indicated by the model on account of increasing spreads.
- Quartile 4 (highest d) comprises cases where the model suggests spreads will fall, and buying bonds of these names is indicated.
- We roll ahead one quarter and check if spreads moved in the right direction. We report the value of the difference in spreads from one quarter to the next by quartile. For each spread, we compute $CS_{i,t+1} - CS_{it}$. If our model is performing well, we expect that this will be greatly negative for quartile 4, where spreads are expected to fall, and we should see this difference change monotonically as we go from quartile 4 to quartile 1.

The results are presented in Table 11. It shows clearly that if model spreads are higher than market spreads for a firm, then it is more likely that spreads will rise for that firm; and *vice versa*. The highest quartile represents spreads that are likely to fall by the greatest amount, and the lowest quartile are those that will increase by the greatest amount. Note that we sorted observations into quartiles based on the model and market differences in spreads, i.e. d_{it}. As we can see, the lowest quartile comprises cases where the actual spread is lower than that from the model and *vice versa* for the highest quartile. The resulting mean change in spreads over the succeeding quarter by quartile shows exactly the pattern expected if the model predicts convergence accurately. Thus, the results here imply that convergence trading in CDS spreads over quarterly horizons is a profitable activity over the sample period using all three models.

5 Concluding Comments

Much of the empirical work on credit default swap spreads has looked at time-series dynamics. In this paper, however, we examined cross-sectional regularities in CDS pricing. Given that CDS spreads are purer indicators of market participants' required compensation for default risk than bond spreads, we use data on over two-thousand CDS transactions with a view to developing an explanatory and predictive model over the cross-section of credit default swap spreads. We compare models that rely on market data versus those that rely on firm financials. Both types of models perform well and explain cross-sectional spread variation more than adequately. A comprehensive model merging both types of explanatory variables does better than each model alone. Thus, adding market variables to a model based purely on financials is statistically useful. Therefore, we may use the financials based model to explain credit spreads even for firms that do not have traded equity, or have infrequent trading, where time-series dynamics may not be exploited empirically. We are able to accurately predict the relative rankings of spreads, though not as well as models that only attempt to rank firms on default likelihood. The levels of explanatory power in our models are sufficient to detect relative spread mispricing, resulting in an ability to generate trading profits from convergence trades.

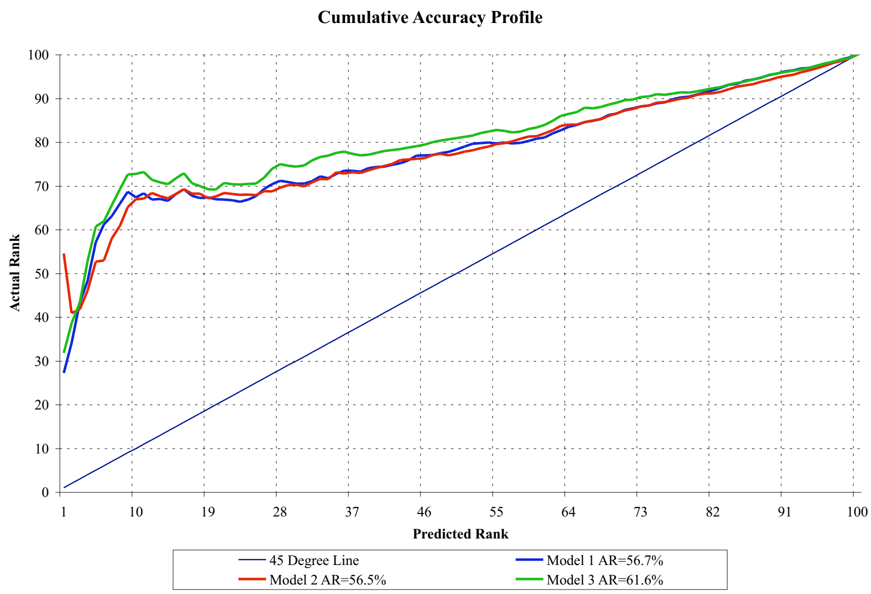

Figure 1: Cumulative accuracy profile (CAP) and accuracy ratio for spreads models. The cumulative accuracy profile consists in ranking the predicted values of $\log \widehat{CS}_{it}$ (log credit spreads) and the corresponding actual values $\log CS_{it}$ independently from highest to lowest. We then create 100 bins and assign the top 1% of all predicted values to the first bin, the top 2% to the second bin and so on and so forth until the 100^{th} bin is populated which of course would consist of the total number of observations. We then repeat this exercise for the actual values. Once our bins are populated we compare how many predicted values in a given bin also have their actual values in that same bin. We then plot that percentage for each bin; the resulting graphic is the cumulative accuracy profile of our model. The accuracy ratio associated with a given cumulative accuracy profile is defined in the manner of Duffie, Saita and Wang (2005) as twice the area that lies between the curve and the 45 degree line.

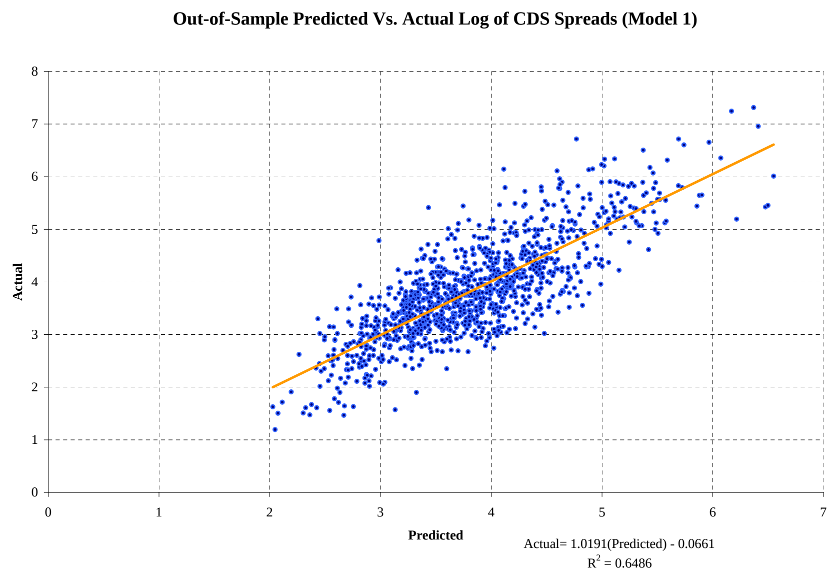

Figure 2: Regression of actual log of spreads ($\log CS_{it}$) on out-of-sample forecasted log of spreads ($\widehat{\log CS_{it}}$) using the financial-based model. The pooled sample is randomly split into an in-sample and out-of-sample of approximately the same size. Model 1 is estimated in-sample and the parameters are used to forecast out-of-sample predicted values. If the predictive ability of the model is strong regressing actual values on predicted values should yield an intercept close to zero and a slope close to one.

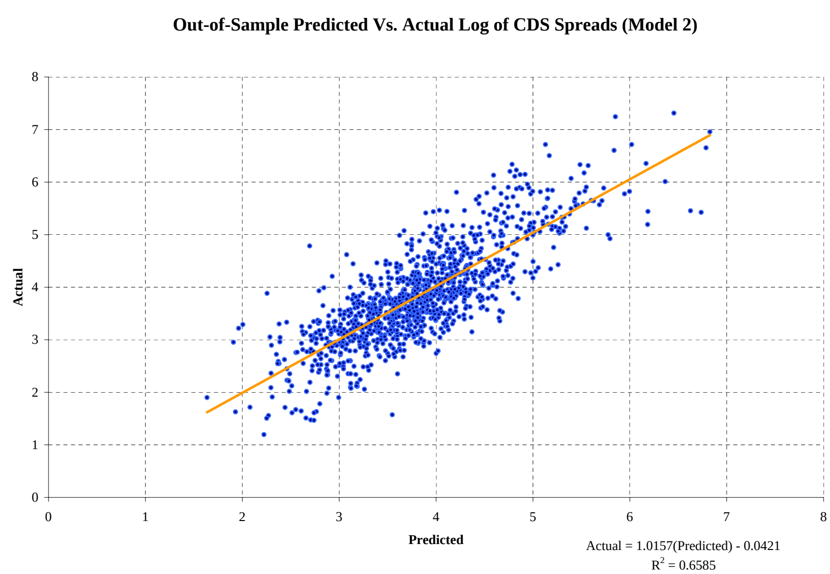

Figure 3: Regression of actual log of spreads ($\log CS_{it}$) on out-of-sample forecasted log of spreads ($\widehat{\log CS_{it}}$) using the market-based model. The pooled sample is randomly split into an in-sample and out-of-sample of approximately the same size. Model 2 is estimated in-sample and the parameters are used to forecast out-of-sample predicted values. If the predictive ability of the model is strong regressing actual values on predicted values should yield an intercept close to zero and a slope close to one.

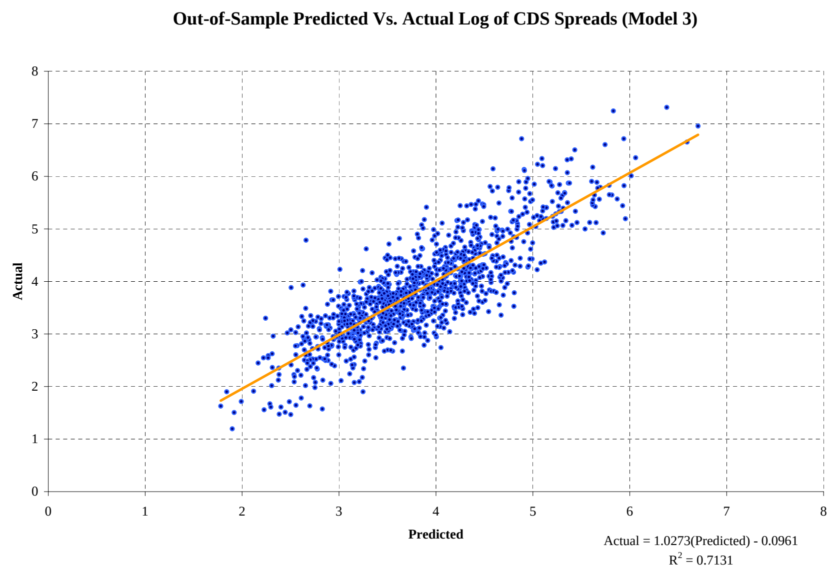

Figure 4: Regression of actual log of spreads ($\log CS_{it}$) on out-of-sample forecasted log of spreads ($\log \widehat{CS}_{it}$) using the comprehensive model. The pooled sample is randomly split into an in-sample and out-of-sample of approximately the same size. Model 3 is estimated in-sample and the parameters are used to forecast out-of-sample predicted values. If the predictive ability of the model is strong regressing actual values on predicted values should yield an intercept close to zero and a slope close to one.

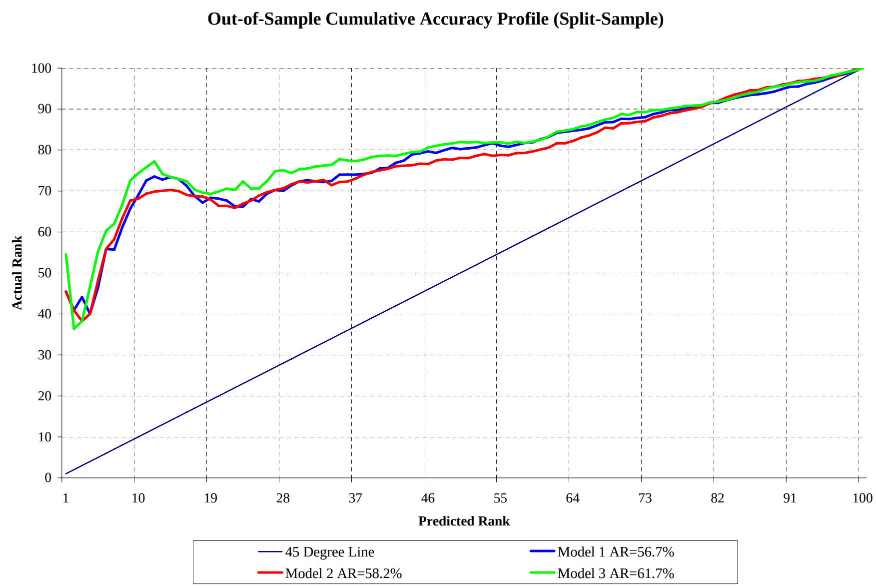

Figure 5: Cumulative accuracy profile (CAP) and accuracy ratio for out-of-sample spread models using the split-sample methodology. The cumulative accuracy profile consists in ranking the predicted values of $\log \widehat{CS}_{it}$ (log credit spreads) and the corresponding actual values $\log CS_{it}$ independently from highest to lowest. We then create 100 bins and assign the top 1% of all predicted values to the first bin, the top 2% to the second bin and so on and so forth until the 100^{th} bin is populated which of course would consist of the total number of observations. We then repeat this exercise for the actual values. Once our bins are populated we compare how many predicted values in a given bin also have their actual values in that same bin. We then plot that percentage for each bin; the resulting graphic is the cumulative accuracy profile of our model. The accuracy ratio associated with a given cumulative accuracy profile is defined in the manner of Duffie, Saita and Wang (2005) as twice the area that lies between the curve and the 45 degree line.

Table 1: Number of observations. Our sample consists of 2,860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis.

	CDS Maturities					
Quarter	1	2	3	5	10	All Maturities
2001Q3				8		8
2001Q4				8		8
2002Q1				23		23
2002Q2				72		72
2002Q3				108		108
2002Q4				121		121
2003Q1	5		4	156		165
2003Q2	33		32	228		293
2003Q3	34	2	34	248		318
2003Q4	22		22	244		288
2004Q1	52		53	221		326
2004Q2	77		78	215	14	384
2004Q3	72		73	209	15	369
2004Q4	67		67	192	14	340
2005Q1	6		6	24	1	37
All Quarters	368	2	369	2,077	44	2,860

Table 2: Industry profile of our sample by year. In this table each firm is allowed to be included only once per reported period. We use the Fama and French (1997) 17-industry classification based on SIC codes obtained from CRSP. As a basis for comparison we report the industry composition of the compustat universe over the same period. Our sample consists of 2,860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis.

	2001		**2002**		**2003**		**2004**		**2005**		**All Years**		Compustat	
Industry	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**
Automobiles			4	3.92	7	3.76	7	3.41	2	10.53	10	4.35	206	1.51
Chemicals			4	3.92	9	4.84	8	3.90	3	15.79	9	3.91	245	1.79
Construction and Construction Materials			1	0.98	6	3.23	6	2.93			12	5.22	482	3.53
Consumer Durables			2	1.96	5	2.69	5	2.44			5	2.17	449	3.28
Drugs, Soap, Perfumes, Tobacco	1	25.00	2	1.96	10	5.38	14	6.83	2	10.53	15	6.52	555	4.06
Fabricated Products													112	0.82
Food			8	7.84	13	6.99	12	5.85	3	15.79	13	5.65	435	3.18
Machinery and Business Equipment			14	13.73	19	10.22	22	10.73	5	26.32	24	10.43	1,847	13.51
Mining and Minerals					1	0.54	1	0.49			1	0.43	297	2.17
Oil and Petroleum Products			9	8.82	13	6.99	16	7.80	1	5.26	17	7.39	669	4.89
Retail Stores	1	25.00	12	11.76	20	10.75	22	10.73	1	5.26	23	10.00	872	6.38
Steel Works Etc			1	0.98	3	1.61	3	1.46			3	1.30	180	1.32
Textiles, Apparel & Footware					1	0.54	4	1.95			4	1.74	255	1.86
Transportation			10	9.80	13	6.99	14	6.83			16	6.96	490	3.58
Utilities			10	9.80	22	11.83	24	11.71			25	10.87	449	3.28
Other	2	50.00	25	24.51	44	23.66	47	22.93	2	10.53	53	23.04	6,130	44.83
All Industries	4	100.00	102	100.00	186	100.00	205	100.00	19	100.00	230	100.00	13,673	100.00

Table 3: Spread descriptive statistics. Our sample consists of 2,860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis.

	CDS Maturity											
	1-Year			**3-Year**			**5-Year**			**10-Year**		
	N	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
2001							16	90.41	88.75			
2002							324	175.4	100			
2003	94	36.88	24	92	52.06	35.66	876	103.4	55.69			
2004	268	30.26	19.38	271	49.61	31.32	837	79.44	47.01	43	89.78	65.1
2005	6	15.11	11.67	6	31.73	26.54	24	85.8	48.61	1	35.95	35.95
All Years	368	31.7	20.5	369	49.93	33.4	2,077	104.7	57.83	44	88.56	64.84

Table 4: Mean and Median CDS spreads by Industry. We use the Fama and French (1992) 17 industry classification based on SIC codes obtained from CRSP. Our sample consists of 2,860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis.

Industry	**2001**			**2002**			**2003**		
	N	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
Automobiles	2	160.88	160.88	22	251.77	212.5	40	220.12	196.75
Chemicals				12	71.51	63.08	47	49.92	44.56
Construction and Construction Materials				9	138.89	130	41	61.38	60.5
Consumer Durables				5	95	64.17	30	86.9	62.95
Drugs, Soap, Perfumes, Tobacco	4	94.28	90.81	13	97.7	98.17	47	114.95	40
Food				14	60.61	54.25	43	45.2	31.67
Machinery and Business Equipment				42	176	77.5	117	92.1	34.75
Mining and Minerals							4	74.06	75
Oil and Petroleum Products				25	91.49	65	60	60.87	44.13
Retail Stores	2	22.38	22.38	41	133.32	80	122	70.27	50.31
Steel Works Etc				3	45.08	48.5	9	92.11	56.5
Textiles, Apparel & Footware							1	37.25	37.25
Transportation				30	139.1	87.17	97	62.55	43
Utilities				23	236.29	156.67	84	126.07	79.13
Other	8	87.88	88.13	85	255.16	207.5	322	107.3	57.4
All Industries	16	90.41	88.75	324	175.36	100	1,064	93.04	50.25

Industry	2004			2005			All Years		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Automobiles	56	143.93	139.96	2	182.6	182.56	122	189.3	179.79
Chemicals	63	34.07	32.5	3	26.06	17.67	125	43.43	36.06
Construction and Construction Materials	73	43.58	32.83	2	128.2	128.18	125	57.64	45.67
Consumer Durables	39	79.22	61.02				74	83.4	62.25
Drugs, Soap, Perfumes, Tobacco	71	90.43	55.75	2	38.83	38.83	137	98.89	66
Food	54	32.81	26.69	5	26.97	19.18	116	40.51	30.28
Machinery and Business Equipment	171	57.74	29.92	16	51.98	29.22	346	83.45	36.19
Mining and Minerals	1	46.5	46.5				5	68.55	71.25
Oil and Petroleum Products	82	56.6	32.72	1	31.25	31.25	168	63.17	41.77
Retail Stores	150	52.54	39.05	1	220	220	316	70.21	46
Steel Works Etc	12	49.43	48.42				24	64.89	50.5
Textiles, Apparel & Footware	7	39.12	41.03				8	38.89	40.52
Transportation	104	37.71	33.01				231	61.31	41.06
Utilities	131	67.42	47.04				238	104.4	58
Other	405	76.98	45.33	5	76.21	28	825	107.3	56.55
All Industries	1,419	64.77	39.87	37	64.22	31.44	2,860	87.95	48.5

Table 5: Mean and Median CDS spreads by S&P credit rating. Our sample consists of 2,860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis. The S&P credit ratings were obtained from Compustat. Pluses or Minuses associated with the credit rating were removed prior to grouping.

S&P Rating		**2001**	**2002**	**2003**	**2004**	**2005**	**All Years**
AAA	Mean		67.45	27.33	23.45		34.35
	Median		62.96	17.63	26.17		26.5
	N		4	8	7		19
AA	Mean	22.38	42.36	22.78	18.35	13.5	24.91
	Median	22.38	35.25	20	16.31	13.5	19.88
	N	2	16	31	30	1	80
A	Mean	78.91	94.77	42.48	33.27	26.07	48.77
	Median	84.25	73.42	34	27.36	20	35
	N	7	108	225	231	8	579
BBB	Mean	109.83	208.41	107.02	69.68	78.39	109.22
	Median	90.5	146.88	71.25	54.3	48.61	68.33
	N	3	166	363	390	8	930
BB	Mean		687.27	351.18	190.81	149.71	277.55
	Median		737.5	278.18	173.5	128.18	214.38
	N		11	60	97	4	172
B	Mean			571.07	351.13	271.25	390.55
	Median			530	340	271.25	343.75
	N			7	26	2	35

Table 6: Variable name and description for each firm i at quarter t. Predicted sign in the regression with $log(CS_{it})$ as the dependent variable are included in the table.

Variable	Variable Description	Predicted Sign
Fundamentals-Based Variables		
$size_{it}$	Asset/CPI	-
ROA_{it}	Return on Asset	-
$incgrowth_{it}$	Income Growth	-
c_{1it}	Interest Coverage $\in [0, 5)$	-
c_{2it}	Interest Coverage $\in [5, 10)$	-
c_{3it}	Interest Coverage $\in [10, 20)$	-
c_{4it}	Interest Coverage $\in [20, 100]$	-
$quick_{it}$	Quick Ratio	+
$cash_{it}$	Cash-to-Asset Ratio	-
$trade_{it}$	Inventories to Cost-Of-Goods-Sold Ratio	+
$salesgrowth_{it}$	Sale Growth	-
$booklev_{it}$	Total Liabilities to Total Asset	+
$retained_{it}$	Retained Earnings to Total Asset	-
Market-Based Variables		
DTD_{it}	distance to default	-
ret_{it}	Annualized prior 100-trading day equity return	-
σret_{it}	Annualized prior 100-trading day equity volatility	-
Macroeconomic Variables		
r_t^{3month}	3-month constant maturity US-Treasury bill rate	-
$indret_{it}$	Prior-year return in the same Fama-French industry	-
$invgrade_{it}$	Equal to 1 if firm is rated above BBB; 0 otherwise.	-
$S\&P_t^{-1yr}$	Prior-year S&P returns	-
Contract-specific Variables		
$seniority_{it}$	Equal to 1 if underlying debt is senior; 0 otherwise.	-
$maturity_{it}$	Maturity of CDS contract (1,2,3,5,10 Years)	+

Table 7: Descriptive Statistics. Our sample consists of 2,860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis. Financial ratios are calculated following the Moody's Private Firm model. Total Assets/CPI is the deflated value of the firms total assets using the Consumer Price Index obtained from the Bureau of Labor Statistics. Net Income growth is calculated as the trailing 4 quarter average of net income over assets minus the previous quarter net income over assets. Interest Coverage is calculated as the trailing 4 quarter average of pretax income plus interest expense over interest expense. The quick ratio is calculated as current assets minus inventories over current liabilities. Sales Growth is the trailing 4 quarter average of the quarterly growth in sales. The distance to default is calculated by iteratively solving the Merton model described in the text using the firms equity value during the quarter, the previous 100 trading day volatility of equity returns from CRSP, the 3-Month Constant Maturity T-Bill obtained from the Federal Reserve Bank, and the Face value of debt computed as current debt plus 1/2 of long-term debt.

Variable	N	Mean	Median	1^{st} Quartile	3^{rd} Quartile
Panel A: Financial Ratios					
Size					
Total Assets/CPI	2,860	232.77	105.48	55.63	203.67
Profitability					
ROA	2,860	0.01	0.01	0	0.02
Income Growth (x1,000)	2,860	0.95	0.57	-0.4	1.74
Interest Coverage	2,860	6.19	3.35	1.64	6.56
Liquidity					
Quick Ratio	2,593	0.96	0.93	0.69	1.16
Working Capital to Asset	2611	-0.35	-0.36	-0.51	-0.23
Cash to Asset	2,860	0.07	0.04	0.02	0.09
Trading Accounts					
Inventory/COGS	2,860	0.65	0.49	0.21	0.79
Sales Growth					
Sales Growth	2,860	0.04	0.03	0.01	0.05
Capital Structure					
Liabilities to Asset Ratio	2,860	0.67	0.67	0.57	0.77
Retained Earnings to Asset	2,701	0.18	0.19	0.06	0.31
Panel B: Market Based Measures of Default					
Distance to Default	2,860	10.12	10.00	6.99	13.17
Equity Volatility	2,860	0.28	0.25	0.2	0.34
Volatility of Assets	2,860	0.25	0.23	0.19	0.31
Equity Value	2,860	31,938	13,555	6,974	31,551
Face Value of Debt	2,860	9,615	3,211	1,571	7,305
Firm Value	2,860	34,697	14,561	7,743	35,785

Table 8: Spread quartiles. This table presents the mean and median CDS spreads by quartile of firm-characteristic. Only 5-year maturity CDS spreads on senior debt are used in this table. Our sample consists of 2,860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms operating in the financial sector were excluded from the analysis. Financial ratios are calculated following the Moody's Private Firm model. Total Assets/CPI is the deflated value of the firms total assets using the Consumer Price Index obtained from the Bureau of Labor Statistics. Net Income growth is calculated as the trailing 4 quarter average of net income over assets minus the previous quarter net income over assets. Interest Coverage is calculated as the trailing 4 quarter average of pretax income plus interest expense over interest expense. The quick ratio is calculated as current assets minus inventories over current liabilities. Sales Growth is the trailing 4 quarter average of the quarterly growth in sales.

		Quartile			
Variable		1	2	3	4
Size					
Total Assets/CPI	Mean	97.94	131.89	85.19	97.99
	Median	53	71.46	55.38	55
	N	453	454	454	454
Profitability					
ROA	Mean	186.29	105.23	66.21	55.48
	Median	135.34	66.02	47.75	31.92
	N	453	454	454	454
Income Growth	Mean	113.84	92.91	86.12	120.17
	Median	61.25	52.62	50.25	64.25
	N	453	454	454	454
Interest Coverage	Mean	170.92	128.66	69.93	43.67
	Median	108.75	82.69	48.28	32.68
	N	453	454	454	454
Liquidity					
Quick Ratio	Mean	96.94	99.43	99.45	109.28
	Median	60.17	55.33	49.98	50
	N	417	417	417	417
Cash to Asset Ratio	Mean	89.38	103.12	108.19	112.3
	Median	56.5	60.56	59.41	48.38
	N	453	454	454	454
Trading Accounts					
Inventory/COGS	Mean	119.26	106.47	100.31	85.38
	Median	65.71	64.38	50	48.75
	N	447	448	448	447
Sales Growth					
Sales Growth	Mean	109.77	111.45	94.19	97.63
	Median	63.17	61.08	47.58	58.17
	N	453	454	454	454
Capital Structure					
Liability to Asset Ratio	Mean	63.3	94.89	104.27	150.49
	Median	41.25	52.48	66.38	85
	N	453	454	454	454
Retained Earnings/Asset	Mean	184.91	92.31	76.98	57.04
	Median	142.19	57.42	51.58	34.5
	N	430	430	431	430

Table 9: Ordinary least-square regressions of the Log of CDS spreads to Financial ratios based measures (Model 1), Market-based measures (Model 2) and both (Model 3). For comparison we keep the sampe size constant across all three models. Our sample consists of 2,860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms in the financial sector were excluded from the analysis. Financial ratios are calculated following the Moody's Private Firm model. Total Assets/CPI is the deflated value of the firms total assets using the Consumer Price Index from the Bureau of Labor Statistics. Net Income growth is the trailing 4 quarter average of net income over assets minus the previous quarter net income over assets. Interest Coverage is calculated as the trailing 4 quarter average of pretax income plus interest expense over interest expense. The quick ratio is calculated as current assets minus inventories over current liabilities. Sales Growth is the trailing 4 quarter average of the quarterly growth in sales. The distance to default is calculated by iteratively solving the Merton model described in the text using the firms equity value during the quarter, the previous 100 trading day volatility of equity returns from CRSP, the 3-Month Constant Maturity T-Bill obtained from the Federal Reserve Bank, and the Face value of debt computed as current debt plus 1/2 of long-term debt. Mean and Volatility of equity returns are also included separately in the regression. T-statistics are reported below the coefficients. Three, two and one star represent 1%, 5% and 10% levels of statistical significance respectively.

	Log of CDS spread					
Variables	Model 1		Model 2		Model 3	
Intercept	5.42	***	4.84	***	4.86	***
	37.89		42.82		31.34	
Size						
Log of Asset	-0.14	***	.		-0.13	***
	-9.74		.		-9.91	
Profitability						
ROA	-8.56	***	.		-3.71	***
	-7.19		.		-3.36	
Income Growth	2.17		.		1.74	
	1.47		.		1.31	
Interest Cov. 1	-0.08	***	.		-0.07	***
	-8.25		.		-8.44	
Interest Cov. 2	-0.02	**	.		-0.01	
	-1.98		.		-1.26	
Interest Cov. 3	0		.		0	
	0.08		.		0.26	
Interest Cov. 4	0	**	.		0	
	-2.3		.		-0.74	
Liquidity						
Quick Ratio	0.07	**	.		-0.01	
	2.08		.		-0.35	
Cash to Asset	0.09		.		-0.14	
	0.42		.		-0.69	
Trading Accounts						
Inventory/COGS	-0.07	***	.		-0.05	***
	-4.11		.		-3.23	
Sales Growth						
Sale Growth	0.04		.		0.26	
	0.25		.		1.81	
Capital Structure						
Liabilities to Asset Ratio	0.7	***	.		0.6	***
	7.64		.		7.2	
Retained Earnings/Asset	-0.5	***	.		-0.5	***
	-8.4		.		-9.24	
Merton Distance to Default						
Distance to Default	.		-0.08	***	-0.04	***
	.		-20.93		-9.76	
Equity Return	.		0.07	*	-0.11	
	.		1.95		-3.43	
Volatility of Equity Return	.		0.96	***	1.51	
	.		5.94		9.52	
Macroeconomic Environment						
3-Month T-Bill Rate	-36.18	***	-13.77	***	-17.85	***
	-15.14		-5.38		-7.76	
Previous 1-Year Industry Return	-2.39	***	-0.58	**	-0.62	***
	-8.63		-1.97		-2.36	
Previous Year S&P Returns	-1.21	***	0.01		-0.12	***
	-16.15		0.1		-1.49	
Debt Characteristics						
Investment Grade Dummy	-1.06	***	-1.19	***	-0.89	***
	-20.66		-23.69		-19.06	
CDS Characteristics						
CDS Maturity	0.18	***	0.2	***	0.18	***
	23.11		25.57		26.69	
Seniority Dummy	-0.05		0.07	*	-0.01	
	-1.34		1.76		-0.36	
R^2	65%		64%		72%	
N	2,242		2,242		2,242	

Table 10: Ordinary least-square regressions of the leading log of CDS spreads (following quarter) to Financial ratios based measures (Model 1), Market-based measures (Model 2) and both (Model 3). For comparison we keep the sampe size constant across all three models. Our sample consists of 2,860 quarterly CDS spreads from 2001Q3 to 2005Q1 obtained from Bloomberg on which financial data for the underlying bond issuer is available in the Compustat quarterly files and price information on at least 50 trading days is available on CRSP. The sample comprises 230 unique firms. Firms in the financial sector were excluded from the analysis. Financial ratios are calculated following the Moody's Private Firm model. Total Assets/CPI is the deflated value of the firms total assets using the Consumer Price Index from the Bureau of Labor Statistics. Net Income growth is the trailing 4 quarter average of net income over assets minus the previous quarter net income over assets. Interest Coverage is calculated as the trailing 4 quarter average of pretax income plus interest expense over interest expense. The quick ratio is calculated as current assets minus inventories over current liabilities. Sales Growth is the trailing 4 quarter average of the quarterly growth in sales. The distance to default is calculated by iteratively solving the Merton model described in the text using the firms equity value during the quarter, the previous 100 trading day volatility of equity returns from CRSP, the 3-Month Constant Maturity T-Bill obtained from the Federal Reserve Bank, and the Face value of debt computed as current debt plus 1/2 of long-term debt. Mean and Volatility of equity returns are also included separately in the regression. T-statistics are reported below the coefficients. Three, two and one star represent 1%, 5% and 10% levels of statistical significance respectively.

	Leading Log of CDS spread					
Variables	Model 1		Model 2		Model 3	
Intercept	4.47	***	5.1	***	4.55	***
	35.43		32.73		26.44	
Size						
Log of Asset	.		-0.15	***	-0.13	***
	.		-9.44		-9.17	
Profitability						
ROA	.		-7.32	***	-5.06	***
	.		-6.5		-4.12	
Income Growth	.		.		4.72	***
	.		.		3.25	
Interest Cov. 1	.		-0.09	***	-0.07	***
	.		-8.57		-7.95	
Interest Cov. 2	.		-0.03	**	-0.02	
	.		-2.43		-1.53	
Interest Cov. 3	.		0.01		0.01	
	.		0.88		1.08	
Interest Cov. 4	.		0	**	0	
	.		-2.57		-1.12	
Liquidity						
Quick Ratio	.		0.05		-0.05	
	.		1.56		-1.4	
Cash to Asset	.		.		-0.12	
	.		.		-0.55	
Trading Accounts						
Inventory/COGS	.		-0.07	***	-0.05	***
	.		-4.45		-3.45	
Sales Growth						
Sale Growth	.		.		0.2	
	.		.		1.29	
Capital Structure						
Liabilities to Asset Ratio	.		0.69	***	0.57	***
	.		6.98		6.14	
Retained Earnings/Asset	.		-0.48	***	-0.45	***
	.		-7.48		-7.49	
Merton Distance to Default						
Distance to Default	-0.08	***	.		-0.04	***
	-19.59		.		-8.84	
Equity Return	0.13	***	.		-0.06	*
	3.51		.		-1.66	
Volatility of Equity Return	0.78	***	.		1.39	***
	4.41		.		8	
Macroeconomic Environment						
3-Month T-Bill Rate	-7.54	***	-30.72	***	-11.86	***
	-2.72		-12.08		-4.7	
Previous 1-Year Industry Return	-0.55	*	-2.14	***	-0.57	*
	-1.71		-7.14		-1.95	
Previous Year S&P Returns	0.24	**	-0.92	***	0.12	
	2.43		-11.47		1.37	
Debt Characteristics						
Investment Grade Dummy	-1.09	***	-0.97	***	-0.8	***
	-19.96		-17.8		-15.69	
CDS Characteristics						
CDS Maturity	0.23	***	0.21	***	0.22	***
	27.31		25.34		28.63	
Seniority Dummy	0.07		-0.09	*	-0.04	
	1.28		-1.72		-0.82	
R^2	0.6		0.62		0.69	
N	2097		2097		2097	

Table 11: Model appropriateness for convergence trading. Here we present evidence that reflects the efficacy of the model in convergence trading. We show that if model spreads are higher than market spreads for a firm, then it is more likely that spreads will rise for that firm; and vice versa. Model spreads are estimated out-of-sample using a rolling 4-quarter window. The highest quartile represents spreads that are likely to fall by the greatest amount, and the lowest quartile are those that will increase by the greatest amount. Note that we sorted observations into quartiles based on the model and market differences in spreads, i.e. $d_{it} = \log \widehat{CS}_{it} - \log CS_{it}$. The resulting mean change in spreads by quartile shows exactly the pattern expected if the model predicts convergence accurately.

		Model 1		
Quartile	N	$d_{it} = CS_{it} - \widehat{CS}_{it}$	Mean$(CS_{i,t+1} - CS_{it})$	Stdev $(CS_{i,t+1} - CS_{it})$
1	497	-1.1256	-3.7128	24.1653
2	510	-0.63642	-5.1573	37.1596
3	520	-0.31642	-6.9069	36.7298
4	503	0.2274	-18.3636	52.872
		Model 2		
Quartile	N	$d_{it} = CS_{it} - \widehat{CS}_{it}$	Mean$(CS_{i,t+1} - CS_{it})$	Stdev $(CS_{i,t+1} - CS_{it})$
1	507	-0.94569	-2.9777	15.9659
2	514	-0.47185	-3.5491	30.6917
3	510	-0.12425	-8.647	42.3129
4	499	0.44132	-19.1584	55.88
		Model 3		
Quartile	N	$d_{it} = CS_{it} - \widehat{CS}_{it}$	Mean$(CS_{i,t+1} - CS_{it})$	Stdev $(CS_{i,t+1} - CS_{it})$
1	506	-1.01834	-3.8504	23.0855
2	513	-0.5333	-4.3309	40.706
3	516	-0.23612	-8.9071	38.1959
4	495	0.23654	-17.2482	50.0333

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