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SURVEY OF THE LITERATURE

CREDIT DEFAULT SWAP SPREADS

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We review the literature on credit default swap spreads, which are fast replacing bond spreads as source data for analyzing and predicting credit risk. We review results that examine the basis, i.e. the difference between bond and CDS spreads, enabling the extraction of liquidity measures. Results show that pure structural models may be enhanced by macro and firm-level variables to better explain spreads; credit premiums extracted from reduced-form models are highly variable; and that there are statistically significant interactions between the term structures of interest rates and spreads.

1 Introduction to CDS

A Credit Default Swap (CDS) can be succinctly described as a traded insurance contract which provides protection against credit risk in exchange for periodic premium payments. More precisely, CDS payoffs are linked to the credit risk of a given entity. The reference entity may be a publicly traded or private firm, the subsidiary of either type of firm, a sovereign government, or a governmental agency.

The buyer of the CDS receives the benefit of protection from credit risk in exchange for periodic payments (usually quarterly) until the contract expires or a predefined credit event occurs. Credit events are determined by the International Swaps and Derivatives Association (ISDA) and include 1-Bankruptcy, 2-Obligation Acceleration, 3-Obligation Default, 4-Failure to Pay, 5-Repudiation or Moratorium, and 6-Restructuring. Since all credit events but restructurings (no longer considered a credit event after 2002), are linked to default by the reference entity the term "credit event" is often replaced by "default". Furthermore, since CDS are traded Over the Counter, contracts with any maturity are possible. However, the most common and liquid maturity is the 5-year swap as is shown in Figure 1.

In the event of default, the buyer of the CDS 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 since the last periodic payment date. The spread on the CDS is the annualized premium rate using an actual/360 day convention which is quoted as

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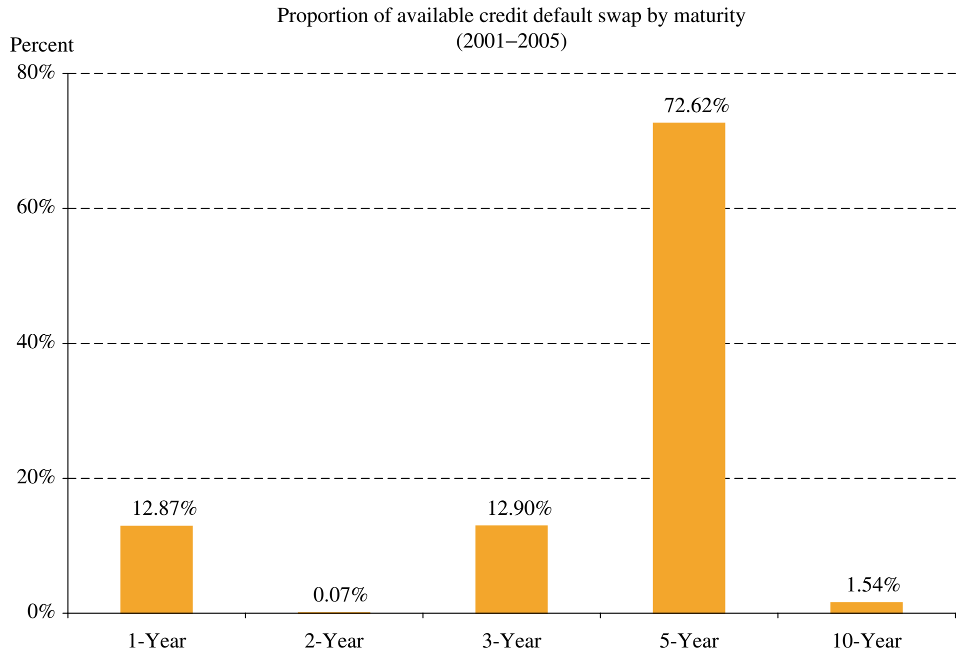

Figure 1 Proportion of available CDS spread quotes by maturity from Das *et al.* (2006). The sample consists of 2860 CDS-quarter Bloomberg quotes on publicly traded firms over the period 2001–2005.

a fraction of the underlying debt's notional value. The spread will thus be higher for CDS on reference entities that possess poor credit quality and *vice versa*. Figure 2 shows 5-year CDS spreads for investment grade firms plotted against Return on Asset (ROA), Return on Equity (ROE), Firm Size and Leverage Ratio percentiles. The plots also show the fitted quadratic regression line with 95% confidence limits for predicted values. The plots show that high credit quality firms–firms with higher performance as measured by ROA or ROE, and firms with low leverage as measured by the ratio of Liabilities to Assets-have CDS securities with low spreads. Additionally, firm size appears to be mildly associated with lower CDS spreads.

When default occurs there are two accepted settlement procedures or "protocols": 1-physical settlement, which is the most widely used, and 2-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. 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 given default or LGD. The recovery rate is calculated by either referencing dealer quotes or by observing market prices over some period after the default occurred.

To illustrate how CDS securities operate, suppose that the buyer of protection purchases a 5-year CDS security with a spread of 300 basis points and that the notional value of the underlying debt on which protection is purchased is \$20 million. Then the buyer of the CDS will make quarterly payments of 0.03 times \$20 million divided by 4 (since the CDS is quoted in annualized rates), which equals \$150,000. In case the reference entity defaults and assuming further that the recovery rate is 40% then settlement is as follows: the seller compensates the buyer for the loss on the face value which is \$12 million and the buyer pays the premium

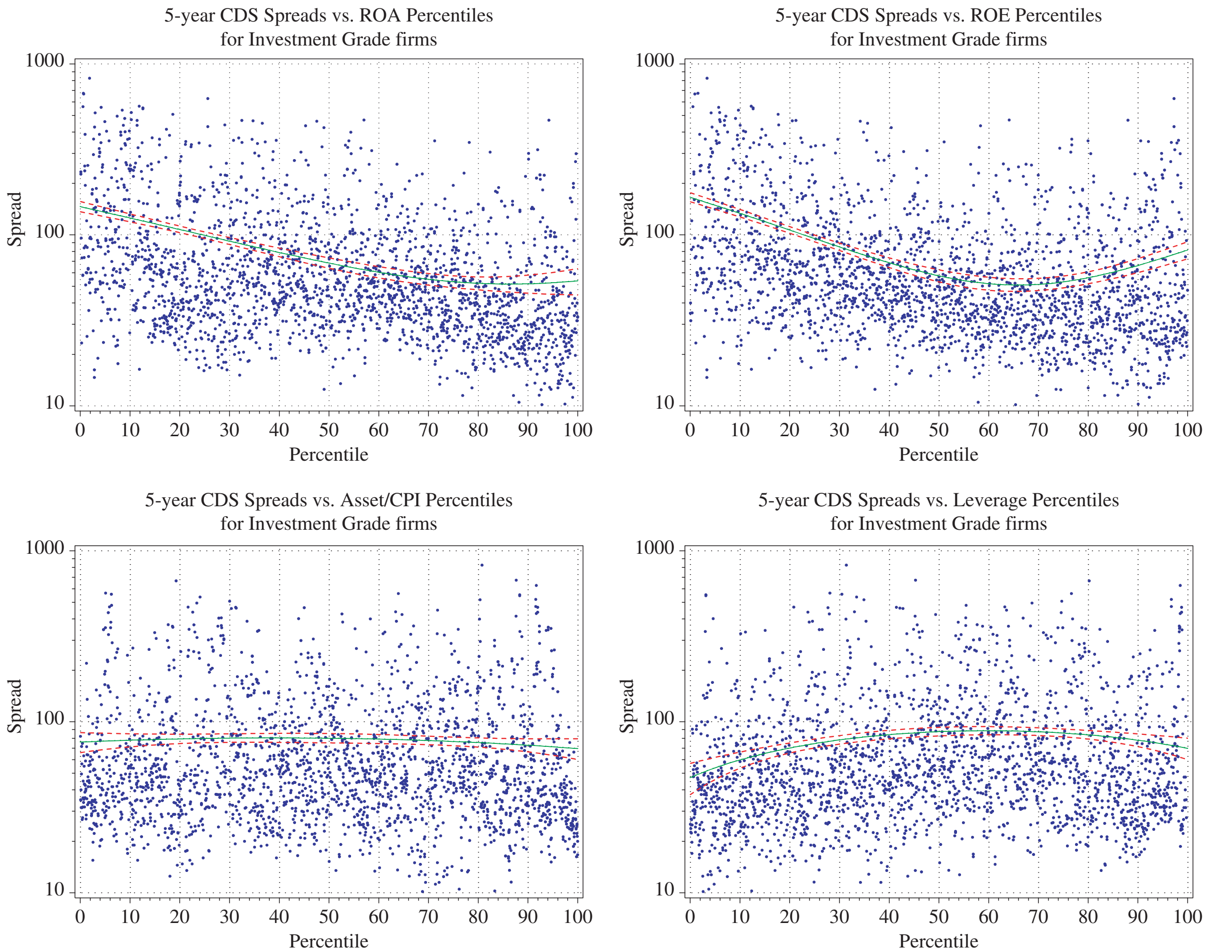

Figure 2 CDS spreads vs Percentiles of Firm-Specific Characteristics. The data consist of 1867 quarterly 5-year CDS spreads on investment grade firms over the period 2001–2005. The data on 5-year CDS spreads are obtained from Bloomberg as in Das *et al.* (2006). Firm specific data is from the quarterly Compustat database. ROA is calculated as Net Income (Item 69) to Assets (Item 44). ROE is defined as Net Income to Common Equity (Item 59). Leverage is Liabilities (Item 54) to Assets. The deflator is the Bureau of Labor Statistics CPI Index. The solid green line is the fitted quadratic regression and the dashed red lines are the 95% confidence limit bands for the predicted values.

which accrued since the last payment. For example, if default occurs 1 month after the last premium was paid the accrued premium would be $150,000 times one-third or $50,000.

Although the concept of protecting suppliers of credit against default is surely quite ancient with letters of credit and credit guarantees (Bystrom, 2005) the innovation of the CDS instrument is to make it easy to trade credit risk separately from the underlying debt. One aspect of the CDS is that it is unfunded, meaning investors do not make an upfront payment, which enables them to leverage their positions. These innovations explain why the CDS market has grown very rapidly over the last few years as in shown in Figure 3. Notably, the ISDA reports that the total notional value of underlying debt grew from $630 billion in 2001 to over

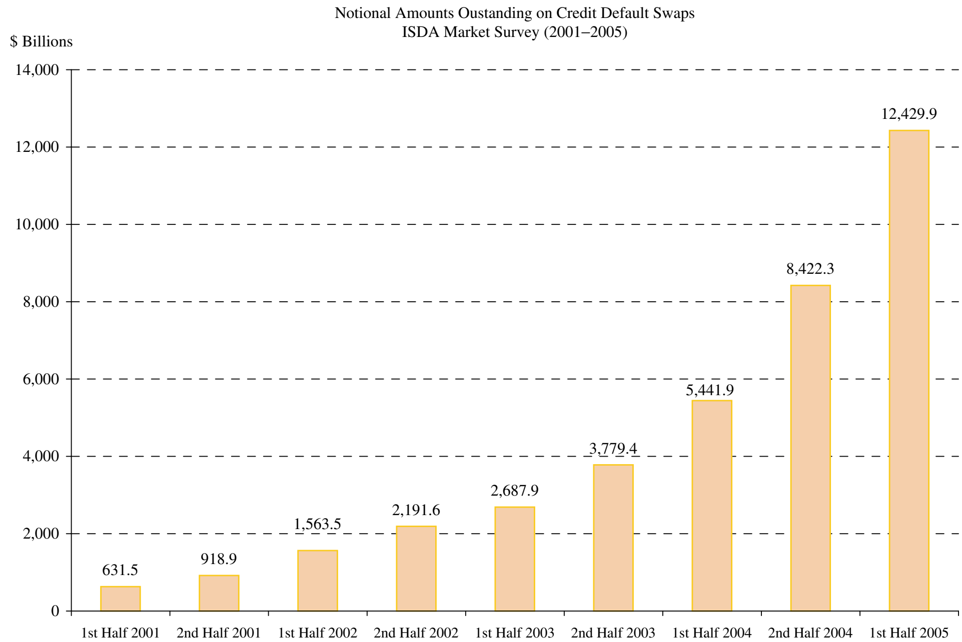

Figure 3 Growth of the CDS market from 2001 to 2005.

$12 trillion in 2005. Particularly, CDS instruments have been very popular among hedge funds wishing to hedge current credit risk exposures or wishing to take a bearish credit view. An important interest to hedge funds is the possibility of long-short CDS trading strategies particularly involving reference entities that are in the process of merging or being acquired. In the latter strategy one reference entity's credit risks are expected to improve, while the other is expected to worsen. Thus, not surprisingly, the most popular CDS contracts are on reference entities with credit ratings that are just short of speculative grade as is shown in Figure 4.

The rest of the article is structured as follows: We first review the recent research that uses CDS spreads in reduced-form models before proceeding to applications in structural models. The last section concludes.

2 CDS spreads in reduced form models

Prior to the development of the CDS market, the term structure of credit spreads was obtained from traded corporate bonds. The CDS market now offers an additional approach to obtaining spreads, and the difference between spreads in the cash/asset market and the CDS market is known as the "basis". The basis is a function of the various differences between the bond and CDS markets. Most notably, these tend to be tax and liquidity effects, as well as other technical differences.

As discussed in Kumar and Mithal (2001), a CDS contract may be replicated using an asset swap. In order to synthesize the position of a seller in a CDS contract, the following sequence of trades may be executed:

1. Purchase the fixed rate reference bond (asset); this results in a periodic inflow of the coupon on the bond, which we denote c.
2. Raise floating financing in the amount required to purchase the asset. This results in a periodic outflow of Libor plus a spread s_1, that is, $L + s_1$.
3. Enter into an interest rate swap to pay fixed rate c and receive floating rate $L + s_2$.

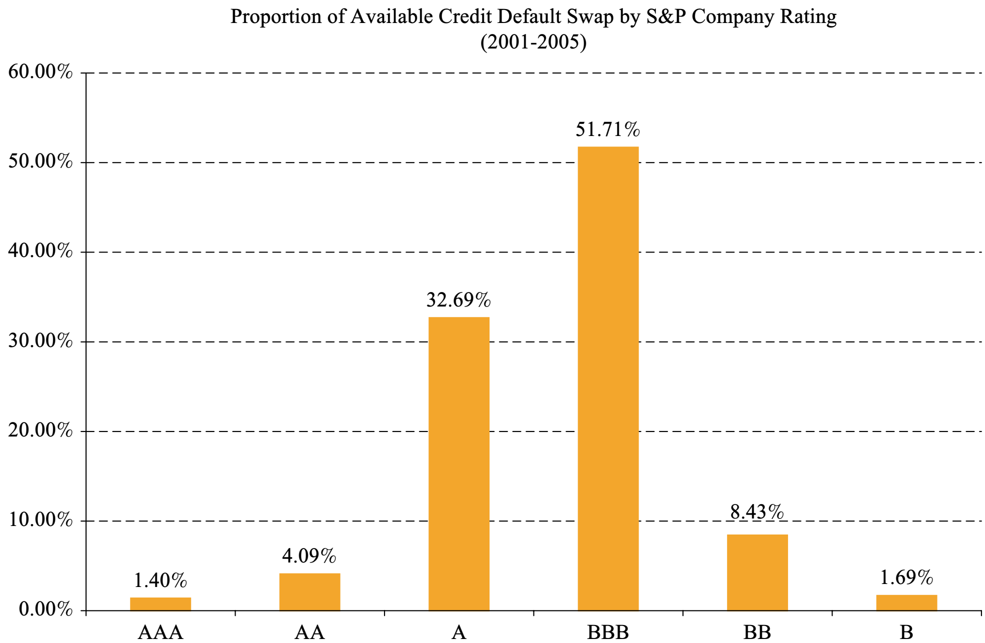

Figure 4 Proportion of available 5-year CDS spread quotes by Standard & Poor's Rating from Das *et al.* (2006). The sample consists of 2077 CDS-quarter Bloomberg quotes on publicly traded firms over the period 2001–2005.

4. This results in a periodic flow of $s = s_2 - s_1$.
5. In the event that the reference instrument does not default over the life of the contracts, the seller of this synthetic CDS receives a spread basis s.
6. In the event of default occurring, the seller of the synthetic CDS unwinds all these transactions. Further, since the reference asset recovers fraction ϕ of the bond, the seller of the CDS loses fraction $(1 - \phi)$ of the fixed rate bond.

Viewed in this manner, there is a simple relationship between the cash and CDS markets that is based on the absence of arbitrage. If the CDS spread basis deviates from zero, then barring transactions costs and structural differences between markets, one should be able to implement a convergence strategy that takes advantage of the divergence (i.e. the basis) between the two markets.

Examining emerging markets, Kumar and Mithal (2001) suggest some reasons why the basis may be non-zero and yet not admit an arbitrage trade. First, since the borrowing and lending in asset swap markets is often undertaken using repos, the basis may arise if the instrument for the repo is on special. Especially in these markets, specialness is often determined by the extent of credit risk in the asset as well. Hence, the probability of specialness is correlated with the credit risk of the reference asset in the asset swap, increasing the likelihood of a non-zero basis. Second, there is recovery risk, and this may be reflected differently in the two markets. Third, the basis often arises on account of liquidity differentials between the asset and CDS markets. If this is the case, then spreads in the asset market, where liquidity is lower than in the CDS market, may be too high to result in the arbitrage trade being profitable after transaction costs. Fourth, there are transaction costs in the unwinding of the synthetic structure that replicates the CDS using an asset swap. These costs may be borne at the maturity of the contract, or on default of the reference asset, and the basis will often comprise the expected transaction costs. Finally, the basis may also be related to differences in the counterparty risk involved in the asset swap versus those in the CDS transaction.

Longstaff *et al.* (2005) examined the basis in a detailed empirical study. Their approach was to use the bond market to extract the data required to price CDS contracts. Thus, they computed bond-implied CDS spreads. Bond-implied spreads are higher than market CDS spreads, and are attributable to liquidity and tax effects. More interestingly, they found that the CDS market and equity markets presaged changes in spreads earlier than the bond markets. The evidence in this paper establishes the growing efficiency of the CDS markets. The ability to hedge credit risk in addition to market risk has achieved a great boost from the development of the CDS markets. Whether these gains in efficiency will translate over to the bond markets remains to be seen. It will be interesting to see whether the magnitude of the basis diminishes over time.

A study by Blanco *et al.* (2004) corroborates the finding that the CDS market provides better indicators of the credit risk of an issuer. They examined the spreads in both markets and found that CDS markets were more efficient than bond markets in the short-term. Over longer horizons, the bond market and CDS were both efficient, with converging views. Interestingly, they found that the correlation of changes in bond and CDS spreads was rather low, often below 30%, and only above 60% for a handful of companies. Using structural models to explain credit spreads, they were able to only explain about 25% of the variation. No doubt the various factors in the basis do not appear in the classic structural model, and hence additional variables are required from outside the framework. Similar results were found in prior published work, for example, in Collin-Dufresne *et al.* (2001).

The basis may be examined directly using data from CDS and bond markets. Individual spreads may be explained using models, and a modeling of the dynamics of the CDS spread is possible with structural or reduced-form models. In the reduced-form class, the dynamics of the default intensity and the recovery rate jointly determine the dynamics of spreads. There is a large amount of research examining the dynamics of default intensities, especially striking in contrast to the paucity of modeling and empirical work on the dynamics of recovery rates. Reduced-form models (or intensity models) of spreads have been found to be especially tractable in fitting the term structures of CDS spreads, as well as in extracting default intensities that appear to predict default occurrence very well. The paper by Duffie *et al.* (2004) uses only four explanatory variables to predict default in an intensity-based model. These four variables are (i) the distance to default, a volatility-adjusted measure of leverage, (ii) the past year's stock return, (iii) the past year's market return, and (iv) the level of short term interest rates. This model is able to predict the rank ordering of defaults to an accuracy level of 88% using receiver-operator characteristic (ROC) curve analysis. Distance to default in this model is a construct from the realm of structural models. Embedding this in a reduced-form intensity-based framework is clearly a flexible and empirically validated approach. In general, this confirms the growing trend towards "hybrid" models of CDS spreads.

If we ignore the dynamics of the recovery rate by assuming recovery to be a constant fraction of asset/bond value (or non-stochastic), as do many extant models, then the dynamics of credit spreads, which are observable, may be used to infer the dynamics of default intensities (the instantaneous rate of default related to default probabilities). These implied intensities of default are risk-neutral, since they are based on an expected value calculation that equates the premium leg cashflows of the CDS to the loss cashflows. Further, a comparison of the risk-neutral default probabilities with those under the physical measure enables an extraction of the premium for default risk. This is usually expressed in the form of the ratio ($\pi = \lambda_Q/\lambda_P$), where λ_Q is the default intensity under the risk-neutral measure and λ_P is the intensity under the real world or physical measure. Hitherto, the paucity of good spread data stymied attempts to understand the dynamics of the risk premium π. Now, with the increasing trading volumes in the CDS market, there is an open avenue for the development of models to examine risk premiums.

Berndt *et al.* (2003) undertake a detailed investigation of risk premiums using a large data set of CDS quotes. Their research looks in detail at three sectors: broadcasting and entertainment, healthcare, and oil and gas. The variation in risk premiums over the period 2000 to 2004 is remarkable. Clearly it is important to understand what drives risk premiums, since this variation comprises a major component of the CDS spread. Given that they find that the median risk premium ratio π varies from 1 to 3 on average, much of the spread variation must come from risk premium variation. The intensity model is also adept at extracting the term structure of credit premiums. Premiums are also seen to increase with maturity for the entertainment and broadcasting industry.

In order to explain the high levels of variation in risk premiums, Berndt *et al.* (2003) offer some possible reasons that might be shortcomings of the model used. First, the expected default frequencies (EDFs) under the real world probability measure that are taken from a commercial vendor (Moodys KMV) may be mis-specified. Second, recovery rates may be dynamic, and since they are not assumed to be so, the stochastic variation in recovery rates may instead be absorbed into the variation in risk-neutral default intensities. Third, supply and demand effects may lead to divergence in CDS spreads from fundamentals, and periodic corrections may result in excess dynamic variation. This type of activity has become heightened with the growing role of hedge funds.

Berndt *et al.* (2003) also find that the probability of default under the physical probability measure, that is known as EDF is useful in explaining the variation in CDS spreads (they find an R^2 of 69%). In particular, the relationship between the logarithm of CDS spreads and the logarithm of EDFs is a linear one, indicating that the relationship in levels follows a power law. However, not all the variation is explained, of course, because the EDF does not account for credit risk premiums.

Das and Sundaram (2002) develop a no-arbitrage model using equity and interest rate market information coupled with that from CDS spreads to extract implied default functions in a jump-to-default model. They calibrate this model to the Dow 30 issuers and examine the risk-neutral default intensities over the period from January 2000 to July 2002. The results here are similar to those of Berndt *et al.* (2003). Similarly, high time variation in risk premiums is seen. A principal components analysis finds that there are two major components of default intensities. The main component is identified with the S&P500 index. This is consistent with the earlier evidence stated from the work of Duffie *et al.* (2004) who found that the past year's S&P500 return is useful in predicting default. This model demonstrates how the information in the CDS market may be used to price various derivatives that may have embedded default risk, in particular complex securities such as distressed convertible bonds. In a similar vein, Carr and Wu (2005) show how information in the equity options market along with CDS spreads maybe used to estimate the price of diffusion and jump risk for defaultable equity.

Reduced-form models of CDS spreads have been extended to incorporate the interaction between the interest rate term structure and the term structure of credit spreads. The aforementioned paper by Das and Sundaram (2002) is a case in point. Their model embeds correlation between equity markets and the term structure of interest rates, inducing correlation between spreads and interest rates as well. Wu and Zhang (2005) develop a model of real and nominal rates in conjunction with credit spreads to explain yields. Spreads are impacted by real growth, inflation and market volatility. Market volatility explains credit spreads to a much greater extent than it explains the variation in the risk free interest rate term structure. Their paper attempts to merge two approaches used to explain spreads. One is a cross-sectional approach in which numerous explanatory variables are used to fit spreads across many issuers; the second one attempts to use a parsimonious set of factors to explain spreads in a dynamic framework. The paper lies more in the latter class of models, and also exploits the interaction between two term structures, that of interest rates and credit spreads. Estimation is undertaken using a Kalman filter approach. Getting a better understanding of credit spread volatility is important, and the empirical results affirm that increases in volatility do translate into increases in credit spreads, especially for financial sector firms. These insights are valuable for traders in the nascent market for CDS options. The dynamic interaction of interest rates and spreads is further explored in the paper by Chen *et al.* (2005). The paper estimates a six-factor model in a dynamic framework to determine how many factors drive the term structure of credit spreads, and its interaction with the term structure of interest rates. Two factors are used to explain the Libor markets, two to explain the spreads of high-liquidity bonds in two industry plus rating categories, and finally, two more factors to explain the default risk and liquidity risk differences between high-liquidity bonds and low-liquidity ones. Estimation is undertaken using a block-recursive scheme—first the Libor term structure is fitted to get the first two factors; these are then taken together with average spread curves for liquid bonds in each sector to determine the next two factors. Finally, the remaining credit and liquidity factors are estimated from the average CDS spread curves of the low liquidity group in each sector (industry, i.e. financial versus non-financial, and rating group, i.e. A vs BBB). Interestingly, the low liquidity issuers have lower credit risk and thus their spreads are composed of more of the liquidity factor relative to the credit factor versus the high liquidity group. Taking all this evidence together, we have that (a) credit spreads are complex in their dynamic behavior, depending on industry and rating, as well as general macro-economic conditions; (b) the interaction between spreads and the term structure of interest rates is important.

The theoretical relationship between interest rates and spreads is negative in the Merton (1974) model. Evidence for this is also provided (amongst others) by Berd *et al.* (2004). Note, that the total yield on corporate debt is impacted less if credit spreads change inversely to interest rates. Hence, the duration of corporate debt is lower in the presence of negative correlation of rates and spreads. This effect is explored further in Berd and Ranguelova (2003) and Berd and Silva (2004).

Most of the literature that aims to explain the dynamics of credit spreads focuses on default probabilities. Pan and Singleton (2005) undertake an empirical examination of CDS spreads on sovereign issuers for three countries: Mexico, Russia and Turkey. By using the entire term structure of CDS spreads over time, they are able to identify both, default intensities and recovery rates [see also Das and Hanouna (2006) for an alternate approach to estimating intensities and recovery jointly from CDS spreads; also, Gray *et al.* (2003) provide a detailed application of the idea in the Merton class of models for application to sovereign debt]. Whereas earlier work [most notably Zhang (2005), among others], finds that sovereign recovery rates are about 25%, they present evidence that recovery might range to as high as 75%. The framework of the paper is applied to three different stochastic process specifications leading to robust conclusions across all of them, resulting in the extraction of default intensities in addition to recovery rates. The extracted intensities appear to be driven by two main factors: one is global credit conditions, and another one is market volatility. These factors induce correlation across countries, implying that international diversification within international bond portfolios may be less easily obtained than might be thought. This paper also concludes that a one-factor model for CDS spreads might be acceptable, though a two-factor model is desirable.

Understanding the dynamics of CDS spreads, especially spread volatility is attaining more importance given the growing market for options on CDS. These options may take two forms: (a) naked CDS options or (b) embedded options to extend or terminate a CDS contract. Pan and Singleton (2005) show how their affine framework is extendable to the pricing of these options. Schönbucher (2003, 2004) develops a modified Black (1976) model for CDS options using T-forward survival measures (also see Brigo, 2005). This measure makes pricing simple, since the CDS option is written on a forward-start CDS contract. Not only will options on CDS make for refined speculative and hedging positions, but these contracts will further the estimation of parameters related to the credit spread dynamics, especially, as one would easily imagine, the volatility of credit spreads.

3 CDS spreads in structural models

A recent stream of research uses the property that CDS spreads are a pure measure of credit risk to 1-compare models that predict default risk cross-sectionally (e.g. Bharath and Shumway, 2004; Zhang *et al.*, 2005; Ericsson *et al.*, 2004a; Das *et al.*, 2006), 2-examine the time-series relationship between the equity and credit markets (e.g. Bystrom, 2005), and 3-examining the integration of bond and credit derivative markets as in Cossin and Lu (2005) and Ericsson *et al.* (2004b).

Bharath and Shumway (2004) compare the KMV-Merton model with a modified version of the KMV-Merton model which uses a rule of thumb to determine the value and volatility of the firm's assets rather than iteratively solving for the two in a system of equations. The horse race between the two models is conducted on three venues. First, they estimate Cox proportional hazard models which explain time to default as a function of the KMV-Merton model and as a function of their alternative model. Second, they test to see how well the two models perform relative to each other in explaining the cross-section of bond spreads. Third, and most interesting to this review, they test how the two models explain the cross-section of CDS spreads. The CDS data used consist of 3833 firm-month observations from the CreditTrade database from December 1998 to July 2003. They first regress CDS spreads on the KMV-Merton model and find an R^2 of 10% compared to an R^2 of 26% when their alternative model is used. When both models and the logarithms of Equity and Face Value of Debt, the reciprocal of the volatility of equity and the interest rate are all thrown in to the regression the R^2 jumps to 40% with the simpler model being slightly more significant.

Zhang *et al.* (2005) develop a new structural model which includes both stochastic volatility and jumps to explain credit spreads. They use as a base the Merton (1974) model and add to it stochastic volatility and jumps into the firm-value process. The resulting model links equity volatility and jumps to credit spreads. Zhang *et al.* (2005) test their model using 5-year CDS quotes on 4952 firm-months over 2001–2003 obtained from Markit. The CDS spreads are regressed on equity returns, volatility, and jumps as well as credit ratings, macroeconomic and firm-specific factors. Jumps are determined by analyzing intra-day data. Although, credit ratings alone explain 56% of the variation in spreads, adding equity characteristics increases the R^2 to 74% and adding macroeconomic and firm-specific factors further increases it to 76%.

Ericsson *et al.* (2004a) analyze the determinants of 5-Year CDS spreads using the CreditTrade database from 1999 to 2002. Using firm leverage, firm volatility and the risk-free rate they are able to explain 61.4% of the variation in CDS spread levels and 22.3% of CDS spread differences. Cao *et al.* (2005) find that historical volatility is less useful than implied volatility in explaining CDS spreads.

Das *et al.* (2006) examine the performance of models that use accounting information to explain credit risk measures relative to market-based measures such as the Merton model. Using 2860 firm-quarters of CDS spreads obtained from Bloomberg over 2001–2005 they find that simple accounting based measures combined with macroeconomic data can explain 65% of the variation in spreads. When they use market-based measures of default such as the combination of distance to default, equity volatility and returns in lieu of accounting-based information the R^2 drops to 64% in the exact same sample. A cocktail of both accounting- and market-based measures increases the R^2 to 72%. These results continue in out-of-sample tests. Das *et al.* (2006) further examine how the competing models fare in determining the rank-ordering of CDS spreads and predicting the future direction of spreads which are important features for hedge fund trading strategies. The results are that accounting based information is important (if not superior to market-based information) in determining rank ordering and future direction of CDS spreads.

Rather than examining the cross-sectional determinants of CDS spreads Bystrom (2005) looks at the time-series properties of the Dow Jones *iTraxx*. The Dow Jones *iTraxx* is an index of CDS securities on 125 European reference entities which resulted from the merging of the *iBoxx* and *Trac-x* indices. The Dow Jones *iTraxx* is further subdivided into seven sectoral indices which are the ones ultimately examined over a period of 10 months from 21 June 2004 to 18 April 2005 on a daily basis. Bystrom (2005) estimates a model that explains the current sector CDS index spread with the previous day spread and the current and lagged values of the equally-weighted returns on the underlying sectoral reference entities. Bystrom (2005) finds that CDS spreads are significantly autocorrelated in all sectors at the 1% level. Furthermore, CDS spreads are also significantly negatively related to the contemporaneous stock returns at the 1% level and the lagged returns in all sectors but in energy, consumers, and financials (senior debt). The R^2 in all cases range from 7% to 25%. Bystrom (2005) further finds that CDS spreads are negatively related in both levels and changes to historical measures of stock return volatility.

Cossin and Lu (2005) examine whether the credit derivative markets and the debt markets are integrated. At first sight the fact that CDS spreads are inconsistent with corporate bond spreads would suggest that the two markets are indeed segmented. However, as Cossin and Lu (2005) point out corporate bond spreads also include a liquidity risk premium in addition to the credit risk premium. Cossin and Lu (2005) get around this problem by first estimating the liquidity premium using a limited dependent variable model which essentially imputes a time-varying and firm-specific liquidity premium using bond yields. Then they compute a synthetic CDS 5-year spread which uses the corporate bond yields, the risk free rate and the liquidity premium imputed previously. The resulting synthetic CDS spread can then be compared with the actual 5-year CDS spread. The actual 5-year CDS data is based on 180 European reference entities from 1 January 2002 to 23 July 2003 on a daily basis from Bloomberg. The bond data on the same corporations are obtained from Reuters 3000Xtra.

The results are that the average differences between the two spreads are 0.7 basis points (with the synthetic spread being higher) which is significantly different than zero at the 1% level of significance. The difference however might be explained by the "cheapest to deliver" (CTD) option. Recall that in a physical settlement the buyer of credit protection delivers the actual bonds to the seller and receives the par value. Recall further that the only requirement on the bonds to be delivered is that they be *pari passu*. This in effect gives a CTD option to the buyer of protection which is more valuable when some bonds are much cheaper than others on the reference entity. Since the CTD option becomes more valuable with higher equity volatility Cossin and Lu (2005) test whether differences in the actual and synthetic spreads are driven by the CTD. In a regression setting they find that the differences are negatively correlated to the implied equity volatility. This suggests that the CTD is important in explaining the differences between the credit derivatives and debt markets.

Ericsson *et al.* (2004b) examine the question as to whether structural models can price default accurately. Previous studies using bond spreads as a measure of default show that structural models underestimate default but as in Cossin and Lu (2005) they point out that the bond spreads are not a pure measure of default and could then include non-default risk premiums as well. Ericsson *et al.* (2004b) using bond transaction from the National Association of Insurance Commissioners and estimating the Leland (1994), Leland and Toft (1996) and Fan and Sundaresan (2000) structural models, and find that all three models underestimate bond spreads. When CDS spreads are used rather than bond spreads the Leland (1994) and Fan and Sundaresan (2000) models still underestimate spreads but by much less and the Leland and Toft (1996) actually overestimates CDS spreads. The CDS data used is from the CreditTrade database and covers the period June 1997 to April 2003 although the data is small prior to 1999. The previous evidence suggests that structural models underestimate bond spreads because they contain additional non-default information. To verify this Ericsson *et al.* (2004b) examine the residuals of the bond spreads and find that only non-default factors are responsible for the additional premiums. When CDS spread residuals are examined they do not correlate against either non-default or default factors.

4 Concluding comments

As the liquidity in the CDS market grows, we obtain an increasing amount of spread data that allows us to explore (a) the determinants of these spreads, and (b) decompositions of the spreads into probabilities of default and recovery rates. Our review of some of the working papers that examine these aspects of CDS spreads leads to the following broad conclusions:

- The literature adequately demonstrates that CDS spread changes are better predictors of credit changes than bond spreads. It will be interesting to observe whether the credit premiums on corporate bonds decline over time as the liquidity of the CDS market grows and provides better information on credit quality.
- The "basis"—the difference between bond and CDS spreads is linked to liquidity and tax effects. Clearly, we need a better model for these aspects of the bond market so that the basis can be modeled more effectively. Whereas there is a growing literature on bond market liquidity (see Das *et al.*, 2003), there is much progress to be made on identifying liquidity well for trading and calibration purposes.
- All of the variation in CDS spreads cannot be explained by pure structural models, and enhancing them with firm-level and macroeconomic variables appears to be useful. In particular,

term structure levels seem to provide additional explanatory power. Empirical evidence does show that principal component decompositions of spreads do show that equity market variables are important. Overall, hybrid models are the likely future direction that this research will take.

- Reduced-form models are being used quite well to extract credit risk premiums from CDS spreads. The evidence shows that the variation in premiums is substantial, and accounts for a large proportion of the total spread variation. Hence, a better understanding of the drivers of risk premiums is predicated, and further research is required here.
- The growing data on CDS spreads has led to explorations of the interaction between the term structures of spreads and that of risk free interest rates. As prescribed by the Merton model, there is a negative relationship between spreads and risk free rates. This has now been explored and confirmed in the realm of reduced form models as well. What this also means for traders is that the duration of corporate bonds will be shorter, since the negative correlation of spreads and interest rates makes corporate bond yields less volatile.
- The range of CDS spreads in the maturity spectrum allows for better identification of recovery rates. These are now known to depend on equity market levels and volatility, as well as interest rate levels. Certainly, our models for recovery rates are nascent, and we will soon see better ways to determine estimates of loss given default now that we have more accurate data to work with.

In the past, ratings were almost as good as sufficient statistics to explain credit spreads. With the advent of both, structural and reduced form models, we are able to explain spreads much better. Indeed, regressions show that even when ratings are used in spread regressions, these new classes of models still explain more than just that which may be attributed to ratings. As the credit derivatives market grows, the better understanding of spreads will lead to improved relative pricing methods.

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