Measuring Credit Risk: CDS Spreads vs. Credit Ratings

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Abstract

The prices of or spread on credit default swaps (CDS) theoretically represent the pure credit risk of a firm. Callen, Livnat and Segal (2007) note that although the CDS premium is related to credit ratings issued by the rating agencies, rather wide variation in CDS spreads are observed for firms having a given rating. Following the recent subprime debacle, rating agencies have come under much scrutiny due to their role in the mispricing of credit risk and questions regarding the validity of the ratings that they issue are being questioned. This paper investigates the relationship between CDS spreads and credit ratings to help explain how market participants perceive and price credit risk. Using daily data obtained from Bloomberg on 391 five-year CDS contracts over the period 2003 to 2008, we model the credit default spreads as well as the variation between CDS spreads and credit ratings. Empirical results indicate that after controlling for market returns, market volatility and interest rates, CDS spreads increase with the subordination of the debt instrument, the put-implied volatility or deteriorating credit quality of the reference entity. We construct a credit quality variable derived from the quintiles of daily CDS spreads. Empirical results reveal statistically significant differences between credit ratings and our spread based credit quality variable. Observed discrepancies can be partly explained by stock market returns, levels of the VIX index, short-term and long-term interest rates as well as credit quality. However, empirical results indicate that a substantial share of the difference between credit ratings and CDS spreads cannot be attributed to either market or reference entity related variables.

I. Introduction and Motivation

Credit Default Swaps (CDS) began trading in the late 1990s, and since then the market has grown at an extremely rapid pace: $180 billion in notional amount in 1997 to $17.1 trillion in 2005, and $26 trillion by mid-2006[1]. Single name CDS represent the most common credit derivative traded in the market today. Like all derivatives, CDS derive their value from the price movements of the underlying reference asset, in this case corporate or sovereign bonds. The complex structure of CDS warrants an intrinsically multifaceted method. One variable that contributes to the valuation of CDS is the credit rating of the reference entity. This reflects that a large component of the price or spread of the CDS theoretically represents the pure credit risk of a firm. If credit ratings represent the relative credit quality of a firm, then it would make sense for there to exist a correlation between CDS spreads and credit ratings of the underlying reference entity.

As noted by Callen et al (2007), although CDS premia are related to credit ratings issued by rating agencies, there is quite a wide variation in CDS spreads that are observed for firms having a given rating. This relationship can be observed in the market by looking at CDS premia associated with a given rating. If CDS spreads reflect a component of pure credit risk (i.e., risk of loss associated with default of the reference on their debt), and credit ratings quantify the relative likelihood of a corporate defaulting on its debt, then should not all CDS on reference entities with a given credit rating be priced similarly? Thus, further research should be done to determine some of the causes of this variation, if it is shown to exist.

Following the subprime debacle starting in the summer of 2007 rating agencies have come under much scrutiny mainly because the market began to question the validity of the ratings they were issuing. Thus, many would say that the rating agencies have played a role in the mis-pricing of credit risk. However, as much of the scrutiny on the rating agencies centers on their inability to properly rate mortgage credit, one would think that such an inability could spill over to the corporate credit market. This seemed especially plausible at a time when the market entered a phase of abundant credit, exuberant growth and low volatility. Following the subprime meltdown investors became more risk adverse and skeptical of all credit products regardless of their credit rating or perceived creditworthiness. Investors who were interested in

[1] Sources: International Swaps and Derivatives Association press release of September 19, 2006 at www.isda.org/press.

credit products began demanding more compensation for taking on the default risk of the issuing entity. These market conditions have only added to the variation in CDS spreads on firms with the same credit rating. Thus, current market conditions add an interesting dynamic to the study of the relationship between CDS spreads and credit ratings. The shift in market sentiment can be seen by analyzing the chart that plots the daily closing prices of the CDX North American Investment Grade Index, the index of comprised of 125 of the most liquid CDS having investment grade ratings. The chart displays an upward shift in the level of the index starting around January 2008. This shift resulted from then existing current market conditions including; the credit crunch, subprime debacle and a drop in the equity markets. The shift represents market participants' demand for a high level of compensation for taking on additional risks, as well as a greater level of intrinsic risk of these securities.

Comments made by Callen et al (2007), as well as a reflection upon current market conditions, has prompted us to research the range that exists between CDS spreads with reference entities having the same rating. This observation motivates our study, as understanding the relationship between CDS spreads and credit ratings can further help explain how market participants perceive and price credit risk. Furthermore, this study examines the spread ranges among each credit rating, and how the range changes as credit quality deteriorates. Lastly, our research examines possible contributing factors that influence this range. While analyzing the relationship between CDS spreads and credit ratings the study also incorporates an overview of different methodologies used to value CDS. In doing so the paper also addresses the variables considered to influence the value of the CDS and tries to connect these variables to the explanation of the range that exists between CDS spreads of reference entities with the same ratings.

II. Literature Review

Hull et al (2004) examine the theoretical relationship between bond yields and CDS spreads, how this is influenced by rating agency announcements and whether high (low) CDS spreads indicate a company is more likely to be downgraded (upgraded). Furthermore, they analyze if the length of time a company has been in a rating category before an announcement influences the extent to which rating changes are anticipated by CDS spreads. Their initial model assumes the simple no-arbitrage relationship[2] that CDS spreads can be derived from subtracting the risk-free rate from the bond yield[3]. The authors find evidence that the CDS market anticipates all three types of negative credit events (downgrade, negative watch and negative outlook[4]) on the announcement day, but no statistical significance for positive rating events. While they hypothesize that this may be due to a lack of sufficient data for positive rating changes, that post-announcement day affects are not statistical significant for even negative credit events. Employing a logistic regression model to test whether or not CDS spreads can be used as estimators for probabilities of a rating event, they find that the adjusted spread levels are significant at the 1% level for downgrades and review for downgrades when all rating categories are pooled, but overall the results for outlooks are not significant[5].

Daniels and Jensen (2005) study the relationship between CDS spreads, credit spreads of corporate bonds and credit rating changes using principal component analysis, regression as well event study methodology. While overall CDS spreads and credit spreads are on average the same magnitude and tend to be a good proxy of each other, the extent to which this holds exhibits heterogeneity with respect to industry sector. Their results show that downgrades significantly impact spreads, and that this effect is accentuated for investment grade issues. Findings further suggest that while both corporate credit and CDS spreads react to rating changes, CDS spreads exhibit greater sensitivity than corporate bond spreads. In a regression model of CDS spreads, after various controls are implemented, corporate spreads and credit rating are both found to be highly significant; and a statistically significant difference in CDS spreads across industry groups remains in the final specification. The results also show that credit spreads are more significant in explaining CDS in the case of high yield as compared to investment grade issues, and that high yield issues tend to exhibit more sensitivity to firm

[2] This relationship holds under the following assumptions: no restrictions on shorting corporate or riskless bonds, no "cheapest-to-deliver" option in the CDS settlement, constant interest rates and no counterparty default risk in the CDS, However, since CDS payoffs reflect the rules set by ISDA, taxation and liquidity reasons cause investors to prefer riskless bonds to a corporate bonds, and CDS gives the holder the right to sell the par bond issued by the reference entity for its face value plus accrued interest. Because of this last assumption, the authors modify their initial model to incorporate the accrued interest component.

[3] The latter is either derived from the Treasury or the swap curve. The authors argue that the actual risk-free rate assumed when pricing CDS lies somewhere between these and find that on average it can be assumed that the rate used is approximately10bps under the swap rate.

[4] The authors use Moody's ratings. The authors separate the data into three categories: Aaa and Aa, A and Baa. They do not consider high yield names.

[5] The authors also develop a non-parametric test based on the concept of the cumulative accuracy profile (CAP) curve, and consistent with the main results of the study, they find significance (insignificance) of adjusted spread levels for positive (negative) rating announcements.

specific factors and credit ratings, as compared to investment grade issues. Finally, motivated by the evidence that credit ratings are among the most important determinants of CDS spreads, an event study shows that while the excess CDS spread is fairly constant for rating upgrades, it is slightly increasing for downgrades. Furthermore, their results suggest that changes in credit ratings have a greater impact on the CDS spreads than on the corporate bond spreads, and that the CDS spread changes are concentrated more around the event date.

Micu, Remolona and Wooldridge (2006) also explore the CDS price impact of rating changes using event study methodology, testing for pricing-relevant information under the hypothesis that rating announcements embody a surprise. Testable propositions include that negative (positive) rating announcements should result in a widening (narrowing) of credit spreads[6], that both corporate bond and CDS spreads should change by about the same magnitude, negative rating announcements that result from changes in a company's leverage should lead to a greater CDS price impact[7] and that two credit rating changes should be more informative than one.[8] The authors analyze not only upgrades and downgrades, but also rating agency outlooks and reviews, and further they control for public announcements that might have a similar impact as a rating announcement. They find that while negative rating announcement do result in a widening of CDS spreads, such changes tend to occur prior to the rating announcements, and this effect is stronger for firms that have split ratings. Negative reviews are found to have the greatest impact on BBB- rated firms, in contrast to the expectation that the trading of "restricted investors" (i.e., pension funds or institutional investors) should only have a temporary price impact; indeed, the study shows that there is no mean reversion for names that cross over from investment grade to high yield, and that rather CDS spreads continue to widen. On the other hand, while positive rating announcements are found to result in a lesser (albeit significant) tightening of CDS spreads, this is most accentuated for BB rated firms just below the investment grade threshold. Larger firms by market capitalization are found to have a smaller rating

[6] Note that in some past studies of the CDS price impact of rating announcements (Hull et al (2004), Norden and Weber (2004)) conclude that the reaction of credit default swap prices is most pronounced for reviews for downgrades.

[7] This is in contrast to the few previous studies to find differential price affects on equity and credit as a result of rating announcements

[8] One may argue that in numerous rating announcements regarding the same firm and the same information then only the first announcement should cause a price reaction.

announcement effect with regard to positive as compared to negative rating announcements, but the impact of positive announcements tends to be stronger for split-rated firms[9].

Carr and Wu (2006) study the similarities between equity option implied volatility and CDS spreads, proposing a dynamically consistent Merton structural framework that allows a joint valuation of instruments written on the same reference entity and estimates the risk-neutral PD and the equity return diffusion variance. The model solves for the CDS spread as the forward PD weighted average of the expected loss-given-default (LGD)[10]. On the equity side, the model decomposes the total risk on an individual stock into the diffusion variance rate and volatility in the default arrival rate. In order to derive the time-series dynamics for the bivariate state vector under the statistical measure the authors assume that the market prices of risks are proportional to the corresponding risk levels. The empirical results confirm previous findings that stock return volatility is stochastic, implied volatilities covary positively with CDS spreads, credit markets sometimes show variation independent of the stock and option markets, and that equity return volatility often increases as the price of equity falls. New to the literature they find that there is more significance in the autocorrelation of CDS spreads than for the implied volatilities of the options, that the implied volatility is negatively skewed, that the correlation between the two variables is strongest during periods of reference entity distress, that return variance and default arrival share common as well as specific risk factors, and that negative risk premia can be attributed solely to the default arrival and not the diffusion variance rate.

Villouta (2006) empirically tests if liquidity in the corporate bond and CDS markets has an effect on the arbitrage relationships that links these markets, through analyzing the effect of liquidity proxies on the CDS basis, as well as on trading strategies that try to profit from arbitrage due to misalignment between the markets[11]. A reduced-form model[12] is employed to

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[9] Some studies find that investors depend more on rating agencies' assessments regarding small cap companies than on large cap companies, while others find that larger companies produce and disseminate more private information than smallest ones.

[10] To price the CDS contracts the authors use the Eurodollar LIBOR for the short end of the curve, and the swap rates for the long end of the curve, sampled at a weekly frequency to avoid the impact of weekends. Note that the results found in some cases significant pricing error for swap spreads.

[11] When the CDS basis (defined as the spread on the CDS contract minus that on the band of the underlying reference entity) is positive (negative), a trader shorts (buys) the corporate bond and sells (sells) credit protection in the corresponding CDS contract, in the hope that the prices of the two will converge and a sure profit earned. However, this series of trades has intrinsic risk, including difficulties in shorting in the cash market when the basis is positive. Therefore, a negative basis trade is easier to execute and more common, which is a force tends to keep the cash market "trading rich" relative to the CDS market.

analyze the linkage between CDS spreads and credit spreads, where deviations from the no-arbitrage restriction are directly modeled[13]. The author develops an empirical test based upon the construction of 4 equally weighted dynamic portfolios depending on the liquidity of the company's bonds and CDS spreads for each maturity, where each bond is given a model based liquidity score and assigned to high and low groups[14]. Main results include that generally, in line with predictions regarding the effect of frictions in the cash market, highly liquid (illiquid) CDS contracts tended to have lower (higher) CDS bases. Furthermore, he finds that the standard deviation of the basis to be considerably higher for low liquidity CDS contracts; but the standard deviation of the CDS basis tends to be non-increasing with maturity of the contract[15].

Das and Hanouna (2007 a) develop a technique to identify and extract the implied forward curve of recovery and default rates on an issue using the CDS spread curve[16]. The authors derive the functions that determine the present value of premiums paid on the CDS for a given maturity given no default, and for the level of losses if the reference entity does defaults, both of which depending on the recovery rate and the probability of default. The authors explore different methods of determining recovery rates and default intensities[17], which in conjunction with CDS spreads and the proportional relationship between recovery rates and default probabilities; they derive the term structure of recovery rates and default probabilities in a

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[12] The author reviews the various methods of valuing CDS contracts including structural models, reduced-form models and Martingale models. It is noted that while reduced-form models are not popular in academic research, they are used by many practitioners.

[13] . The no-arbitrage restriction between the two markets is violated do to the following reasons First, the risk-free rate varies over time, and the relationship looks at par floating bonds when in reality most bonds in the market are coupon fixed. In the case of default the buyer of a CDS contract needs to pay accrued premium. Second, most CDS contracts have an embedded cheapest-to-deliver option, and this can distort the spread. Further, the definition of a credit event could lead to conflicting view between the buyers and sellers of protection. Finally, transaction costs can easily erode arbitrage opportunities.

[14] The liquidity score model is based on the issued amount, coupon, age, number missing prices and the bid-ask spread. A threshold is defined for each measure and then a weighted average Is computed in order to qualify a bond or CDS as having high liquidity or low liquidity.

[15] Results are shown robust to alternative testing methodologies, the Friedman Test for statistical evidence of the effect of liquidity (the only exception being maturity of 7 years), and a Kolmogorov-Smirnov Test that leads to the conclusion that the distributional properties of CDS Basis indeed vary significantly with maturity of the contract.

[16] They adopt a cross-sectional calibration method to study the implied recovery rates and default probabilities of the underlying reference entities. First, they establish the standard relationship of CDS spreads to default intensities and recovery rates. Second, they represent default intensities in term of spreads and recovery rates, implying an inversion of the spread curve that yields the default intensity term structure. Finally, exploiting the functional relationship of recovery rates and default intensities, they obtain the recovery rate term structure.

[17] These include a constant recovery rates, time-dependent recovery rates, an approach that identifies recovery rates separately from default intensities, and a structural model approach incorporating information from the equity markets. The latter framework accounts for evolving leverage of the reference entity, stochastic interest rates and stochastic volatility.

structural-form model framework[18]. Empirical results reveal that recovery rates are inversely proportional to expected default rates, that the standard deviation of the absolute recovery increases with the probability of default increases, as well as that correlation between recovery rates and default probability becomes decreases over time. The latter pattern suggests that additional contagion risk in defaults may be manifest in recovery levels. Variables found to be most correlated with recovery rates are the 1-month risk-free interest rate and the VIX index, with the former interest rate level being the primary determinant of recovery rates. On the other hand, expected default probabilities are found to depend upon the term structure, correlation between the levels in the term structure and the equity market volatility, the inflation rate and the excess return on the market, illustrating that there exist additional components in default probability that are not present in recovery rates.

Das and Hanouna (2007 b), motivated by the common assumption in the academic literature on the CDS-bond basis that CDS spreads represent pure credit risk, study the link between illiquidity in the equity market and credit default swap spreads. Use of a structural model to analyze hedging CDS[19], as well as regression analysis to study the correlation between equity illiquidity and CDS spreads, reveals that CDS spreads contain a liquidity component[20]. The institutional basis for these results centers on that fact that many CDS sellers of protection engage in hedging activities, typically the seller (buyer) of protection taking a short (long) position in the equity of the reference entity. When there are liquidity frictions (both systematic and unsystematic) in the equity market[21], the cost of delta hedging the short position rises, implying that CDS markets may trade richer than the cash bond market (i.e., lower CDS spreads or a negative basis). The authors derive the hedge ratio of CDS contracts to number of equities,

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[18] The model uses the stock price, stock volatility and debt per share to solve for the value of the firm and the volatility of the firm's value. The other inputs of the model are the forward curve and the CDS spread curve. For each maturity the default probabilities as well as the recovery rates were computed. A structural model is estimated with equity information to identify the relationship between recovery rates and default probabilities, and then these outputs are combined with information from the CDS market in order to decompose spreads into their default probability and recovery components based upon the application of an iterative fixed-point algorithm.
[19] The authors employ a simplified version of the Merton structural model used by Ericsson and Renault (2002). Inputs of this model include firm value, the risk-free rate, volatility of firm assets and the value of equity determined by call options that assumes a strike price of the face value of a zero-coupon debt.
[20] The authors used Bloomberg to obtain CDS spread levels (USD denominated publicly traded company contracts), while firm-level information was retrieved from COMPUSTAT and CRSP.
[21] The authors account for illiquidity in their regression analysis with three measures: the bid-ask spread, the ILLIQ measure of Amihud (2002) and the LOT measure of Lesmond, Ogden and Trzcinka (1999).

and show that this quantity is proportional to the hedging costs[22]. Results further show that the distance to default greatly increases in the explanatory power of the regression, but the T-Bill rate and bid-ask spread has no significance.

Schneider, Sogner and Veza (2007) examine the relationship between the LGD and PD by looking at the former across ratings as a crude proxy for credit quality. The authors find a discontinuity that mostly affects broad ranges in the CDS maturity spectrum, where changes in CDS spreads at the discontinuity is mostly positive, and that the one year CDS spread exhibits time-series variation that higher maturity spreads do not share. The authors use an intensity-based framework that postulates a latent Cox process whose first jump time determines the default time of the obligor, allowing them to price both a risk-free and then a defaultable bond with zero recovery, and parsimoniously model LGD based on the Duffe and Singleton (1999)[23]. Pricing of CDS involves analysis that separates the premium and protection paying parts of the spread, modeling the short rate underlying the riskless discount facto and the default intensity reflecting the instantaneous default probability of the obligor, as well as all possible dependencies between these two processes[24]. They find that distribution of mean observation errors for the short (1 and 3 year maturities) are negatively skewed, which they interpret as the rareness of negative movements in the short maturity CDS spreads; whereas, the distributions of the mean observation errors for the longer maturities are almost symmetric. The estimated results confirm that it is possible to disentangle LGD from default risk, as parameters of the LGD distribution are well identified as inferred from confidence bands of the posterior distributions. Using regression analysis, the authors deduce that sectors and ratings explain approximately 37% of variation in LGD, and are most significant when a firm's rating improves to the BBB level and better[25]. Further analysis reveals that relative jump sizes in the long-run mean are highly distinguishable between sectors, and that sectors with substantial tangible assets are expected to

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[22] The authors also control for financial conditions of the firm using ROA, interest coverage ratio, industry and equity volatility.

[23] The *recovery of market value* in which separation is impossible without resorting to securities non-linear in LGD.

[24] The estimation of the model is performed in two steps. First, the riskless model is estimated on a panel of riskless zero yields, the riskless discount factor employing a three factor affine stochastic volatility jump-diffusion model (Duffe et. al., 2000).). Then the default risk model is estimated at the issuer level using the results of the former, using a 2-factor model, to capture short-term behavior vs. the stochastic long-run mean of the default intensity. This estimation is implemented by means of the *Markov Chain Monte Carlo* (MCMC) technique.

[25] Further statistical tests reveal that upgrades from speculative to investment grade, as well as further rating improvements, give rise to reductions in the number of jumps per year. This dependence on rating grades is explained as that creditworthy obligors are more likely to run into financial distress due to sudden exogenous shocks, but these are very rarely observed.

recover more in default. The final test examines the affect of equity volatility on default intensities, showing that the correlation between them implies the market volatility is associated with higher long-term and short term default factors.

Ashcraft and Santos (2007) investigate if the CDS market has reduced the cost of debt for corporate borrowers, including both corporate bonds and bank loans[26]. Using a matched sample approach to control for the potential endogeneity, they investigate the effect of CDS trading on interest rates firms pay in the cash market, segmenting their results by risk and informational opacity of firms. Initial analysis in fact identifies an increase in the cost of debt (especially for bank loans); albeit these average results are not statistically significant. However, focusing on timing differences within the sample of firms that became traded in the CDS market relative to firms that will later become traded, versus firms that are never traded but have similar characteristics to those that eventually do[27], they show that CDS markets have a significant beneficial (detrimental) impact for safer (riskier) firms, with risk measured by financial leverage or implied volatility. Findings also suggest that CDS trading benefits (hurts) the most transparent (opaque) firms, as measures by either analyst coverage, volatility of earnings forecast error or the bid-ask spread on the firm's stock price. Finally, their findings suggest that liquidity, as measured by the number of quotes on a given business day for a specific contract, plays an important independent role on the effect of CDS trading on firms' future cost of debt, as less liquid firms experience an adverse impact on their cost of debt due to the onset of CDS trading.

Chen, Cheng, and Wu (2008) use a large data set of CDS spread quotes in order to perform a joint analysis of the term structure of interest rates, credit spreads, and liquidity premia, with a focus on the dynamic interactions between the sources of risk. The authors proxy for liquidity by the number of days when a contract has no quotes (Collin-Duffresne, Goldstein and Martin (2001)) and control difference in default risk not captured by ratings by a "distance to default" measured according to the Moody's KMV™ default prediction model. The authors find higher spreads for contracts of lower credit quality, financial firms as compared non-financial firms and less liquid firms. They also find a positively sloped term structure for the average

[26] Corporate bonds may have embedded options and secondary markets may be sometimes illiquid, so that investors may more easily for take positions in CDS contracts. A related issue in examined in the literature is that the CDS market may lead the bond market in price discovery of changes a firm's credit profile, implying that that the CDS market may trade on additional information.

[27] This later approach does not require an assumption that timing is exogenous, but it does require the use of the firms in the control group which appear to be similar.

CDS. Analyzing the average spreads by industry group vs. rating group, they observe stronger co-movements between the spreads within each industry sector than across rating groups, evidence of common shocks within each industry sector, and that within each sector and rating class the higher-liquidity contracts have a much lower mean spread as compared to a less liquid group. The authors also employ a reduced-form model approach similar to that of Duffie and Singleton (1999), modeling the default intensity of a reference entity as a Poisson process, employing an instantaneous liquidity spread and a two-dimensional Markov process for the term structure dynamics; and the authors compare this to structural model approaches[28]. The results of these additional tests illustrate that, especially in the quadratic framework, two interest-rate factors can well explain the term structure of the benchmark interest rates in each industry sector and rating class; as well as for low-liquidity firms. They conclude that firms with active CDS trading tend to have higher credit risk than firms with low CDS trading activity, and that low-liquidity firms have a flatter term structure of credit spreads.

II.a Default/Credit Risk

Credit risk makes up perhaps the largest risk an investor bares when buying a bond,, which theoretically effects all bonds with the exception of certain entities that are effectively default remote (such as the U.S. government). Credit risk is defined as the uncertainty associated with potential loss of either principle or interest on a fixed income obligation, and can be decomposed into the probability of loss and the loss given default. In many cases credit risk is synonymous with default risk, in that default is associated with the inability or unwillingness of a borrower to make payments. However, the concept of credit risk is broader, in that in the event that a borrower suffers severe credit deterioration (e.g., a multi-notch downgrade or steep decline in the price of debt), then is becomes likely that the lender will not receive any future anticipated cash flows and a loss may have to be recognized. Indeed, even in the case of marketable bank debt, a borrower may be deemed unlikely to pay even if the loan is performing. It is for these reasons market participants use derivatives to mitigate such risks using CDS.

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[28] The authors use a three step quasi-maximum likelihood method. The first step estimates the interest-rate factor dynamics using LIBOR and swap rates. In the second step, they take the latter as given and estimate the credit-risk factor dynamics by industry sector and credit rating class using the seven average credit default swap spread series of the more liquid group. In the third step, the authors estimate the additional credit-risk and liquidity-risk factor dynamics for each industry sector and credit rating class using the CDS spreads on the low-liquidity firms.

II.b Credit Ratings

According to the policy and guidelines issued by the Nationally Recognized Statistical Rating Organizations (NRSROs)[29] at any given time credit rating on an issue of debt reflects its relative credit quality. This has the interpretation that a credit rating embodies information on probability of default (PD) relative to a cohort, potentially allowing for a standard comparison of likelihood of default and severity of loss in the event of default. Therefore, ratings represent an opinion of the rating agency regarding potential loss, a firm's capacity to pay back all its sources of financing, as well as the recovery of a particular in the event of default (Micu, Remolona, and Wooldridge 2006). However, there are some subtle differences between the rating agencies (Standard and Poor's (S&P), Moody's and Fitch), as well as the type of ratings that they issue. S&P has historically issued primarily a senior unsecured debt rating, presumably a ranking or pure default risk, and in cases where there is subordinated debt a separate rating that may be worse to reflect the greater recovery risk. On the other hand, Moody's claims to have always issues a debt specific *expected loss* (EL) based rating, such that every debt of an issuer could have different ratings reflective of varying expected LGDs amongst different parts of the capital structure; and in cases where there is senior unsecured debt, a rating that reflects more purely the PD.

However, ratings typically are issued for a firm and not for individual firm debt, since in many cases all of a firm's outstanding debt will have the same rating; this is typically the case of a simple capital structure, such as a firm issuing mostly pari pasu bonds, as opposed to complex capital structures of the very largest firms. The agencies claim that only if a *fundamental* change occurs in a borrower's creditworthiness will they modify the firm's relative credit quality, implying that they would not be reacting to systematic events that affect all firms equally but do not impact relative credit quality[30]. In addition to issuing credit ratings, rating agencies issue rating reviews and outlooks, announcements that signal that material events have occurred that potentially will have an impact on a firm's fundamental credit quality and signal a possible rating

[29] The three most prominent if these are the rating agencies Standard & Poors, Moody's Investors Services and Fitch.
[30] Thus is sometimes terms the *through-the-cycle* philosophy of ratings, as compared to the *point-in-time* orientation of market-based rating schemes.

change. However, a rating change does not have to be preceded by a rating review or outlook, as the latter need not imply an eventual rating change (Micu, Remolona, and Wooldridge 2006)

Rating agencies base their rating assignments on many different factors, some public, as in financial statements or capital markets information, and some private, as in an assessment of management quality or industry position. (Hull, Predescue and White 2004). The agencies also differ in cosmetic ways, as Moody's investment grade credit ratings[31] are coded such that they range from Aaa to Baa3, whereas S&P's and Fitch's corresponding rating codes are AAA to BBB-.

II.c Variables Affecting CDS Spreads

While under certain ideal conditions the theoretical the CDS spread should represent pure credit risk, in practice there are many cases in which this does not hold true. First, one may would argue that both systematic and unsystematic factors *independently* influence spread levels (e.g., interest rates), and pure measures of credit risk should only be influenced systematical factors to the extent that fundamental credit quality is a function of such. For example to the extent that worsening macroeconomic conditions effect the risk aversion of CDS market participants, this may affect spreads above and beyond the detrimental impact on the credit quality of the reference entity (i.e., greater PD). Other variables affecting spread may be said to lay somewhere between systematic and unsystematic factors; a prime example being liquidity, in that we can think of systematic as well as idiosyncratic notions of liquidity[32]

Five of the most common variables found to affect CDS spread include the equity market's implied volatility, industry, leverage of the reference entity, the risk-free rate, and liquidity of the CDS contract. Scneider, Sogner and Veza (2007) find evidence that equity market volatility as measured by the VIX index is positively correlated with long term and short term default factors that directly influence the valuation of the CDS. In the Carr and Wu (2006)

[31] These are issues or issuers considered relatively highly unlikely to default and give rise to a loss and thus relatively safe investments. Below Baa3 and BBB- represent speculative or high yield ratings, firms or issues considered to have a relatively higher likelihood of default or high expected losses, respectively.

[32] As for any traded security, liquidity affects the price of CDS, but unlike the corporate bond market the CDS market exhibits generally higher liquidity as market practitioners can easily get long or short in the CDS market. However, as the CDS market is an OTC market and as such pricing information may not be as easily accessible as in the cash market, it becomes difficult to determine the liquidity of a particular CDS. Theoretically one would assume that CDS contracts that are represented in the CDX indices should be more liquid. To this point, it is difficult to find past research done on CDS valuation that incorporates liquidity of specific contracts.

joint valuation framework for both equity options and CDS contracts shows the influence of the risk-free curve on model implied CDS spreads. Daniels and Jensen (2005), using the Treasury yield curve as a proxy for the risk-free term structure, illustrate the dependence of the value of the CDS contract on the risk-free rate[33].

III. Data

The data was obtained from Bloomberg's 'CDSD' page. The data set began with 2412 Bloomberg supported CDS tickers. The first step was to select companies that had debt types of either 'Senior', 'Subordinate' or 'Other'. The second step was to select from this set CDS contracts with 5 year maturity when we did this 3 CDS contract did not have a 5 year contract. Third, we eliminate 15 CDS contracts that did not have an Equity ticker. At this point we had 1334 CDS contracts with 5 year maturity out of these contract 834 were US Dollar contracts.

The daily spread for each of these contracts were collected from Bloomberg API for the period beginning February 28, 2003 and ending February 28, 2008. Next, any contract with less than 100 days of trading activity were eliminated leaving a sample set containing 391 5-year CDS contracts.

We then used Bloomberg to collect the current Standard and Poor's credit rating for each of these contracts. Because we are looking at data over the period of five years we needed to collect any rating changes that transpired during that time. Once again this information was obtained from Bloomberg. This information was retrieved by using the reference entities equity ticker to look up the firm rating. Bloomberg provides a history of the firm's long term S&P credit rating. We manually extracted all rating changes for the period between February 28, 2003 and February 28, 2008. We chose to use S&P's Long Term credit Rating because our study focuses on the 5 year CDS contract. The 5 year CDS contract's spread represents the risk of the reference entity defaulting within the next five years; thus it is important to represent S&P's long term credit expectations. This information is critical to this study because the study focuses on analyzing the price discrepancies among CDS with the same rating.

The next set of variables we obtained for each contract represented each reference entities' option volatility. We chose four measures of option volatility. The metrics used include

[33] Hull and White (2004) argue the best risk-free curve to use when pricing CDS lies somewhere between the Treasury and the Swap curve. However, ,many practitioners prefer to use the Swap curve, as this is the curve used most often in derivative pricing.

the Historical Put Implied Volatility, Historical Call Implied Volatility, Put Implied Volatility 30 Day, and Call Implied Volatility 30 Day. For the first two data points we extracted the daily prices for the period beginning on February 28, 2003 and ending on February 28, 2008. For the second two data points we collected the daily prices for the period of beginning January 3, 2005 and ending February 28, 2008. The timeframe discrepancy resulted from the lack of availability on Bloomberg. This data was extracted using Bloomberg and referencing the reference entities' equity ticker. This date is incorporated into our regression models. As previous research shows equity market and option market volatility remain key components of CDS valuation. After extracting the information our data set was further reduced as a result of the unavailability of data for non US corporations. The remaining set contained 288 reference entities; some reference entities have 5 year CDS contracts on both their senior and subordinate debt. The remaining set consists of 338 CDS contracts.

To incorporate various market variables into our regression analysis, we extracted numerous market indicators. Using Bloomberg, we obtained the daily prices for the following variable for the period beginning February 28, 2003 and ending February 28, 2008: S&P 500 Index level, VIX Index level, US 5 year Swap yields, and 5 year US Treasury Note yields. We chose their variables based on results from past research. Schneider, Sogner and Veza's (2007) find a relationship between CDS prices and the VIX index. Studies done by Hull and White (2004) determine the best risk-free curve to use when pricing CDS lies between the Treasury and the Swap curve, thus we will incorporate both measures of the risk-free rate into our regression model.

We then categorized the CDS data into groups determined by credit rating. Because credit rating changes overtime the number of names in each category also changes. We determined 5 groups (Rating Categories) including: AAA to AA-; A+ to BBB-; BB+ to B-; CCC+ to CCC-; and D. There exists a sixth group, NR (Not Rated), references entities that had history of NR typically where unrated for a short period of time and then returned to being rated. Approximately 10 percent of the entire data set went unrated for a period of time between February 28, 2003 and February 28, 2008. The groups allow for us to better analyze the implied rating the price of the CDS illustrates. From the daily prices we were able to establish descriptive data for the 20^{th} percentile, 40^{th} percentile, 60^{th} percentile, 80^{th} percentile, 100^{th} percentile. In theory every name in each group will fall within their corresponding percentile. Thus, if a CDS contract has a given rating but does not fall in its corresponding percentile one can conclude the market implied a different relative credit quality than the rating agencies. Figure 1 displays the distribution of daily CDS spreads by rating categories.

IV. Empirical Analysis

The main empirical results of this study are shown in Tables 1 through 3. In Table 1 we present our leading two models for the logarithm of the CDS spread, LCDS. Table 2 tabulates the results of the models for the CDS Category (CDSC) and the Rating Category (RTGC). CDSC is oriented such that 1 is lowest daily quintile of the CDS spread (i.e. best in terms of the CDS credit signal), and 5 is the highest quintile of the CDS spread (i.e., the worst CDS credit signal). RTGC represents a simple re-coding of the S&P rating, oriented in the same manner as CDSC, such that 1 is the best rating and 5 is the worst rating. In Table 3 can be found the results of models for CDSC and RTGC agreement (AGREE), as well as for the distance between the CDSC and RTGD (DIST). AGREE is an indicator that takes the value 1 if TGC and CDSC are the same and 0 if they are different. DIST is CDSC minus RTGC, such that if this is positive (negative), then the CDS credit signal is worse (better), or that the issue is priced more cheaply (richly) in the CDS market as relative to that implied by the agency rating [34]. All models are cross-sectional time series regression models estimated using the method generalized least squared (GLS). Across all models, we note that in all cases all coefficient estimates are statistically significant at the 1% level, and overall goodness of fit measures compare favorably with what has been seen in the literature.

In the LCDS regression of Table 1, where we show our two leading models, we see that our set of covariates can explain anywhere from 29% to 40% of the variation in CDS spreads. However, note that Model 1, having market capitalization in lieu of trading volume in Model 2, is slightly better by this metric than Model 2. Model 1 has an r-squared between (across) cross-sectional groups of 39.6% (37.8%), while the respective statistics for Model 2 are 32.0% (29.0%).

[34] For example, example is cds=5-rating=1 distance=+4 which means cds' credit signal is the worst (high spread) but rating's credit signal is the best(like AAA). Then using your terminology CDS spread is expensive compared to ratings. So if distance is (-) an example is cds=1-rating=5 distance=-4 which means cds' credit signal is the best (low spread) but rating's credit signal is the worst (like CCC). Then using your terminology CDS spread is cheap compared to ratings.

We first note that our the sign on our S&P 500 index return (SP500) state of the market variable is positive. The fact that LCDS increases with decreasing SP500, which says that when the market is down overall then CDS spreads are higher on average, is intuitive if we think that better performing equity (or general market performance) moves firms further from their default points and results in narrowing of CDS spreads. The magnitudes of the estimates suggests that every 1% increase in the S&P5000 return lowers CDS spreads on average by 5%-8%, all else equal, which is economically meaningful.

It is also the case that LCDS increases with increasing VIX. The measure of aggregate option-implied equity market volatility (the "fear index"), which tells us that when expected market-wide risk is higher than CDS spreads are higher as well. This too makes since, since greater market volatility implies a greater likelihood of large drops in equity values, which implies greater default risk and is accompanied by a widening of credit spreads. The size of the estimates imply that for every percentage point increase in the VIX, CDS spreads go about 2% higher from their base level, which we deem to be an economically significant result.

Next, we observe that LCDS is increasing with the slope of the yield curve, or the Term Premium (TP), as measured by the difference between the 5-year Treasury note yield and 3-month Treasury bill yield. This may or may not be consistent with prior expectations, as one story that can be told is that a steeper yield curve implies better future macroeconomic performance, which should portend better firm-level performance and lower default risk, which in turn we would expect to be associated with lower CDS spreads. On the other hand, it is equally plausible that a steepening yield curve signals higher expected inflation, which is usually accompanied by tightening of monetary policy by the Federal Reserve, and in turn is likely to be detrimental to economic growth and associated with higher default risk and inflated CDS spreads. According to the magnitude of the coefficient estimates, we can interpret this result as that a 1% absolute increase in the TP is associated with an 0.20% proportional rise in average CDS spreads, ceteris paribus, an economically substantial reaction.

The LCDS spread is found to be increasing in the yield premium (YP), measured as the difference between 5-year swap rate and the 5-year Treasury note yield. As this difference is an approximate measure of credit risk amongst participants in the inter-bank market, and when this is higher there is greater aggregate credit risk particular to this sector, then we believe that this result is sensible. Furthermore, the YP also captures potential liquidity issues amongst banks, and as this risk is reflected to some extent in the CDS spread, we have further justification for the sign of this coefficient. The economic significance of this variable is the highest amongst all the explanatory variables in this regression, as just about a 1% proportional change in CDS spreads is accompanied by a 1% absolute increase in the YP.

The more senior is the debt in the capital structure, the lower the log of the CDS Spread, as measured by a dummy variable for a senior (as opposed to a subordinated) debt issue (SEN). This is as expected, as there is lower recovery risk associated with issues further up in the pecking order, and recovery risk is a component of the CDS spread (i.e., credit loss can be decomposed into the product of a probability of default and a loss in the event of default component, and the latter is one minus the recovery rate). The magnitude of the coefficient estimate suggest that for every rung higher on the capital structure is the issue, the lower is the CDS spread on average by a proportion 0.17%-0.24%.

The LCDS is increasing in put implied volatility (PIV), which is the equity volatility as implied from put options on the equity shares of the reference entity. We consider this to be well in line with the conventional theories of CDS spread determination, as more volatile equity returns are consistent with a depressed distance-to-default of the issuer, and a concomitant increased default risk. This result is also economically significant, as a 1% higher PIV leads to a 0.8 to 1.2 positive percentage change in CDS spreads.

Next, we consider two alternative proxies for the liquidity of the debt issue, the logarithms of market capitalization (LMCAP) and trading volume (LTVOL), both with respect to the equity of the issuer, which distinguish the two models of LCDS that we present herein. We observe that both measure MCAP and TVOL are inversely related to LCDS, with a $1M ($1#) increase in LMCAP (LTVOL) implies a 0.51% (0 .03%) proportional decrease in CDS spreads. This is quite intuitive, as it is well-known that there is a liquidity component to CDS spreads.

The higher is the issuer’s ratio of long-term debt to shareholder’s equity (LEV), the higher are the CDS spreads. This has a natural interpretation that more levered borrowers, who are more likely to default, have wider CDS spreads that reflect this increased risk. We note that this variable is the second most economically significant, as the coefficient estimate implies that a proportional change in CDS spreads ranging from 5% to 10% follows a 1% in creased in an issuers LEV.

Higher earnings estimates, as measured by Bloomberg's collection of analysts' EPS forecasts (EPSAE), are associated with lower CDS spreads. This is another intuitive result, as higher profitability lowers the default risk, as well as the CDS spreads.

Finally, we examine the time trend variable (TIME), which is positive and significant. As we see in the summary statistics by year and the time plots, CDS spreads have increased over the time period covered by the sample, which is consistent with the sign of this coefficient estimate. We put this variable in the regression in order to account for this strong trending and possible issues with non-stationarity of the dependent variable. The magnitude of the estimates suggests that spreads increased proportionately on average 0.05%-0.07% per year during this period.

In the CDSC and RTGC regressions of Table 2, we show our leading model, which has the same set of explanatory variables across both dependent variables. Our set of covariates explains anywhere from 29.5% (across cross-sections) to 41.4% (within cross-sections) of the variation in CDSC, but only 16.7% (across cross-sections) to 23.9% (within cross-sections) of the variation in RTGCs. It is no surprise to us that the latter has lower explanatory power, as agency ratings are "sticky" as compared to ratings implied from relative CDS spreads.

We first note that our the sign on our S&P 500 index return (SP500) state of the market variable is negative for both CDSC and RTGC, which is in line with our results in table 1 for LCDS, which is as expected since CDSC is simply a discretization of the spreads (and spreads are positively correlated with ratings). The fact that CDSC and RTGC increases with decreasing SP500, which says that when the market is down overall then CDS spreads are higher and agency ratings are worse on average, is intuitive if we think that better performing equity moves firms further from their default points and results in lower default risk.

It is also the case that CDSC and RTGC both decrease with increasing VIX. The measure of aggregate option-implied equity market volatility tells us that when expected market-wide risk is higher then, CDS implied ratings as well as agency ratings are higher (worse) as well. This too makes since, since greater market volatility implies a greater likelihood of large drops in equity values, which implies greater default risk and is accompanied by a widening of credit spreads.

Next, we observe that CDSC and RTGC are both increasing with the slope of the yield curve TP. This may be consistent with prior expectations, as a steepening yield curve may signal heightened inflationary expectations, which is typically followed by higher short term interest rates at the behest of the Federal Reserve, which in turn is likely to imply slower economic growth and higher default risk.

CDSC and RTGC are both found to be increasing in the YP. As YP is an approximate measure of credit risk amongst participants in the inter-bank market, when this is higher there is greater aggregate credit risk particular to this sector, which is likely associated with greater CDS spreads (and the ratings implied from those) and rating agency downgrades. Furthermore, the YP also captures potential liquidity issues amongst banks, which is likely impounded into CDSC and RTGC measures.

The more senior is the debt in the capital structure, as measured by SEN debt issue indicator, the better the CDSC and RTGC. This is as expected, as there is lower recovery risk associated with issues that are better ranked in the capital structure, and the Loss given Default (or LGD, one minus the recovery rate) enters multiplicatively into the theoretical CDS spread.

Both the CDSC and RTGC. is increasing in PIV, a result in line with the theory of CDS spread determination, as more volatile equity returns imply shorter distance-to-default of the issuer. The latter is accompanied increased default risk, and hence higher CDS implied ratings (CSDC), as well as agency rating downgrades (RTGC).

Consider a proxy for the liquidity of the debt issue, LMCAP is inversely related to both the CDSC and RTGC. This is quite intuitive, as it is well-known that there is a liquidity component to CDS spreads as well as to the rating criteria of the agencies, and when liquidity is better we expect better ratings as implied from CDS spreads, as well as better ratings as received from the agencies.

The higher is the issuer’s LEV; the worse is either the CDSC or RTGC rating. This has an intuitive interpretation that more levered borrowers, who are more likely to default, have both wider CDS spreads (and hence worse CDSC) as well as worse agency ratings (higher RTGC), that reflect this increased risk..

Higher earnings estimates, as measured by the Bloomberg EPSAE forecast, are associated with worse CDSC and RTGC. This is another intuitive , as we may easily think that the higher is expected profitability, then the lower default risk; and this will be reflected in either lower CDSC (when CDS spreads are lower) or lower RTGC (firms are upgraded).

Finally, we examine the time trend, and see that TIME is positively related to both CDSC and RTGC. As seen in the diagnostic plots, CDS spreads have increased over the time period covered by the sample, which is consistent with deteriorating credit quality over this time period. That is expected to be associated with widening spreads, reflected worse CDS implied ratings CDSC, as well as downgrades by the rating agencies, seen in higher RTGC.

Our models for AGREE and DIST, the regression results for which shown in table 3, have a little less overall explanatory power as compared to the previous models for LCDS, RTGC or CDCC: r-squareds of 21.8% and 27.1% (17.1% and 22.9%) for AGREE (DIST) across and within cross-sections, respectively.

SP500 increases the estimated chances of agreement and decreases the distance between the CDSC and RTGC. We interpret this as reflective of an increased flow of information during down markets which could augment the differences between agency and market-based assessments if credit risk – i.e., the agencies are taking a "through-the-cycle" on credit risk, or have trouble keeping up. Alternatively, during declining markets factors that tend to drive this wedge, such as liquidity or investor risk aversion, are more prominent during such episodes. The magnitudes of the coefficient estimates suggest that a 1% increase in the SP500 is associated with a 2 (1) bp increase (decrease) in the odds of agreement (probability of a 1-notch discrepancy).

Consistent with our result on the SP500, we see that matters are reversed with respect to the VIX, as our fear gauge is associated with either lower odds of agreement or greater odds of a more severe credit assessment in the CDS market as compared to the rating agencies. This is explainable as that in more volatile environments, investor risk aversion is heightened and it is therefore more likely that not only does the CDS market not agree with the agencies, but that it reflects a more severe measure of credit risk. Magnitudes of coefficient estimates tell us that for every 1% increase in the VIX we can either expect the probability of agreement to decline by 0.8%, or the probability of an additional one rating difference from CDSC and RTGC to increase by about 1%.

An increasing TP is associated with either a lower predicted likelihood of agreement or a greater distance between CDS implied and S&P ratings. We speculate that to the extent a that the yield curve becomes more upwardly sloping, which can lead to central bank tightening and a worsening economic environment, then the rising investor distress that would accompany such a downturn might be reflected in CDS spreads at a faster rate than ratings would change for the worse. An alternative explanation is that rating agencies would be looking ahead to better economic conditions, while the CDS market would tend to maintain a shorter term view, which would lead to and declining AGREE or widening DIST. The size of the coefficient estimates suggest substantial economic significance of the TP in explaining these discrepancies, with every 1% widening implying a -2% decline in the chances of agreement, or a 7% increase estimated probability of the CDS implied rating moving one notch above an S&P rating.

However, we are seeing a result for YP that in a sense is at variance with the previous regression results, as here we see that AGREE is increasing and DIST is decreasing in YP. What we observed previously is that on average CDS spreads, the ratings implied from them or assigned by the agencies all imply higher credit risk as YP increases. The story is that increased credit risk amongst the inter-bank market participants is indicative of a worse credit market environment and riskier issues. The only possibility is that the rating agencies behave differently in such environments, and are in greater harmony with the CDS market. The results are also robust in terms of economic impact, with a 1% rise in the YP associated with a 7% greater probability of agreement and -19% lower chance of the CDS implied rating moving one additional notch worse than the S&P rating.

More senior issues are associated with either higher probabilities of agreement, or a shorter distance, between the CDSC and RTGC. This result is readily explainable, in that less senior debt is likely to be evaluated with greater skepticism amongst risk averse investors in the CDS market, in contrast to analysts at S&P. The size of the estimates implies that senior issues have a 3% lower probability of a divergence in the credit risk ranking between the agencies and the CDS market, as well as a 42% higher probability of the CDS implied rating exceeding the S&P rating by an additional category.

We see from Table 3 that greater put implied volatility of the issuer's equity decreases the estimated probability of an agreement, and increases the odds of a positive increment in distance, between the CDSC and RTGC. The intuition is rather simple in our opinion – to the extent that PIV is associated with increasing distress of the issuer, we would expect this to be impounded to a greater extent into the CDS market's measure of credit risk, as it accounts for factors like investor risk aversion and liquidity that the rating agencies may not incorporate into their rating assessments. This variable has very high economic significance, as a one percentage increase in PIV gives rise to and 18% decline in the chances that the CDS market and S&P agree upon the relative credit quality of the issue, as well as more than a 50% rise in the estimated probability that the CDS implied rating becomes one notch worst than the agency credit rating.

Our results imply that the debt of larger issuers are more likely to have debt ratings from S&P that are in harmony with the CDS spread implied rating, as well as that the latter tend to be closer to the former according to our DIST measure. We venture to speculate that for such larger firms, better quality and volume of information is a mitigant to phenomena that likely drive a wedge between the credit risk assessments of the CDS market and the rating agencies (e.g., credit risk premia or liquidity effects). Furthermore, this effect is robust in magnitude, implying that roughly for every tripling in market capitalization of the issuer, it is 4.5% more probable that S&P agrees with the CDS market, and that there is a reduction in the distance between the respective ratings by a category of about -32.5%.

More levered issuers are less likely to have debt that is rated similarly according to S&P and the CDS market, and is more likely that the divergence will widen. In line with the previously discussed results, as leverage is associated with an increase in the default boundary and elevated risk of default, which in turn increases risk premia demanded in the CDS market above and beyond risk of credit loss that is the focus of the ratings agencies. Our estimates are economically meaningful, as we see that every 1% increase in leverage results in a -4.9% reduction in the likelihood that the S&P rating and our CDS spread derived rating agree, as well as an 11.0% inflation in the estimated probability that the discrepancy between the two widens by one in the direction of a worse CDS implied rating relative to S&P.

An improving EPS estimate amongst analysts is associated with a greater probability of agreement, as well as a lesser difference, between CDS implied and S&P credit ratings. We interpret this result as that to the extent that better analysts' EPS estimates of the issuer imply lower credit risk; the this leads to a decline in the factors that would drive a wedge between the RTGC and CDSC, such as investor risk aversion. The magnitudes of the coefficient estimates are such that every 1% increase in EPSAE results in a 1.3% greater estimated probability of agreement, or a -6.8% lesser chance of a one notch disagreement, in the CDS implied and S&P assigned credit rating.

Finally, in examining the time trend, we observe that over the sample period on average there has been less agreement and greater difference between the credit ratings as implied in the CDS market and assigned by S&P. This makes sense, in that we approach the financial crisis and economic downturn period toward the end of the sample period, where issuers are generally in a state of worse credit quality, wherein factors such as investor risk aversion or liquidity are give rise to more severe credit assessments in the CDS market vis a vis the rating agencies. As we advance one year, the estimated probability of agreement declines by -0.07%, and the probability of the difference between the CDSC and RTGC increasing by an additional notch increases on average by 0.06%.

V. Conclusions

CDS spreads theoretically represent the amount of compensation demanded for taking on pure credit risk of the underlying reference entity. As noted by Callen, Livnat and Segal (2007) although CDS premium is related to credit ratings by rating agencies, there is quite a variation in CDS spreads that are observed for firms with a given rating. Our results confirm with their finds. Marian Micu, Eli Remolona and Philip Wooldridge (2006) find that more often than not CDS price changes occur prior to rating announcements. Rating announcements are still an important source of information.

Our finds indicate similar results found in previous research done on CDS. Our model for explaining the CDS spread incorporated many of the variables that other researchers found to be significant. Furthermore, all our models are statistically significant. Both our coefficients and statistical significant of variables such as Put Implied Volatility, VIX Index, and 5 year T-Note yielded similar results to prior research. Our findings suggest that The VIX index, 5 yr T-Note, Implied Put Volatility and Credit Quality are facts that can better determine CDS Spread. Thus, CDS Spreads reflect not only pure credit risk of the reference entity, but also macro market factors that affect a company's likelihood of default.

When using regressions to explain Rating Categories our results concluded that both CDS specific as well as macro market factors are statistically significant when trying to determine the daily Rating Categories for a given CDS. CDS spreads are the asset specific variable included in our models.

In the models used to explain CDS Categories most variables are always statistically significant at above the 90th percentile. We observe differences in the Rating and CDS Categories. Much of our data had a given rating and a CDS Spread that did not reflect that rating meaning the market perceives the average CDS in a given Rating Category as either more or less risky than its credit rating would dictate. These observations were evident throughout our observed period from February 28, 2003 to February 28, 2008. We used to models to better explain the factors that could lead to this. Both models are statistically significant.

Our results suggest that credit ratings do not always correspond with relative riskiness of a reference entity. The market prices risk soon than rating agencies. The price of risk that the market demands is a function of more macro and micro factors that can be explained using statistical analysis.

References

Ashcraft, Adam B. and Santos, João A.C., "Has the CDS Market Lowered the Cost of Corporate Debt?" Available at SSRN: http://ssrn.com/abstract=995728

Callen, Jeffrey L., Livnat, Joshua and Segal, Dan, "The Impact of Earnings on the Pricing of Credit Default Swaps" (February 15, 2007). Available at SSRN: http://ssrn.com/abstract=949322

Chen, Ren-Raw, Cheng, Xiaolin and Wu, Liuren, "Dynamic Interactions between Interest Rate, Credit, and Liquidity Risks: Theory and Evidence from the Term Structure of Credit Default Swap Spreads" . Available at SSRN: http://ssrn.com/abstract=779445

Daniels, Kenneth N. and Shin Jensen, Malene, "The Effect of Credit Ratings on Credit Default Swap Spreads and Credit Spreads" . Journal of Fixed Income, December 2005 Available at SSRN: http://ssrn.com/abstract=868688

Das, Sanjiv Ranjan and Hanouna, Paul E, "Implied Recovery" (March 1, 2007). Available at SSRN: http://ssrn.com/abstract=1028612

Das, Sanjiv Ranjan and Hanouna, Paul E, "Hedging Credit: Equity Liquidity Matters" (October 9, 2007). Available at SSRN: http://ssrn.com/abstract=1028735

Hull, John C., Predescu, Mirela, and White, Alan, “The Relationship Between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements” Journal of Banking & Finance Volume 28, Issue 11, November 2004, Pages 2789-2811

Hull, John C, *Fundamentals of Futures and Options Market*, Fifth Edition 2005, Prentice Hall, Upper Saddle River, New Jersey

Micu, Marian, Remolona, Eli M. and Wooldridge, Philip D., "The Price Impact of Rating Announcements: Which Announcements Matter?" (June 2006). BIS Working Paper No. 207 Available at SSRN: http://ssrn.com/abstract=911598

Schneider, Paul Georg, Sögner, Leopold and Veza, Tanja, "The Economic Role of Jumps and Recovery Rates in the Market for Corporate Default Risk" (November 21, 2007). Available at SSRN: http://ssrn.com/abstract=961341

Villouta, Christian, "Empirical Study of Liquidity Effects in the Relation between Corporate Credit Spread and Credit Default Swaps" (June 2006). Available at SSRN: http://ssrn.com/abstract=906165

Wu, Liuren and Carr, Peter P., "Stock Options and Credit Default Swaps: A Joint Framework for Valuation and Estimation" (September 26, 2006). Available at SSRN: http://ssrn.com/abstract=748005

Table 1

	Ln (CDS Spread)				Ln (CDS Spread)		
Explanatory Variables	**Coefficient**	**z**	**P>|z|**		**Coefficient**	**z**	**P>|z|**
S&P 500 Index	-0.00051	-30.50	0.000		-0.00076	-43.49	0.000
VIX	0.02129	68.49	0.000		0.01960	60.23	0.000
Yield Curve slope= 5yrTnote rate - 3moTbill rate	0.19998	75.55	0.000		0.19621	71.33	0.000
Yield premium= 5yrSwap rate - 5yrTnote rate	1.01307	93.39	0.000		1.04658	92.79	0.000
Senoir debt?	-0.17272	-2.94	0.003		-0.24221	-3.92	0.000
Put implied volatility	0.00801	78.74	0.000		0.01226	121.74	0.000
Ln (Market Capitalization)	-0.50884	-117.93	0.000				
Ln (Trading Volume)					-0.02641	-14.57	0.000
Debt/Equity Ratio	0.05216	13.68	0.000		0.09640	24.46	0.000
EPS estimate	-0.00023	-9.06	0.000		-0.00085	-3.84	0.000
Time trend	0.00070	51.93	0.000		0.00057	40.90	0.000
Constant	7.86501	87.78	0.000		2.76891	31.71	0.000
Number of observations	270,191				270,191		
R^2 between	0.3956				0.3202		
R^2 overall	0.3781				0.2897		
Wald Chi^2	144,789				81,650		
Prob > Chi^2	0.000				0.000		

Table 2

	CDS Category			Rating Category		
Explanatory Variables	**Coefficient**	**z**	**P>|z|**	**Coefficient**	**z**	**P>|z|**
S&P 500 Index	-0.00017	-4.63	0.000	-0.00008	-8.75	0.000
VIX	0.01195	17.49	0.000	0.00324	21.98	0.000
Yield Curve slope= 5yrTnote rate - 3moTbill rate	0.07756	13.34	0.000	-0.00121	-1.20	0.230
Yield premium= 5yrSwap rate - 5yrTnote rate	0.22034	9.24	0.000	0.01253	1.92	0.055
Senoir debt?	-0.53738	-5.15	0.000	-0.05448	-1.96	0.050
Put implied volatility	0.00684	30.58	0.000	0.00059	9.88	0.000
Ln (Market Capitalization)	-0.50707	-53.75	0.000	-0.17810	-92.54	0.000
Debt/Equity Ratio	0.10259	12.30	0.000	0.01205	7.48	0.000
EPS estimate	-0.00407	-8.72	0.000	-0.00319	-28.89	0.000
Time trend	0.00046	15.40	0.000	0.00012	19.22	0.000
Constant	7.66292	44.99	0.000	3.71576	79.65	0.000
Number of observations	270,191			270,191		
R^2 between	0.4144			0.2391		
R^2 overall	0.2953			0.1668		
Wald Chi^2	12,877			6,903		
Prob > Chi^2	0.000			0.000		

Table 3

	Agreement				Distance		
Explanatory Variables	**Coefficient**	**z**	**P>|z|**		**Coefficient**	**z**	**P>|z|**
S&P 500 Index	0.00019	14.28	0.000		-0.00011	-2.81	0.005
VIX	-0.00823	-37.51	0.000		0.00972	13.70	0.000
Yield Curve slope= 5yrTnote rate - 3moTbill rate	-0.01573	-10.52	0.000		0.07276	12.06	0.000
Yield premium= 5yrSwap rate - 5yrTnote rate	0.06849	7.06	0.000		-0.18743	-7.57	0.000
Senoir debt?	0.03355	2.37	0.018		-0.42278	-4.18	0.000
Put implied volatility	-0.00178	-19.94	0.000		0.00640	27.55	0.000
Ln (Market Capitalization)	0.04476	16.24	0.000		-0.32500	-33.25	0.000
Debt/Equity Ratio	-0.00494	-2.12	0.034		0.11026	12.75	0.000
EPS estimate	0.00126	8.01	0.000		-0.00677	-13.98	0.000
Time trend	-0.00014	-15.36	0.000		0.00032	10.29	0.000
Constant	-0.59236	-15.59	0.000		3.74358	22.09	0.000
Number of observations	270,191				270,191		
R^2 between	0.2706				0.2286		
R^2 overall	0.2178				0.1706		
Wald Chi^2	8,211				6,320		
Prob > Chi^2	0.000				0.000		

Figure 1

Distribution of Daily CDS Spreads by Rating Categories