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Option-implied Sentiment Measures and Credit Default Swap Spreads

Abstract

This study sheds light on the role of option-implied investor sentiment in the credit default swap (CDS) market. Due to the limits to arbitrage caused by credit or counterparty risk and margin requirements, CDS spreads may deviate from fundamentals under the influence of sentiment-driven investors who possess excessively bearish or bullish perceptions to the market or to the firms. I derive several systematic and firm-specific sentiment measures from index options and individual stock options, respectively, and I investigate their impacts on CDS spreads. The sentiment influence is significant, even after controlling the fundamental variables, and is more pronounced for lower-rated CDS obligors during a turbulent period, which is consistent with the limits to arbitrage theory.

1. Introduction

There is an increasing consensus in the literature that a significant portion of credit spread is driven by common external factors because the default risk of the target firm can account for only a small part of the spread (so-called the credit spread puzzle). A number of studies have pointed out that critical components of systematic risk may be missing in credit risk modeling (Collin-Dufresne et al., 2001; Elton et al., 2001; Ericsson et al., 2009). Remolona et al. (2008), Weigel and Gemmill (2006) and Baek et al. (2005) claimed that credit asset prices are driven by fundamentals as well as by investor appetite for risk. They found that market sentiment and investor attitude affect the bond spreads. Tang and Yan (2010) argued that investor sentiment is the most important determinant of credit spreads. As evidenced by the recent crisis in 2007-2008, credit spreads have widened significantly. The BIS Quarterly Review (2007) stated that a large part of the ongoing re-pricing may be attributed to the sudden changes in investor sentiment toward risk.

In contrast to previous studies that emphasized credit spreads from bond markets, I relate sentiment to CDS spreads because CDS spreads provide a valuable market-based assessment of credit conditions for hedging, speculating and arbitraging and because CDS prices lead credit spreads from bond markets in price discovery (Blanco et al., 2005). Speculative investors, rather than institutional hedgers, have dominated CDS market since 2002 (Smithson and Mengle, 2006). Sentiment apparently affects the demand and prices of securities that are subject to speculation, but it has little effect on the prices of securities driven by hedging demand (Lemmon and Ni, 2010). Because speculation activity is increasing in the CDS market, our primary goal is to determine how investor sentiment derived from options markets influences CDS premiums. In particular, I illustrate that the limits to arbitrage play a role in this relationship. Arbitrage requires no capital and entails no risk, but in reality, arbitrage is constrained and risky. If limitations on arbitrage exist, then sentiment may have a greater impact on security prices (Shleifer and Vishny, 1997; Wurgler and Zhuravskaya, 2002). CDS arbitrageurs who are rational and free of sentiment face two types of risks that limit their willingness to take positions against sentiment-driven traders. The first type is *credit risk*. If CDS traders are overly pessimistic, then they are willing to pay more for protection against default. Arbitrageurs can sell the overvalued CDS contracts and hold the bond of the reference entity to neutralize an arbitrage position. If the reference entity defaults, then arbitrageurs are obliged to pay the difference between the bond value and the bond's nominal value in cash settlement. Even though arbitrageurs hold a bond to hedge credit risk, *funding liquidity*[1] imposes a restriction on these transactions (Bhanot and Guo, 2011). Conversely, if the reference entity's creditworthiness improves, then arbitrageurs face a *counterparty risk* because the protection buyer holds a contract with negative market value.

[1] "Funding liquidity," named by Brunnermeier and Pedersen (2009) and Bhanot and Guo (2011), is the ability of the arbitrageur who finances the bond purchase via a repurchase agreement using the asset as collateral.

Subsequently, arbitrageurs may lose the outstanding premiums. Thus, when arbitrage is risky or limited, CDS spreads move in response to fundamentals as well as sentiment.

Option-implied sentiment measures can provide *forward-looking* indications of uncertainty about stock market and investor risk preference. In this study, two types of sentiment measures are extracted from option markets: systematic and firm-specific. The sentiment measures from index futures or index options assess systematic uncertainty and risk attitude, whereas the firm-specific measures from individual stock options identify investor sentiment and risk appetite toward a specific firm. I hypothesize that both systematic and firm-specific sentiment measures affect CDS spreads. I expect that systematic sentiment measures can explain the credit spread puzzle, and firm-specific sentiment measures may complement firm-level CDS determinants such as stock return and implied volatility. This focus differs from the work of Tang and Yan (2010), whose sentiment measure was based on the conference board consumer confidence index that considers only the average prospect of the economic conditions. If as many stocks are affected by the bullish sentiment as by the bearish sentiment, then their aggregate measures may be misleading. More importantly, the sentiment measures from survey data may be out of date by the time they are published, particularly when the market is volatile (Simon and Wiggins, 2001).

The second goal of this paper is to assess whether the response of CDS spread to investor sentiment is regime-dependent. This enquiry can extend our understanding of the interaction between market risk and default risk. Tang and Yan (2010) empirically examined the impact of this interaction, but they did not consider its possible dependence on the bullish or bearish market conditions. Alexander and Kaeck (2008) showed that the behavior of CDS spreads displays a pronounced regime-specific pattern. By examining the CDS indices, they found that CDS spreads in a turbulent market are extremely sensitive to stock volatilities. Yu (2005) indicated that single-name CDS spreads behave quite differently during volatile periods. In this paper, I consider the possible asymmetries in the responses of CDS spreads to investor sentiment, and I expect a more prominent sentiment effect during a turbulent period.

I use the single-name CDS spreads of U.S. dollar-denominated, five-year CDS contracts written on the unsecured senior debts of American obligors from 2003 to 2007. Our sample comprises 375 firms with 38,653 daily quotes on their CDS spreads. I find that both systematic and firm-specific sentiment measures have significant influences on CDS spreads, even after controlling the fundamental variables suggested by the theoretical and empirical studies. The limits to arbitrage theorem illustrates that sentiment measures are more powerful in explaining CDS spreads during market turbulence, especially for high-yield CDS spreads (usually of lower-rated firms). The margin requirement will be high as the credit of a reference entity deteriorates or as CDS market becomes volatile. Our findings are in accordance with the study by Cao et al. (2010), who found that information from options markets can be useful in explaining CDS spreads.

The paper is organized as follows. In Section 2, various sentiment measures are introduced and discussed. Section 3 describes the data and methodologies. Empirical results are analyzed in Section 4. In Section 5, several robust checks are conducted to confirm our results, followed by the conclusion.

2. Sentiment measures

Sentiment indicates the excessively bullish or bearish expectations of market participants. Investor sentiment also reflects the aggregate error in investor beliefs (Han, 2008). Brown and Cliff (2004) considered sentiments to be market anomalies. In a competitive and rational market, investor sentiment should not affect asset valuation. However, some investors may not be fully rational, and their demand for risky assets is affected by sentiments that are not fully justified by fundamentals. In addition, arbitrage by rational investors can be risky or even costly (Shleifer and Summers, 1990; Shleifer and Vishny, 1997; Wurgler and Zhuravskaya, 2002). These impediments reduce the willingness of arbitrageurs to bring asset prices toward fundamentals. Thus, investor sentiment may be related to CDS spreads due to limited arbitrage activities.

Analyzing the relationship between sentiment and mispricing is difficult for two reasons (Rehman and Vilkov, 2009). First, evaluating whether a stock is genuinely mispriced is difficult. Second, identifying a measure of investor sentiment for a specific stock and ascribing the degree of mispricing is even more difficult. Brown and Cliff (2004) classified sentiment proxies into direct and indirect measures. Direct measures are usually based on surveys from market participants, whereas indirect measures are extracted from trading activities and market performance. Many studies have proposed various measures; however, relatively few studies have utilized the information in derivatives, which are supposed to contain more valuable and forward-looking assessments about future market conditions and investor's risk attitudes. Simon and Wiggins (2001) noted the problems with the survey-based sentiment measures. In contrast, option-implied sentiment measures are observed in real time and reflect both the market power of the participants and the intensity of bullishness or bearishness.

2.1. *Systematic sentiment measures*

Four market-wide systematic proxies implied by the derivative markets are used in our empirical tests. The first and the second proxies, initiated by Brown and Cliff (2004), are derived from trading activities in S&P 500 options and futures, which can be obtained from the Commitments of Traders (COT) reports published by the Commodity Futures Trading Commission (CFTC). The CFTC requires large traders with holding positions above a specific level to report on a daily basis. The breakdown of the open interests from these reported data is released each Tuesday in the COT report, which contains the contract numbers of long and short positions for both reporting and non-reporting traders. Non-reporting traders usually refer to small and foreign traders, whereas reporting traders ("commercial" and "noncommercial") are regarded as large traders. Commercial traders are required to register with CFTC and report which futures are used for hedge purposes. Noncommercial traders are large speculators such as market professionals who trade S&P 500 futures. Importantly, noncommercial traders (speculators) have a tendency to follow market sentiment, whereas commercial traders (hedgers) trade against market sentiment (Wang, 2003).

The first systematic sentiment proxy (***Individual***) is the net position of small investors, which is calculated as the number of long non-reported contracts minus the number of short non-reported contracts and scaled by the total open interest in S&P 500 futures. This proxy represents sentiment from individual/small investors. A positive net position is regarded as a bullish indicator from individual investors. The second systematic sentiment proxy (***Speculative***) is the net position of noncommercial investors, which is calculated as the number of long noncommercial contracts minus the number of short noncommercial contracts and scaled by the total open interest in S&P 500 futures. A positive net position is regarded as a bullish indicator from speculative investors. Wang (2003) found that speculators increase net positions when the market has turned bullish. Han (2008) applied this proxy to analyze its impact on the risk-neutral skewness of S&P 500 index. Instead of using the net positions of commercial traders who are mostly hedgers, the net positions of noncommercial traders, mostly speculators, are considered to convey more sentimental content.

The third systematic sentiment proxy (***PCRatio***) is the ratio of CBOE total equities put-call trading volume.[2] This proxy is calculated by dividing the total trading volume of all equity put options by the total trading volume of all equity call options in CBOE. This ratio is commonly considered a bearish sentiment index, with a higher put-call ratio indicating pessimism (Simon and Wiggins, 2001; Dennis and Mayhew, 2002; Brown and Cliff, 2004). As market participants become bearish, it is believed that they buy puts either to hedge their portfolios or to make bearish bets. This ratio is usually considered the broadest measure of market sentiment in the US equity market.

The last systematic sentiment proxy (***MarketVane***) is the bullish consensus collected by Market Vane for S&P 500 futures. The bullish consensus of Market Vane is the degree of bullish sentiment for a particular asset, such as gold, commodities, or S&P 500 index. Market Vane tracks the buy/sell recommendations of leading advisers[3] in the futures market for that specific asset. For instance, a bullish consensus of 65% for S&P 500 futures implies that 65%

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[2] There are many types of put-call ratios and different ways to interpret them. The equity put-call ratio measures the equity-based options, such as stock options, whereas the index put-call ratio measures the index-based options, such as the SPX. The equity put-call ratio includes the "Individual Equity Put-Call Ratio," which measures the put-call ratio of an individual stock, and "Total Equities Put Call Ratio," which measures all equities in the market. The most authoritative total equities put-call ratio in the United States is the CBOE Total Equities Put-Call Ratio.

[3] These recommendations are collected from the following sources: 1. Reading current market letters from these advisers. 2. Calling hotlines provided by advisers. 3. Contacting major brokerage houses to learn what the house analysts recommend for different markets. 4. Reading faxes and e-mails sent from advisers. The buy/sell recommendations from each adviser are tracked during the day to verify the entry and exit of each trading position. The bullish consensus is compiled at the end of the day to reflect the positions of the advisers.

of the traders are bullish and expect S&P 500 futures prices to rise. If the consensus for S&P 500 futures becomes bearish, CDS sellers will charge higher default premiums.

2.2. *Firm-specific sentiment measures*

Unlike systematic sentiment, which aggregates the sentiment effects across firms, firm-specific sentiment reflects idiosyncratic responses from the trading activities of its stock options. I employ a skew-based measure (***Skew***) as the first firm-specific sentiment proxy to explain CDS premiums. This measure is based on the "skewness" of risk-neutral distribution of stock returns and was derived by Bakshi, Kapadia, and Madan (BKM) (2003). BKM (2003) extracted model-free estimates of implied volatility, skewness, and kurtosis from a rich collection of options with the same underlying asset. They showed that the risk-neutral skewness is related to the coefficient of relative risk aversion. Option-implied skewness represents the market perception of the asymmetry in future return distribution, corrected for investor risk aversion. The more negatively skewed the return distribution, the higher the probability associated with more negative price movements. Rehman and Vilkov (2009) interpreted this skew-based measure through prospect theory and empirically confirmed that it is a natural candidate for the proxy of stock-specific sentiment. They also applied this skew-based sentiment factor to asset pricing and found that it carries a significant risk premium in stock returns.

The second firm-specific sentiment proxy (***RelativeDemand***) is measured by the ratio of the open interests for out-of-the-money (OTM) puts to the open interests for near- and at-the-money stock options. A higher demand for OTM put options signals a bearish expectation for future stock performance. Cao et al. (2010) pointed out that the value of OTM put is the most sensitive to the left tail of the risk-neutral stock return distribution, as is the CDS spread. I expect that the demand for OTM put options is relevant to CDS spreads.

3. Data and methodology

3.1. *Data description and variables*

CDS spreads data are collected from DataStream for the period of 2003 to 2007 because CDS trading became active after 2003[4] and are halted due to the 2007 financial crisis (BIS Quarterly Review, 2008). Considering the liquidity of CDS contracts, I limit our samples to US dollar-denominated, five-year CDS contracts for senior corporate bonds written on US entities that are not in the financial or government sectors. The associated credit ratings are obtained from the S&P credit agency. I only include reference entities with complete five-year quote data on their stocks, options, CDS contracts, and credit ratings. The sample comprises 375 firms with 38,653 daily CDS spread quotes. I regard the firms with credit ratings above

[4] According to the British Bankers' Association (BBA) Credit Derivatives Report (2006), the credit derivatives markets grew from USD 40 billion notional value in 1996 to USD 4 trillion in 2003. DataStream provides CDS data only after 2003.

BBB as investment-graded and below BB as speculative-graded. Approximately 33 percent of the obligors are rated below BB.

Stock options data are from IvyDB (OptionMetrics), which contain the options of US exchange-listed equities and market indices. I collect all individual stock options with maturities ranging from 10 to 180 days. Only OTM options are included to diminish the influence of the early exercise premiums from in-the-money and near-the-money options[5]. I further eliminate the options with prices violating the arbitrage boundaries. To calculate the implied volatility and the skew as derived by BKM (2003), quotes for options are needed over a range of strike prices and maturities. Unfortunately, options listed for trading are limited, potentially resulting in a bias when applying numerical integration. The accuracy of the integral approximation should be enhanced by applying smoothing techniques developed by Jian and Tian (2005). The cubic spline interpolation and extrapolation technique is implemented in the first step to construct an implied volatility curve. Cubic spline is used to diminish discretization errors between listed strike prices, and extrapolation is employed outside the range of listed strike prices to reduce truncation errors. In the second step, these implied volatilities are converted to form the fitted call or put prices, depending on whether

[5] Individual stock options are American options and may be subject to an early exercise problem. Following BKM (2003), I only include OTM options because they have negligible early exercise premiums. In addition, I apply the moneyness defined by Bollen and Whaley (2004).

the strike price is below or above the current underlying price. As a result, the cross section of well-represented OTM calls and puts are obtained.

Since model-free implied volatility and skew vary with time to maturity, I use options with one-month time to maturity for standardization. For most of the sample dates, there were no options traded with exactly one-month time to maturity. In this case, the risk-neutral skew is linearly interpolated or extrapolated from the skews of two options with time horizons closest to one month.

Table 1 reports the summary statistics of variables used in the subsequent analysis. Panel A provides the statistics for all CDS spreads and firm-specific variables, such as *Skew*, *RelativeDemand*, implied volatility and return. Panels B and C list the statistics for investment-grade and speculative-grade firms, respectively. Panel D summarizes the systematic sentiment proxies. Panel E reports the statistics of the systematic fundamental variables I considered, such as the S&P 500 index return, the implied volatility of S&P 500 index, the interest rate level and market-level credit risk. The five-year US swap rate is used as the overall risk-free interest rate level, and market-level credit risk is measured as the average yield of U.S. corporate bonds rated Baa by Moody's. The correlations between sentiment proxies have been checked to exclude the collinearity problem.[6]

[6] Their pairwise correlations are rarely larger than 0.50.

As shown in Table 1, the mean CDS spread of speculative-grade firms is obviously higher than that of investment-grade firms. The standard deviation of speculative CDS spreads is also larger. The mean *Skew* is negative; it tends to be more negative for speculative-grade firms. This indicates that investors perceive more negative skewness of future return distribution, more negative price movements, or more bearish sentiment for these firms. *RelativeDemand* is higher for speculative-grade firms, which means a higher demand for its OTM put options relative to the near- and at-the-money options, reflecting a bearish sentiment. For other firm-level variables, the implied volatility and return of speculative-grade firms are also higher due to higher market risk.

[Insert Table 1 here]

3.2. *Quantile regression methodology*

To explain the nature of heteroskedasticity in a panel of diverse CDS spreads, I apply a quantile regression approach. Quantile regression provides a convenient linear framework for examining how quantiles of a dependent variable change in response to a set of regressors. It alleviates problems such as the presence of outliers, heterogeneity, and non-normal errors. Pires et al. (2009) encouraged the use of quantile regression to produce a robust and complete picture of the determinants of CDS spreads. I use it to explore how CDS spreads behave in different quantiles of credit risk distribution. In particular, the responses of CDS spreads to changes in explanatory variables may be different between the firms in the left tail (low credit risk firms) and those in the right tail (high credit risk firms), which cannot be identified by a linear regression.

After controlling for some firm-specific and systematic variables, the panel quantile regression of Eq. (1) is used to empirically investigate the explanatory power of sentiment measures to CDS spreads under different quantiles θ.

$$Q_{\theta}(CDS_{it}|\boldsymbol{X}_t) = \alpha_{\theta} + \boldsymbol{F_t}'\boldsymbol{\beta_{\theta}^{F}} + \boldsymbol{M_t}'\boldsymbol{\beta_{\theta}^{M}} + \boldsymbol{MS_t}'\boldsymbol{\beta_{\theta}^{MS}} + \boldsymbol{FS_t}'\boldsymbol{\beta_{\theta}^{FS}}, \tag{1}$$

where $i = 1, \dots, n$ is a cross-sectional firm observed over $t = 1, \dots, T$ days; CDS_{it} is the CDS spread for firm *i* at time *t;* $\boldsymbol{X}_t$ is a vector of independent variables; $\boldsymbol{F}_t$ is a vector of firm-specific fundamentals, with $\boldsymbol{\beta_{\theta}^{F}}$ as its θ_{th} quantile coefficient vector; $\boldsymbol{M_t}$ is a vector of systematic fundamentals, with $\boldsymbol{\beta_{\theta}^{M}}$ as its θ_{th} quantile coefficient vector; $\boldsymbol{MS_t}$ is a 4×1 vector of systematic sentiment proxies, with $\boldsymbol{\beta_{\theta}^{MS}}$ as its θ_{th} quantile coefficient vector; and $\boldsymbol{FS_t}$ is a 2×1 vector of firm-specific sentiment proxies, with $\boldsymbol{\beta_{\theta}^{FS}}$ as its θ_{th} quantile coefficient vector. Quantile regression yields a series of quantile coefficients for selected quantiles. The coefficients of five different quantiles, the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} quantiles, are estimated. These coefficients are interpreted as different responses of CDS spreads in various quantiles to the same set of explanatory factors. Standard errors of the coefficients are estimated from the bootstrap resampling method.

3.3. *Markov regime-switching models*

One of our purposes is to investigate whether the responses of CDS spreads to investor sentiment are regime-dependent. The Markov regime-switching regression model allows the influence of explanatory variables to be state-dependent. In this approach, regression coefficients change dynamically according to a particular transition probability that reflects their state dependence. To incorporate regime-dependence in the response of CDS spread to investor sentiment, I consider the following regression model, which allows regime-dependence in sentiment measures and in volatility:

$$CDS_{it} = \alpha + \boldsymbol{MS_t}'\boldsymbol{\beta}_{\boldsymbol{S_t}}^{\boldsymbol{MS}} + \boldsymbol{FS_t}'\boldsymbol{\beta}_{\boldsymbol{S_t}}^{\mathbf{FS}} + \varepsilon_{it} \qquad (2)$$

$$\varepsilon_{\mathrm{it}} \sim \mathrm{i.i.d.\,N}\left(0, \sigma_{S_t}^2\right),$$

where $\mathrm{S_t}$ is an unobserved latent variable that follows a two-state Markov process with a constant probability of transition, p_{ij}, from regime i to regime j, and $\sigma_{S_t}^2$ is the regime-dependent variance of $\mathrm{CDS_{it}}$. The coefficient vectors of $\boldsymbol{\beta}_{\boldsymbol{S_t}}^{\boldsymbol{MS}}$ and $\boldsymbol{\beta}_{\boldsymbol{S_t}}^{\boldsymbol{FS}}$ are all regime-dependent with $\mathrm{S_t} \in \{0,1\}$ and can be estimated by the maximum likelihood method.[7]

4. Empirical results

4.1. *Relationship between CDS spreads and sentiment variables*

As discussed in the previous sections, CDS prices may respond to sentiment variables due to the limitation on arbitrage. CDS premiums can thus be decomposed into the sentiment component and the fundamental component. I then regress CDS premiums on the chosen sentiment measures and use fundamental factors as control variables. Table 2 reports the

[7] For parsimony and convergence in maximum likelihood estimation, α is not allowed to switch states, and other control variables are not included.

results of our regression models, which adopt the robust standard error approach of Peterson (2009) to account for both firm and time effects in large panel data sets. First, I investigate how firm-specific sentiment measures influence the corresponding CDS spreads. Two measures are used: *Skew* and *RelativeDemand*. As shown in Model 1 of Table 2, the coefficients of firm-specific sentiment proxies are all statistically significant. The negative coefficient for *Skew* indicates that the more negative the risk-neutral skewness perceived by investors, the higher for CDS spreads. Once investors perceive bearish sentiment from a firm's stock options, they reassess the corresponding CDS quotes to reflect the increased credit risk. The positive coefficient for *RelativeDemand* means that a bearish sentiment evidenced by a strong demand for OTM put options is related to higher CDS spreads.

Model 2 in Table 2 examines the relationship between systematic sentiment measures and CDS spreads. The coefficients for both *Individual* and *Speculative* sentiment proxies are significantly negative, indicating that as the sentiment extracted from S&P 500 futures and options markets becomes bullish (higher values for *Individual* and *Speculative* measures), CDS spreads subsequently decline to reflect the decreased credit risk perceived by investors. Moreover, the coefficient and the t-statistics for *Speculative* are higher than those for *Individual*, implying that the sentiment of speculators is more influential than that of small traders. This finding is in accordance with the study by Röthig and Chiarella (2010), who found that small traders follow the large speculators and are less well informed than the large speculators.

For other systematic sentiment measures, *PCRatio*, the put-call volume ratio, is significantly and positively related to CDS spreads, indicating that a bearish sentiment, larger put trading volume relative to call trading volume, causes an increasing adjustment in CDS spreads. The coefficient of *MarketVane*, a bullish consensus tracking buy/sell recommendations from leading advisers, is also significant. However, the meaning of its sign is unclear. Model 3 reports the regression result considering both firm-specific and systematic sentiment proxies. The possibility that they are substitutive to each other is rejected.

[Insert Table 2 here]

4.2. *Controlling fundamental variables*

Models 4, 5, and 6 in Table 2 check the robustness of the relationship between CDS spreads and investor sentiment by controlling several fundamental variables. Model 4 considers idiosyncratic fundamentals such as implied volatility and stock return. Implied volatilities are calculated in a model-free fashion, as developed by BKM (2003). Tang and Yan (2010) claimed that implied volatility is the most significant determinant of default risk among firm-level characteristics. Cremers et al. (2008) found that implied volatility from individual stock options contains useful information for credit spreads. However, their implied volatilities were extracted from at-the-money stock options. Due to the volatility smile, the nature of moneyness is important in calculating implied volatilities. Recent studies by Britten-Jones and Neuberger (2000), BKM (2003), and Jian and Tian (2005) have shown that the information content of model-free implied volatility is superior to that of Black-Scholes implied volatility. The result of Model 4 shows that the relationship between sentiment proxies and CDS spreads remains significant even in the presence of the idiosyncratic fundamentals. However, the magnitude and statistical significance becomes less pronounced.

Model 5 considers the implied volatility of S&P 500 index, the S&P 500 index return, the level of risk-free interest rate and market-level credit risk, which is the average yield of U.S. corporate bonds rated Baa by Moody's. After controlling these market-wide fundamental variables, the sentiment proxies remain significant. However, I find only a slight improvement in the explanatory power, from 20.95% to 21.22%, compared with a relatively better result (20.95% to 23.74%) from idiosyncratic variables. This finding is consistent with the consensus of previous studies in which idiosyncratic variables are essential in measuring credit risk (Tang and Yan, 2010; Collin-Dufresne et al., 2001; Benkert, 2004). Overall, the relationship between sentiment proxies and CDS spreads is robust after controlling both market-wide and firm-level fundamentals, as shown in Model 6.

4.3. *Grouping by credit rating*

To investigate the sensitivity of CDS spreads to sentiment measures across the samples, I inquire whether this relationship is particularly pronounced for speculative firms with lower credit ratings. This conjecture is in line with those of Remolona et al. (2008) and Baek et al. (2005). It also corresponds to the International Swaps and Derivatives Association (ISDA) standard that margin requirement is risk sensitive and will be higher if the default risk of a reference entity is higher. This marks up the transaction cost of a CDS arbitrageur if the lower-rated firm is the target. Shleifer and Vishny (1997) showed that margin requirement limits arbitrage effectiveness. As a result, the limits to arbitrage hypothesis predicts a prominent relationship between the CDS spreads of lower-rated reference entities and the option-implied sentiments that reflect investors' risk attitude.

Table 3 reports the regression results for the groups with different credit ratings. As shown by the R-squares, our selected sentiment proxies explain CDS spreads of speculative firms well. In particular, the sensitivity of CDS spreads to investor sentiment proxies is significantly increased from investment group to speculative group. For instance, a higher-rated firm has a coefficient of -0.0104 on its *Skew*, whereas the impact on a lower-rated issuer is -0.0639. Due to the salient influence of sentiment on high-yield CDS spreads, I suggest that investors of speculative-grade firms or high-yield bond portfolios should be more aware of the sentiments implied in the derivative markets.

[Insert Table 3 here]

4.4. *Quantile regressions*

To produce a complete picture of the relationship between CDS spreads and investor sentiment, I conduct a quantile regression to explore how CDS spreads react to sentiment proxies in different quantiles of credit risk distribution. The conventional regression in Table 2 constrains the coefficients of sentiment proxies to be the same for all firms, which implies that their impacts on CDS spreads are similar for both high-grade and low-grade firms. However, the impacts may differ between firms in the left tail (low credit risk firms) and those in the right tail (high credit risk firms). Table 4 shows the estimated results for the 10th, 25th, 50th, 75th, and 90th quantiles with the same set of explanatory variables. Our empirical results indicate that the relationship between CDS spreads and sentiment proxies is extremely strong in the upper tail of the distribution. The significance of *Skew* only exists for firms whose CDS spreads are located in the 75th and 90th quantiles. I am unable to identify a similar relationship below the 75th quantile. The magnitude of the *Skew* coefficient in the 90th quantile is the largest, and similar findings can be obtained for other sentiment coefficients. The protection sellers who trade the CDS of firms above the 75th quantile are required to fulfill additional margin requirements to reduce counterparty risk. Because of higher arbitrage costs, sentiment plays an important role in the upper quantiles of CDS premiums.

[Insert Table 4 here]

4.5. *CDS spreads and composite index for systematic sentiments*

Each systematic sentiment proxy discussed in Section 2 may not fully reflect the complete measure of sentiment and may have its own idiosyncratic nature. Following Ho and

Hung (2009) and Baker and Wurgler (2006), I construct a composite sentiment index (***SenIndex***) using principal component analysis to extract the common factors contained in the four systematic sentiment measures. The first principal component, which explains 45.4% of the total variance, is

$$SenIndex_{\mathrm{t}} = 0.282PCRatio_{\mathrm{t}} + 0.649Individual_{\mathrm{t}} - 0.631speculative_{\mathrm{t}} - 0.317MarketVane_{\mathrm{t}}.$$

I investigate again the relationship between CDS spreads and this composite index for systematic sentiment and report the results in Table 5. The coefficient of the composite sentiment index in the 90$^{\mathrm{th}}$ quantile is higher than that in the 50$^{\mathrm{th}}$ quantile, and I am unable to find any explanatory ability in the 10$^{\mathrm{th}}$ quantile. Therefore, the relationship between CDS spreads and the composite sentiment index is stronger in the upper tail of the distribution, similar to the result for each systematic sentiment proxy (Table 4).

[Insert Table 5 here]

4.6. *Regime-dependent response of CDS spread to investor sentiment*

To investigate whether the response of CDS spread to investor sentiment is regime-dependent, I seek to identify its differences across two regimes. Table 6 reports the parameter estimates with standard errors and t-statistics under two regimes. For speculative-grade firms, the firm-specific sentiment coefficient ($\beta_{S_t}^{Skew}$) is -0.0063 in Regime 1 and -0.1476 in Regime 2, whereas the systematic sentiment index coefficient ($\beta_{S_t}^{IS}$) is 0.4195 in Regime 1 and 3.7448 in Regime 2. For investment-grade firms, sentiment measures are significant in Regime 2 but insignificant in Regime 1. I note that the sensitivity of CDS spreads to investor sentiment is more pronounced for speculative-grade firms that have higher t-statistics of estimates in both regimes.

To demonstrate the validity of the Markov switching model, I apply the likelihood ratio test to distinguish between the nested models. The null hypothesis refers to no regime switching, whereas the alternative refers to two regimes. The LR statistics in Table 6 are 57.0808 for speculative-grade firms and only 14.9284 for investment-grade firms. However, due to the problem of nuisance parameters, the conventional LR test is not applicable. Garcia (1998) tabulated critical values for the simple two-mean, two-variance model. The LR statistic of speculative-grade firms is much larger than the 99% critical value, 14.02. This result suggests that the Markov region-switching model is suitable, especially for the speculative-grade firms.

Obviously, for speculative-grade CDS spreads, there are regime-dependent responses to sentiment measures. Because the sensitivity in Regime 2 is higher than that in Regime 1, Regime 2 can be characterized as the “more sensitive” regime. However, the standard errors of the estimates in Regime 2 (0.0244 for firm-specific sentiment and 0.3024 for systematic sentiment measures) are much higher than those in Regime 1 (0.0012 for firm-specific and 0.0483 for systematic sentiment measures). The higher standard errors of the estimates in Regime 2 are caused by the higher residual standard deviation, which is 0.1909 in Regime 2 and only 0.0637 in Regime 1. Therefore, these two regimes can be characterized by significant differences in their standard deviations. This finding is consistent with Alexander (2008), who identified high- and low-volatility CDS regimes. The standard deviation in the turbulent regime is almost three times higher than that in the calm regime. In comparison with Regime 1, Regime 2 is characterized by higher volatility in CDS markets, making it difficult to determine CDS spreads. A volatile CDS market impedes arbitrage activities because the arbitrageur, being either a protection seller or a buyer, faces higher counterparty risk and needs to provide more margins.[8] Bhanot and Guo (2011) found that high CDS volatility increases the capital required per unit of investment. The limits to arbitrage hypothesis illustrates our findings that CDS spreads are more sensitive to sentiment during a volatile period.

[Insert Table 6 here]

5. Robust tests

I perform two tests to examine the robustness of our empirical results. The variations include the separation of rational updating on credit risk exposure from the errors in investors beliefs and an alternative measure of risk-neutral skewness to confirm its influence on CDS spreads.

5.1. *Error in beliefs or rational updating*

[8] The protection sellers have to post additional collateral for a marginal requirement, which prevents counterparty risk or credit risk of the reference entity, whereas the protection buyers may be obliged to post collateral if the contract holds a positive market value for the protection sellers.

The significant relationship between investor sentiment and CDS spreads, as presented in the previous sections, implies an impact of aggregate errors in investor beliefs on CDS spreads. However, the sentiment measures may include rational components. For instance, the results of bullish consensus may reflect errors in investor beliefs or new information incorporated into investor's subjective probabilities. Hence, it is necessary to distinguish rational updating on exposure to credit risk from errors in investor beliefs on credit risk. To address the possibility that the results contain a rational assessment of credit risk, I decompose the sentiment measures by regressing each sentiment proxy on a set of rational predictors of default risk to obtain the residual sentiment proxies, and then, I regress CDS spreads on the residual sentiment proxies. If the relationship is partly driven by the rational components, it will be substantially weaker in the presence of these rational control variables. Baker and Wurgles (2006) and Han (2008) used this approach to decompose investor sentiment proxies when studying the pricing effect of sentiment in the stock and option markets. The rational variables I use include (1) *level* of the risk-free interest rate (i.e., the five-year US swap rate); (2) *slope* of the yield curve, or the "term spread" (i.e., the difference between the ten-year swap rate and the two-year swap rate); (3) demand for *liquidity* (i.e., the difference between the 3-month USD swap interest rate and the treasury yield); and (4) the *Baa-Aaa spread* (i.e., the difference between the average Baa yield and the average Aaa yield of U.S. corporate bonds). These selected variables are motivated by Tang and Yan (2010), Benkert (2004) and Collin-Dufresne et al. (2001).

Table 7 reports the results after controlling these rational components. The residual *Skew* measure is still significantly related to CDS spreads, whereas the residual *Speculative* measure becomes insignificant. This finding implies that the *Speculative* sentiment measure contains rational updating in CDS spreads valuation. For other sentiment measures, the magnitudes of their coefficient estimates barely change in the presence of the rational component variables.

[Insert Table 7 here]

5.2. *Alternative measures of risk-neutral skewness*

The implied volatility smile is tantamount to negative skewness of the risk-neutral density of the stock return (Bollen and Whaley, 2004; Han, 2008). Toft and Prucky (1997) proposed a skewness metric proportional to the slope of the implied volatility curve (or "smile") divided by the implied volatility of at-the-money options. BKM (2003) verified a high correlation between the risk-neutral skewness and the slope of the implied volatility curve. Although I consider risk-neutral skewness as a firm-specific sentiment measure rather than the slope of the implied volatility curve, there is a one-to-one mapping between these two measures. A negative slope of the volatility smile, where the implied volatilities of OTM puts are higher than those of at-the-money or in-the-money puts, corresponds to negative skewness in the risk-neutral density. I therefore regard the slope of the implied volatility curve as an alternative measure of risk-neutral skewness and expect an analogical association with CDS spreads.

Following Bollen and Whaley (2004), the slope of the implied volatility curve is measured as the ratio of the average implied volatility for OTM puts (those with $-0.375 < \Delta_{\mathrm{P}} \leq -0.125$) to the average implied volatility for near- and at-the-money options (for call options with $0.375 < \Delta_{\mathrm{C}} \leq 0.625$ and for put options with $-0.625 < \Delta_{\mathrm{P}} \leq -0.375$), where the put option delta and call option delta are denoted Δ_{P} and Δ_{C}, respectively. Table 8 reports the results from regressing CDS spreads on the slopes of the implied volatility curves (indicated as ***Slope***), other sentiment proxies, and control variables. I find that the implied volatility slopes are significantly and positively related to CDS spreads. A higher CDS spread is associated with a steeper slope, whereas a lower CDS spread is associated with a flatter slope. Similar results can be found in the investigation of the 50^{th} and 90^{th} quantiles, where the coefficient of the 90^{th} quantile is higher than that of the 50^{th} quantile. These results are consistent with our findings in the previous sections.

[Insert Table 8 here]

6. Conclusions

This paper sheds new light on the importance of investor sentiment to CDS valuation. Investors assess the corresponding CDS spreads to reflect their excessively bearish or bullish perceptions toward a firm's credit risk. Systematic and firm-specific sentiments are introduced and derived mainly from index options and individual stock options, respectively. After controlling fundamental variables, the influence of investor sentiment remains significant, confirming that it affects the CDS spreads. In particular, its effect is more pronounced as CDS market becomes volatile. Furthermore, the CDS spreads for lower-rated firms are more sensitive to option-implied sentiments.

Our findings are consistent with the limits to arbitrage theorem. A volatile CDS market impedes arbitrage activities due to higher transaction costs from increased counterparty risk and margin requirements, especially for lower-rated reference entities. Therefore, option-implied sentiment affects CDS spreads, and its impact becomes even stronger if there are higher impediments to arbitrage in the CDS markets.

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Table 1

Summary Statistics

	Mean	Standard deviation	25th Quantile	75th Quantile
Panel A: All samples				
CDS spreads	0.2916	0.4095	0.1290	0.3080
Skew	-1.3199	1.2264	-1.9541	-0.5629
RelativeDemand	0.0410	0.6262	0.0066	0.0201
ImpliedVolatility	0.0446	0.0167	0.0351	0.0508
Return	0.0341	1.5570	-0.6410	0.7281
Panel B: Investment-grade				
CDS spreads	0.2608	0.2558	0.1260	0.3020
Skew	-1.3162	1.1932	-1.9523	-0.5690
RelativeDemand	0.0382	0.6102	0.0067	0.0200
ImpliedVolatility	0.0445	0.0162	0.0352	0.0507
Return	0.0347	1.5664	-0.6462	0.7341
Panel C: Speculative-grade				
CDS spreads	2.3372	1.5859	1.0290	2.7250
Skew	-1.3294	1.5034	-1.9723	-0.5993
RelativeDemand	0.2455	1.3998	0.0046	0.0457
ImpliedVolatility	0.0596	0.0345	0.0393	0.0685
Return	0.0398	1.4627	-0.6132	0.6354
Panel D:Systematic sentiment variables				
Individual	0.0331	0.0331	0.0159	0.0530
Speculative	0.0010	0.0364	-0.0193	0.0933
MarketVane	0.6444	0.0546	0.6200	0.6900
PCRatio	0.6333	0.1085	0.5600	0.6900
Panel E:Systematic fundamentals				
IndexReturn	0.0417	0.6657	-0.3396	0.4315
IndexVolatility	0.1353	0.0228	0.1178	0.1496
Level	0.0466	0.0064	0.0415	0.0516
Baa rate	0.0671	0.0074	0.0624	0.0688

Notes: This table presents descriptive statistics of all the sample firms in Panel A, investment-grade firms in Panel B and speculative-grade firms in Panel C. The sample consists of 38,653 daily observations from 2003 to 2007. Skew is defined as the skewness of risk neutral distribution of stock returns, which is implied in the stock options. RelativeDemand is measured by the ratio (in percentage) of the open interest for OTM put to the open interest for the near- and at-the-money stock options. ImpliedVolatility is stock implied volatility defined by BKM (2003). Return is stock return. Panel D reports the summary statistics for systematic sentiment variables. Individual is calculated as the number of long non-reported contracts minus the number of short non-reported contracts, scaled by the total open interest in S&P 500 futures. Speculative is defined as the number of long noncommercial contracts minus the number of short noncommercial contracts, scaled by the total open interest in S&P 500 futures. PCRatio is the ratio of CBOE total equity put to call trading volume. MarketVane is the bullish consensus for S&P 500 futures. Panel E summarizes systematic control variables. IndexReturn is the S&P 500 index return, and its implied volatility is IndexVolatiltiy. The five-year U.S. swap rate represents the overall risk-free interest rate level. Baa rate is the average yield of U.S. corporate bonds rated Baa by Moody's to represent market-level credit risk. Credit ratings are from the S&P credit agency.

Table2

Sentiment measures and credit default swap spreads

Model	(1)	(2)	(3)	(4)	(5)	(6)
Skew	-0.0115		-0.0114	-0.0060	- 0.0111	-0.0058
	(-6.8665)		(-6.8228)	(-3.4766)	(-6.6357)	(-3.4026)
RelativeDemand	0.0076		0.0077	0.0084	0.0077	0.0084
	(2.3390)		(2.3749)	(2.6451)	(2.3799)	(2.6511)
Individual		-0.3117	-0.3238	-0.3080	-0.2233	-0.2226
		(-3.5518)	(-3.6913)	(-3.5737)	(-2.4187)	(-2.4529)
Speculative		-0.9275	-0.9326	-0.8183	-0.3560	-0.3875
		(-11.7256)	(-11.7975)	(-10.5301)	(-3.4118)	(-3.7785)
MarketVane		0.1982	0.2003	0.2272	0.2654	0.2526
		(5.0008)	(5.0568)	(5.8388)	(6.4147)	(6.2108)
PCRatio		0.1003	0.0984	0.0767	0.0652	0.0634
		(5.0656)	(4.9726)	(3.9202)	(2.9562)	(2.9255)
ImpliedVolatility				4.4341		4.3657
				(34.2151)		(33.4908)
Return				0.2868		0.2394
				(2.2182)		(1.7115)
IndexReturn					0.8357	0.3804
					(2.5955)	(1.1113)
IndexVolatility					0.8943	0.4387
					(7.1650)	(3.5533)
Level					-3.2218	-3.0645
					(-6.6367)	(-6.4217)
Baa rate					0.1474	0.1242
					(5.5243)	(4.7335)
CreditRating	0.2323	0.2351	0.2334	0.2122	0.2337	0.2130
	(89.3042)	(90.9376)	(89.8916)	(80.8888)	(90.0906)	(81.1542)
Adjust R^2 (%)	20.40	20.28	20.95	23.74	21.22	23.88

Notes: This table reports the results of regression models that examine the relation between CDS spreads and the investor sentiment proxies. The dependent variable is the CDS spreads for 375 sample firms with available stock options data. The independent variables include firm-specific sentiments (Skew, relative demand for OTM put), systematic sentiments (Individual and Speculative sentiments, bullish consensus for S&P 500 futures from MarketVane, the ratio of CBOE total equity put-call trading volume) and other fundamental variables such as stock return, implied volatility, the S&P 500 index return and its implied volatility, overall risk-free interest rate level measured by five-year U.S. swap rate, the average yield of U.S. corporate bonds rated Baa and credit ratings. The numbers in parentheses are *t*-statistics.

Table 3

Sentiment measures and credit default swap spreads: Grouped by credit rating

Sample	Investment-grade	Speculative-grade
Skew	-0.0104	-0.0639
	(-2.1026)	(-2.3919)
RelativeDemand	-0.0022	-0.0286
	(-0.9658)	(-0.6880)
Individual	-0.2969	-13.5669
	(-4.9786)	(-5.7361)
Speculative	-0.8275	-13.38713
	(-14.0095)	(-4.8835)
MarketVane	0.2423	-2.4717
	(8.7524)	(-2.4854)
PCRatio	0.0562	0.1624
	(3.7972)	(0.2425)
ImpliedVolatility	3.9481	17.8812
	(43.8940)	(9.2736)
Return	0.3411	2.1793
	(3.5603)	(0. 5299)
IndexReturn	0.6009	- 22.7315
	(2.5477)	(-2.4205)
IndexVolatility	0.1862	16.8511
	(2.1907)	(5.1786)
Level	-3.5371	0.5936
	(-10.7820)	(4.1589)
Baa rate	0.1413	3.7887
	(7.8764)	(2.8814)
Adjust R^2 (%)	10.74	38.02

Notes: This table demonstrates the sensitivity of CDS spreads to sentiment measures across samples with different credit ratings. The dependent variables are the CDS spreads for investment-grade and speculative-grade firms with available stock options data, respectively. The independent variables include firm-specific sentiments (Skew, relative demand for OTM put), systematic sentiments (Individual and Speculative sentiments, bullish consensus for S&P 500 futures from MarketVane, the ratio of CBOE total equity put-call trading volume) and other fundamental variables such as stock return, implied volatility, the S&P 500 index return and its implied volatility. The numbers in parentheses are *t*-statistics.

Table4

Sentiment measures and credit default swap spreads by quantile regression

Quantile	0.10	0.25	0.50	0.75	0.90
Skew	0.0001	0.0003	-0.0024	-0.0062	-0.0063
	(0.8309)	(1.0190)	(-0.0001)	(-8.8843)	(-3.9095)
RelativeDemand	0.0005	-0.0004	-0.0004	0.0000	0.2728
	(1.4934)	(-0.8137)	(-0.3729)	(-0.0018)	(1.8906)
Individual	-0.0999	-0.1984	-0.3804	-0.4495	-0.9596
	(-6.3632)	(-11.7105)	(-12.7355)	(-9.9502)	(-3.1247)
Speculative	-0.2356	-0.2222	-0.2004	-0.3645	-0.6065
	(-12.3885)	(-10.9794)	(-5.5882)	(-6.8704)	(-4.1416)
MarketVane	0.0869	0.1022	0.1727	0.1983	0.1901
	(13.1760)	(12.7163)	(11.8694)	(10.9684)	(3.2006)
PCRatio	0.0014	0.0116	0.0240	0.0221	0.0445
	(0.2983)	(2.6962)	(2.9409)	(2.3488)	(1.6907)
ImpliedVolatility	0.5637	1.0147	1.4973	1.8939	7.3114
	(10.6048)	(21.7427)	(18.4981)	(14.1448)	(13.2294)
Return	0.0871	0.0864	0.1237	0.0526	0.2260
	(2.1610)	(2.3728)	(2.1686)	(1.0572)	(1.6594)
IndexReturn	0.1306	0.1679	0.2798	0.4900	0.3761
	(1.8677)	(2.5364)	(2.3055)	(3.0905)	(0.9876)
IndexVolatility	0.1756	0.1640	0.3880	0.7739	0.0245
	(7.4619)	(6.4939)	(10.2751)	(13.8655)	(0.1542)
Level	-1.2307	-2.0650	-3.8826	-4.2321	-1.2367
	(-14.1463)	(-22.8903)	(-25.9577)	(-16.6770)	(-1.9413)
Baa rate	-0.3439	0.8682	0.8119	1.7967	1.9513
	(-5.9410)	(1.4642)	(9.2378)	(16.6975)	(5.1119)
CreditRating	0.0565	0.0754	0.1006	0.1337	0.2030
	(86.7618)	(103.1234)	(78.2061)	(80.3209)	(36.3680)

Notes: The estimated results for the 10th, 25th, 50th, 75th, and 90th quantiles with the same set of explanatory variables in each quantile are reported. The dependent variables are the CDS spreads under the different quantiles. The *t*-statistics in parentheses are computed using a bootstrapped resampling method.

Table 5

Credit default swaps spreads and composite index for systematic sentiments

Quantile	0.10		0.50		0.90	
Skew		0.0003		-0.0027		-0.0066
		(1.1710)		(-4.6784)		(-4.1420)
RelativeDemand		0.0005		-0.0008		0.2705
		(1.1786)		(-0.5770)		(1.9132)
SenIndex	-0.0152	-0.0147	0.0633	0.0611	0.1852	0.1684
	(-1.8688)	(-1.7468)	(3.3878)	(3.3158)	(2.6972)	(2.3154)
ImpliedVolatility	0.3461	0.3408	1.4831	1.4201	7.6837	7.4911
	(6.5975)	(6.5516)	(21.3180)	(21.4504)	(14.8151)	(14.3026)
Return	0.0363	0.0440	0.1118	0.1202	0.2260	0.2568
	(0.7450)	(1.1050)	(2.0250)	(2.0112)	(1.5859)	(1.6640)
IndexReturn	0.2413	0.2428	0.2920	0.2907	0.5272	0.5605
	(2.9391)	(2.8681)	(2.2364)	(2.1658)	(1.4137)	(1.4512)
IndexVolatility	0.2479	0.2490	0.4197	0.4146	-0.0576	-0.0316
	(10.1244)	(10.6553)	(9.9666)	(10.1266)	(-0.3355)	(-0.1784)
Level	-2.3589	-2.3664	-4.7681	-4.8478	-3.3589	-3.1264
	(-25.2061)	(-25.8907)	(-31.1573)	(-31.5479)	(-6.0758)	(-5.6787)
Baa rate	-0.5263	-0.5310	0.3657	0.3408	1.6392	1.5398
	(-6.6156)	(-6.7091)	(4.9305)	(4.2847)	(4.3875)	(3.8005)
CreditRating	0.0452	0.0452	0.1031	0.1031	0.2042	0.2046
	(57.2398)	(58.5003)	(85.5064)	(79.9461)	(37.0162)	(36.7796)

Notes: This table reports the relation between CDS spreads and the composite index for systematic sentiments. We construct a composite sentiment index (***SenIndex***) using principal component analysis to extract the common component contained in the four systematic sentiment measures. The *t*-statistics in parentheses are computed using a bootstrapped resampling method.

Table 6

Markov regime-switching regression results

	$\beta_{S_t}^{Skew}$	$\beta_{S_t}^{SI}$	Standard deviation	P_{ii}	LR statistic
Panel A: Speculative-grade sample					
Regime1	-0.0063	0.4195	0.0637	0.97	57.0808
	(0.0012)	(0.0483)			
	[-5.0159]	[8.6853]			
Regime2	-0.1476	3.7448	0.1909	0.58	
	(0.0244)	(0.3024)			
	[-6.0491]	[12.3836]			
Panel B: Investment-grade sample					
Regime1	0.0015	0.0019	0.0015	0.98	14.9284
	(0.0011)	(0.0016)			
	[1.3636]	[1.1875]			
Regime2	-0.0032	0.0278	0.0028	0.52	
	(0.0015)	(0.0036)			
	[-2.0294]	[7.6208]			

Notes: This table investigates whether the responses to investor sentiment are regime-dependent. Regime switching in CDS spreads is modeled as below.

$$CDS_{it} = \alpha + \beta_{S_t}^{Skew} Skew_{it} + \beta_{S_t}^{SI} SenIndex_t + \varepsilon_{it}$$

$$\varepsilon_{it} \sim \text{i.i.d. } N\left(0, \sigma_{S_t}^2\right),$$

where S_t is an unobserved latent variable that follows a two-state Markov process with a constant probability of transition, p_{ij}, from regime *i* to regime *j*, and $\sigma_{S_t}^2$ is the regime-dependent variance of CDS_{it}. $Skew_i$ is defined as the skewness of a risk-neutral distribution of firm *i*, and *SenIndex* is a composite sentiment index that comprises four market-wide sentiments. $\beta_{S_t}^{Skew}$ is the state coefficient from Skew, and $\beta_{S_t}^{SI}$ is the state coefficient from the systematic sentiment index. The coefficients $\beta_{S_t}^{SI}$ and $\beta_{S_t}^{Skew}$ are regime-dependent with $S_t \in \{0,1\}$. The standard deviations from both regimes are reported. P_{ii} is the transition probability. The likelihood ratio statistic of the regime-switching model against the null is calculated. Regime-dependent coefficients and corresponding standard errors (in parentheses) and t-statistics (in brackets) are reported.

Table 7

Robust check to exclude rational components

Model	(1)	(2)	(3)	(4)
Skew	-0.0116		-0.0118	-0.0057
	(-6.9390)		(-7.0628)	(-3.3035)
RelativeDemand	0.0074		0.0073	0.0082
	(2.2765)		(2.2416)	(2.5760)
Individual		-0.2264	-0.2528	-0.2732
		(-2.4119)	(-2.6919)	(-2.9649)
Speculative		-0.0573	-0.0394	0.0510
		(-0.4653)	(-0.3206)	(0.4214)
MarketVane		0.1646	0.1629	0.2729
		(3.9569)	(3.9195)	(6.5626)
PCRatio		0.0786	0.0749	0.0154
		(3.8512)	(3.6739)	(0.7237)
ImpliedVolatility				4.3611
				(33.4317)
Return				0.2345
				(1.6735)
IndexReturn				0.5490
				(1.5995)
IndexVolatility				0.9460
				(9.7141)
CreditRating	0.2323	0.2338	0.2320	0.2118
	(89.3348)	(90.2242)	(89.2016)	(80.6939)
Adjust R^2 (%)	20.41	20.36	20.50	23.63

Notes: This table investigates whether the sentiment measures include rational components. Rational updating on exposure to credit risk is distinguished from errors in investor beliefs on credit risk. The first step is to decompose the sentiment proxies by regressing each sentiment proxy on a set of rational predictors of default risk to obtain the residual sentiment proxies. The second step is to regress the CDS spreads on the residual sentiment proxies. The rational variables I used include (1) *level* of risk-free interest rate (i.e., the five-year US swap rate); (2) *slope* of the yield curve, or the "term spread" (i.e., the difference between the ten-year swap rate and two-year swap rate); (3) demand for *liquidity* (i.e., the difference between the 3-month USD swap interest rate and the treasury yield); and (4) the *Baa-Aaa spread* (i.e., the difference between the average Baa yield and the average Aaa yield of U.S. corporate bonds). The numbers in parentheses are *t*-statistics.

Table 8

Credit default swaps spreads and slope of implied volatility curve: An alternative measure of risk-neutral skewness

Model	Conventional Regression	Quantile Regression		
		0.10	0.50	0.90
Slope	0.5270	0.0059	0.1625	0.4813
	(23.2427)	(0.7283)	(6.0611)	(5.9911)
RelativeDemand	0.0082	0.0005	0.0006	0.2641
	(2.6109)	(1.2745)	(0.4406)	(1.9118)
Individual	-0.1581	0.0356	0.3867	0.2454
	(-1.7640)	(2.1276)	(12.8040)	(1.6305)
Speculative	-0.3451	-0.2326	-0.1879	-0.6516
	(-3.4090)	(-11.4443)	(-5.4824)	(-3.6820)
MarketVane	0.3004	0.0737	0.1626	0.2965
	(7.4425)	(9.6451)	(13.5250)	(4.3624)
PCRatio	0.0690	-0.0036	0.0229	0.0677
	(3.2253)	(-0.8611)	(3.2231)	(2.4258)
ImpliedVolatility	4.4997	0.3766	1.5846	7.7311
	(36.4807)	(7.4295)	(19.3236)	(12.7746)
Return	0.2063	0.0612	0.0836	0.2764
	(1.4935)	(1.1095)	(1.4812)	(1.1720)
IndexReturn	0.2816	0.1721	0.2528	0.0171
	(0.8335)	(2.3124)	(2.0355)	(0.0394)
IndexVolatility	0.4799	0.1392	0.3806	-0.0745
	(3.9336)	(5.0677)	(9.5338)	(-0.3594)
Level	-2.5764	-1.4718	-3.6041	-0.6239
	(-5.4667)	(-13.3794)	(-20.9210)	(-0.8689)
Baa rate	0.1360	-0.1732	0.8295	2.5610
	(5.2562)	(-1.8656)	(8.8215)	(5.9537)
Rating	0.2094	0.0452	0.1021	0.1993
	(80.7202)	(50.0157)	(75.0288)	(32.4366)

Notes: Slope of implied volatility curve is regarded as an alternative measure of the risk-neutral skewness. *Slope* is defined as the ratio of average implied volatility for OTM puts (those with $-0.375 < \Delta P \leq -0.125$) to the average implied volatility for the near- and at-the-money options (for call options with $0.375 < \Delta_C \leq 0.625$ and for put options with $-0.625 < \Delta_P \leq -0.375$). Δ_P and Δ_C are put option delta and call option delta, respectively. The dependent variables are the 10th, 50th, and 90th quantiles of CDS spreads. The numbers in parentheses are *t*-statistics.

行政院國家科學委員會補助國內專家學者出席國際學術會議報告

100 年 10 月 18 日

附件

報告人姓名	陳怡璇	服務機構及職稱	中華大學財務管理學系 助理教授
會議 時間 地點	100 年 4 月 6 日至 100 年 4 月 8 日 紐西蘭，皇后鎮	本會核定補助文號	NSC 99-2410-H-216-002
會議名稱	(中文)2011 財務學會亞洲研討會 (英文) 2011 FMA Asian Conference		
發表論文題目	(英文) Regime Dependent Information Contents of Model-Free Volatility: Evidence from the Eurodollar Options Markets		

報告內容應包括下列各項：

一、參加會議經過

此篇論文報告於 Session 23 “Volatility and Risk Management”，報告順序為第三，並且本人亦評論Section 20 " The Valuation of Equity Futures on the Tokyo Stock Exchange 1920-1923"的論文

二、與會心得

與國際知名學者交流，獲得頗多正面的意見

三、考察參觀活動(無是項活動者省略)

四、建議

國際學術研討會對於研究績效有非常實質的助益，希望有更多的經費可補助及鼓勵國內學者多參加，將有助於國際學術交流

五、攜回資料名稱及內容

註冊費收據及會議議程紙本資料

六、其他

表 Y04

國科會補助計畫衍生研發成果推廣資料表

日期:2011/10/21

國科會補助計畫	計畫名稱: 選擇權市場的投資人情緒與信用違約交換之研究
	計畫主持人: 陳怡璇
	計畫編號: 99-2410-H-216-002- 學門領域: 財務

無研發成果推廣資料

99 年度專題研究計畫研究成果彙整表

計畫主持人：陳怡璇　　計畫編號：99-2410-H-216-002-

計畫名稱：選擇權市場的投資人情緒與信用違約交換之研究

成果項目			量化			單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
			實際已達成數（被接受或已發表）	預期總達成數(含實際已達成數)	本計畫實際貢獻百分比		
國內	論文著作	期刊論文	0	1	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	1	0	100%		於台灣韓國財務金融學會聯合研討會報告。日期：100 年 9 月 24 日。地點：台灣大學
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	0	0	100%	人次	
		博士生	1	1	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	1	1	100%		2010 FMA Asian Conference, Singapore
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	無

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

■達成目標

□未達成目標（請說明，以 100 字為限）

□實驗失敗

□因故實驗中斷

□其他原因

說明：

2. 研究成果在學術期刊發表或申請專利等情形：

論文：□已發表 ■未發表之文稿 □撰寫中 □無

專利：□已獲得 □申請中 ■無

技轉：□已技轉 □洽談中 ■無

其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

投資人情緒與信用違約交換的關係，可由近期的歐債事件獲得證實。歐債信用違約交換的高溢酬，除了反應信用風險外，還反應了投資人悲觀的情緒