Investor Sentiment and Credit Default Swap Spreads During the Global Financial Crisis

Jeehye Lee, Sol Kim, and Yuen Jung Park*

This paper examines whether investor sentiment can predict credit default swap (CDS) spread changes. Among several proxies for investor sentiment, change in equity put–call ratio performs best in predicting variation in CDS spread changes in both firm- and portfolio-level regressions; in particular, the explanatory power of this proxy is greater for non-investment-grade firms than for investment-grade firms. More importantly, sentiment may be a critical factor in determining CDS spread changes during the global financial crisis and may best explain the differences in CDS spread in the group of firms whose leverage ratio and stock volatility are highest. © 2016 Wiley Periodicals, Inc. Jrl Fut Mark

1. INTRODUCTION

Recent literature investigating credit spread changes focuses on finding the systematic determinant to resolve the weak explanatory power of theoretical variables.[1] Avramov, Jostova, and Philipov (2007) conduct a linear time series regression of differences in corporate bond credit spread using a structural model incorporating macroeconomic dummies and the Fama and French (1993) three factors (hereafter, FF factors). These authors report that although the FF factors are significant in the total sample, the explanatory power of the FF factors are not observed when corporate bonds are categorized by the three credit risk groups—low, medium, and high. Galil, Shapir, Amiram, and Ben (2014) propose a model for CDS spread changes by analyzing the FF factors along with the Pastor and

Jeehye Lee is a graduate at Hankuk University of Foreign Studies, Seoul, Korea. Sol Kim is at College of Business, Hankuk University of Foreign Studies, Seoul, Korea. Yuen Jung Park is at Department of Finance, Hallym University, Gangwon-do, Korea. We thank the editor, Robert Webb, and an anonymous referee for their valuable comments. We also thank discussant Professor Chan Shik Jung and seminar participants for helpful suggestions at the 2015 Conference of the Asia-Pacific Association of Derivatives. This study was written while the first author was a student at the Korea Advanced Institute of Science and Technology. This work was supported by the Hallym University Research Fund, HRF-201602-009. This work was supported by Hankuk University of Foreign Studies Research Fund of 2017.

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*Correspondence author, Department of Finance, Hallym University, 1 Hallymdaehak-gil, Chuncheon, Gangwon-do, Korea. Tel: +82-33-248-1855, Fax: +82-33-256-3424, e-mail: yjpark@hallym.ac.kr

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[1]The theoretical model shows a large gap from the historically observed credit spread. For example, Collin-Dufresne et al. (2001) show that the variables of the theoretical model explain only a limited portion of credit spread changes of bonds. In addition, using credit default swap (CDS) spreads as a proxy of credit risk, Ericsson et al. (2009) show that theoretical variables have low explanatory power for credit spread changes.

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Stambaugh (2003) liquidity factor and the Chen, Roll, and Ross (1986) five factors (henceforth, CRR factors). Although the coefficients are significant only in the FF factor model, insignificant coefficients are observed in the CRR and FF factor models in addition to the Pastor and Stambaugh (2003) liquidity factor.

The poor performance of such empirical studies of rational CDS spread determinants motivates us to undertake a study considering factors beyond traditional structural determinants. In this paper, we suggest a novel approach to the determination of corporate credit spread and investigate whether credit default swap (CDS) spread changes can be well predicted by investor sentiment proxies, utilizing a structural model that embeds theoretical factors as control variables. Thus, we test the hypothesis that investor sentiment plays a role in common or systematic risk factors for CDS spread changes, and we explore which sentiment measure is the most effective determinant of CDS spread changes.

In addition, a second, more important hypothesis in the present research is that investor sentiment explains CDS spread changes better in turbulent periods. Tang and Yan (2010) empirically show that the interaction between default risk of CDS spread and investor sentiment can be dependent on market states, such as bullish or bearish markets. Further, Stambaugh et al. (2012) show that when sentiment is widespread in the market, limitations on short sales play a major role in increasing the severity of asset mispricing. These authors also hold that a higher level of sentiment, in turn generally considered as an indicator of a downturn, is associated with more overpricing. Based on the theory of Stambaugh, Yu, and Yuan (2012) as well as the results from Tang and Yan (2010), we conjecture that, in bad economic times, overpricing boosted by the impediment to short selling hinders the hedging of CDSs by equity or equity options and increases CDS spreads, whereas in stable periods the effect of market-wide sentiment should not be strong, due to the absence of short selling restrictions. Therefore, to examine the framework set forth in Stambaugh et al. (2012), we divide the sample period into two periods: the pre-crisis period as a normal term and the Global Financial Crisis period as a representative turbulent term.

This paper restricts examination to the Global Financial Crisis and does not include the post-crisis period in the comparative sample. The reason for this is that asset prices in the U.S. market were externally influenced by several events originating in the debt problems of Greece in the post-crisis period. Many studies report a contagion effect of the European debt crisis. See for example, Beirne and Fratzscher (2013), Gorea and Radev (2014), Kim, Park, and Ryu (2016), and Mink and Haan (2013), among others. In this regard, the post-crisis period in the U.S. market cannot be considered either a purely normal or purely (endogenously) turbulent term.

To test our hypotheses, we perform both firm- and portfolio-level regressions. Although most studies on credit risk conduct regression analyses only at the firm-level, a regression analysis at the portfolio level is carried out here to alleviate the problem of idiosyncratic risk in firm-level regressions. We build our 5×5 portfolios using the leverage ratio and stock volatility of individual firms.[2]

The main results of our empirical tests are as follows. First, most of the sentiment proxies are economically significant factors that explain CDS spread changes. Among the sentiment measures, change in equity put–call ratio performs best in predicting CDS spread

[2]In detail, the process of constructing portfolios follows Kim et al. (2017). We first compute the time series averages of volatility and leverage ratio for each corporation over the full sample period. Next, we set the upper and lower limits of five groups classified by the magnitude of the average leverage ratio and then, within a leverage ratio group, set the upper and lower limits of five groups classified by the magnitude of the average volatility. Each of the 285 firms are allocated to 1 of the 25 portfolios, classified by five volatility and five leverage ratio ranges. Finally, we calculate the cross-sectional averages of the CDS spread, volatility, and leverage ratio for each portfolio, and generate the time series of each variable for the 25 separate portfolios.

changes in both firm-level and portfolio-level regressions. Second, the results from the portfolio-level regressions show that changes in equity put–call ratio show outstanding explanatory power that is almost three times as high as that of structural model. From our detailed observations of the results of each portfolio, we find that sentiment can explain CDS spread best in the group whose leverage ratio and stock volatility are highest, and vice versa. Also, the gap in the ability to predict CDS spread changes between the two polarized portfolios is substantial. Finally, when we divide the sample period into pre-crisis and crisis periods, sentiment models explain CDS spread changes much better in a turbulent period than in a stable period.[3]

The remainder of this paper proceeds as follows. In Section 2, the related background literature is outlined. In Section 3, we describe the data used in our empirical analysis. Section 4 introduces the analytical models. Section 5 presents the results from the individual and portfolio regressions. Finally, Section 6 summarizes our empirical results and remarks.

2. LITERATURE REVIEW

Investor sentiment has been applied to numerous theoretical and empirical financial considerations. Concerning stock asset pricing, Yu and Yuan (2011) test how investor sentiment is related to market risk and return. These authors report that expected excess return is high in low-sentiment periods, while variance has a weaker negative correlation with the expected risk premium in high-sentiment periods, since the role of sentiment traders is larger during high-sentiment periods and sentiment traders can erode the risk premium. Further, investor sentiment shows outstanding results in options markets. Han (2008) documents that investor sentiment proxies in the stock market are related to index option volatility when the risk-neutral skewness in the Standard and Poor's (S&P) 500 index option is measured as in Bakshi, Kapadia, and Madan (2003). These results cannot be explained by the rational option pricing model.

However, for credit risk, investor sentiment has not been widely considered, with only a few studies addressing this variable. Tang and Yan (2010) incorporate the Conference Board Consumer Confidence (CBCC) Index as a proxy for changes in risk aversion that alter the market risk premium. These authors show that investor sentiment strongly predicts credit spread. However, their study focuses more on the influence of market risk on CDS spread changes through the structural model, with sentiment not fully investigated. Further, general participants in derivatives markets are large, often institutional, investors, rather than small investors, such as individuals. Considering only individual sentiment, such as the CBCC Index, may provide only weak evidence. Therefore, we strive to consider both individual and institutional sentiment in various derivatives markets.

Chen and Wang (2010) incorporate investor sentiment in a model as determinants of CDS spread from 2004 to 2007. They categorize diverse sentiments into two groups: market-wide sentiment and firm-specific sentiment derived from options markets and report that investor sentiment explains CDS spread directly and indirectly by affecting stock and options markets.

Saka, Fuertes, and Kalotychou (2015) discover that, only during the pre-announcement of the Outright Monetary Transactions (OTM) program[4] in the Eurozone from July 26, 2011 to July 25, 2012, frequent, large adverse shocks simultaneously influence five Eurozone countries, as detected by country-specific regressions of CDS spreads on systematic risk

[3]Some studies find that the sample period categorized by regimes has economically important meaning in explaining CDS spreads (Alexander & Kaeck, 2008; Cesare & Guazzarotti, 2010).
[4]Saka et al. (2015) state that the European Central Bank (ECB) can buy or outright transactions in the secondary sovereign bond markets of the ECB members to relieve the liquidity pressures through the OTM program.

factors. This finding supports the De Grauwe (2012a,b) fragility hypothesis and the underlying multiple-equilibria theory of crisis. The latter adds that panic boosts exogenous shocks and can push an otherwise solvent country toward default in times of enormous economic adjustment. This result implies that there is an additional factor beyond a strong association between sovereign credit spreads and fundamentals in the 2009 Eurozone debt crisis. Without contradicting the role of fundamentals, multiple-equilibria theorists insist that a self-fulfilling dynamic driven by market sentiments of fear and panic has played a critical role in the region, pushing countries toward a worse equilibrium than is explained by fundamentals alone.

To fill the gap in the CDS spread studies, this paper differs in several facets from preceding studies. First, we use various measures for sentiment and examine which market sentiments best predict CDS, with the goal of exploring a representative proxy of sentiment. We assume that since many studies describe credit risk as being related to the risk of other markets, such as stock and options markets, the sentiments observed in these markets may have some explanatory power for CDS spread changes. Hence, to examine whether sentiment explains variation in CDS premia, we embed diverse sentiment proxies from different sources, that is, other sentiment proxies calculated with the stock market, especially the S&P 500 return, in addition to individual sentiment proxies, such as the Michigan Consumer Sentiment Index and the American Association of Individual Investors Index.[5] Moreover, as Han (2008) indicates, individual sentiment is relatively unrelated to the derivatives market, because individuals are not major participants in the market. Thus, we incorporate market-wide sentiment from the options market as well as the futures market.

Second, compared to research involving only linear regression of the CDS spread on the sentiment variables in Chen and Wang (2010), our study is based more on a structural model embedding theoretical factors as controlling variables. Moreover, the sample period of Chen and Wang (2010) does not include the Global Financial Crisis, which is an extremely important term for CDS studies, whereas we expand the research period from 2006 to 2009 to include the period of the Global Financial Crisis.

Third, while Saka et al. (2015) explore the increasing role played by pessimistic market sentiment, which may have triggered defaults, for sovereign CDS spreads during the 2009 eurozone debt crisis, this paper focuses on the influence of sentiment beyond the fundamental factors to determine U.S. corporate CDS spreads during the Global Financial Crisis period.

3. DATA

3.1. CDS

We use CDS data of senior unsecured USD-denominated debt with a modified restructure clause and 5 years of maturity obtained from Markit. In addition to excluding firms with unknown ratings, we removed firms from the utility and financial sectors, consistent with prior CDS literature (e.g., Ericsson, Jacobs, & Oviedo-Helfenberger, 2009; Kim, Park, & Park, 2017). This common practice is employed for the following reasons. First, "high leverage is normal for financial firms and thus does not have the same meaning as for non-financial firms, where high leverage more likely indicates distress"(Fama & French, 1992, p. 429). Second, utility firms tend to operate their business as a monopoly or oligopoly and make financial decisions under regulations and thus their credit risk is less meaningful than that of unregulated firms.

[5]These sentiment proxies are generally referred to as individual sentiment, since the respondents to the survey are individuals.

By matching stock price data from the Center for Research in Security Prices (CRSP) and accounting data from Compustat, 667 firms remain in our sample. Then, 285 firms with complete monthly observations for the 44-month period from January 2006 to August 2009 remain.[6]

To date, research has addressed credit risk using pure credit spread in terms of level and change. However, as many studies document, this method of measuring credit risk has statistical problems. Greatrex (2008) cast doubt on findings with CDS spread levels, rather than differences. Unit root test results indicate that CDS spread levels are mostly non-stationary, which means the data are statistically inappropriate to use in time-regression analysis as a variable. Moreover, Duffie, Saita, and Wang (2007), and Duffie, Eckner, Horel, and Saita (2009) show that corporate default rate has an exponential relationship with structural model variables, such that the variables have a linear relationship with natural logarithm differences of CDS, rather than with the pure differences of CDS

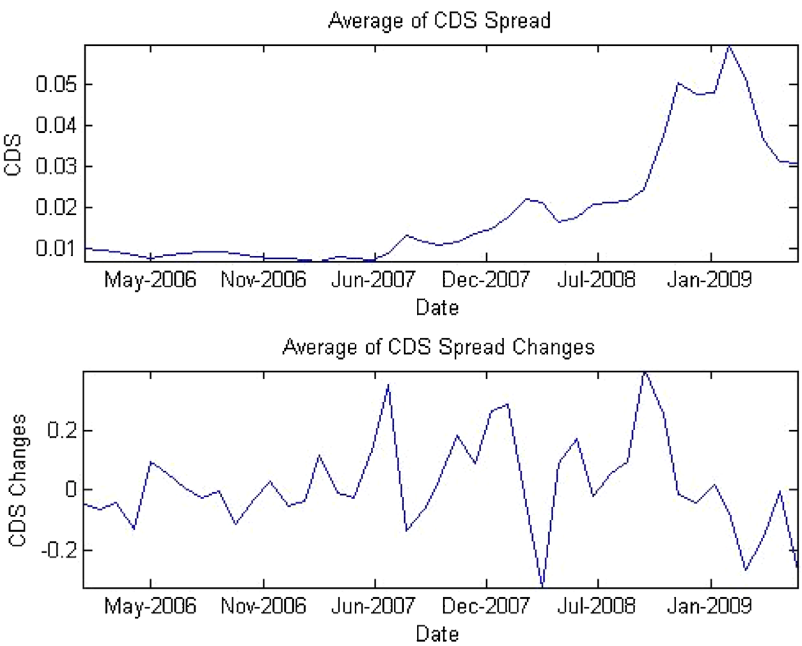

FIGURE 1

Trend of Average CDS Spread and Average of CDS Spread Changes

The upper graph represents the time series of average of CDS spread, and the lower graph shows time series of the average of CDS spread changes for the entire period, January 2006 to August 2009. [Color figure can be viewed at wileyonlinelibrary.com].

spread. In fact, reduced-form model studies (e.g., Pan & Singleton, 2008), which represent another approach to credit risk, have established that a model using logarithmic stochastic process has the best predictive power. Given these considerations and following the Remolona, Scatigna, and Wu (2008) methodology, we use the differences in CDS spread

[6]We select monthly data along as in previous research (Collin-Dufresne et al., 2001; Ericsson et al., 2009; Kim et al., 2017), and we report the results utilizing data for the first trading day of each month. In addition, we confirm similar results when using data from the last trading day of each month.

natural logarithm as the dependent variable. That is, the CDS spread changes are calculated as below:

$$\Delta log\ (\mathrm{CDS}_{i,t}) = log\ (\mathrm{CDS}_{i,t}) - log\ (\mathrm{CDS}_{i,t-1}), \tag{1}$$

where log $(\mathrm{CDS}_{i,t})$ is the natural logarithm of CDS spread in month t for firm i.

Figure 1 depicts the time series of average CDS spread and average of CDS spread changes from January 2006 to August 2009.

3.2. Investor Sentiment

3.2.1. *Michigan Consumer Sentiment Index*[7]

The Michigan Consumer Sentiment Index (*SentMi*) is a survey-based consumer confidence index conducted monthly by the Survey Research Center at the University of Michigan, normalized to have a value of 100 in December 1966. The survey questions concern primarily three broad areas: personal finances, business conditions, and buying conditions of consumers statistically designed to be representative of all American households.[8] According to Cooper and Gubellini (2011), the index serves as an indicator of the future state of the overall economy. Thus, we use *SentMi* as a proxy for the sentiment for the business cycle.

3.2.2. *American Association of Individual Investors bull-bear spread*

The American Association of Individual Investors (AAII) bull-bear spread (*SentAA*) is a survey-based investor sentiment measure issued on a weekly basis. Individuals selected from the ranks of the AAII membership are questioned as to whether the stock market will be bullish, bearish, or neutral for the next 6 months, and the results are used to calculate the index. We utilize the bull-bear spread, computed as the AAII bullish percentage minus the AAII bearish percentage, as a proxy for sentiment.[9] As Qiu and Welch (2006) insist that survey-based sentiment performs better than other sentiment formulations in the stock market, we use *SentAA* as another individual sentiment measure in addition to *SentMi*.

3.2.3. *Baker and Wurgler*

Following the equation presented by Baker and Wurgler (2007), Sentiment of Baker and Wurgler (*SentBW)* is calculated as the weighted sum of closed-end fund discount detrended log turnover, number of initial public offerings (IPOs), first-day return on IPOs, dividend premium, and equity share in new issues.[10] As it measures sentiment in the stock market (Baker & Wurgler, 2007), we use this as a proxy for stock market sentiment.

[7]As Tang and Yan (2010) insist that the correlation between Michigan Consumer Sentiment Index and Conference Board Consumer Confidence Index is high, we report the results of the Michigan Consumer Sentiment index as only one of individual sentiment.

[8]As it is monthly data and announced at the middle of the month as a preliminary and late in the month as a final index, we use one-month lagged sentiment, which is the closest result to the CDS data.

[9]As SentAA is weekly data, not daily, the date does not match with CDS data, which is daily. Therefore, we have to convert weekly data to daily data, by matching the CDS date with the week of SentAA, which includes the CDS's date, because we think that the CDS is affected at the time when it is announced. For example, SentAA announced at September 2, 2010 lasts until September 8, 2010, when the following value is announced. Thus, the CDS data from the 2nd to the 8th is matched with SentAA data announced at September 2, 2010.

[10]As it is monthly data and announced not at the first trading date, we use one-month lagged sentiment, which is the closest result to the CDS data.

3.2.4. *Equity put–call ratio*

In accordance with Chen, Lung, and Tay (2005), we assume that the equity put–call ratio (*SentEPCR*) represents a measure of options market sentiment. These authors show that the equity put–call ratio is a credible measure for discerning good and bad news information embedded in options trades, because it considers information reflected in both options trading volumes and premia.

These authors seek to establish the relationship between stock returns and options trading activity and identify a measure for discerning "good news" versus "bad news" information embedded in options trades. They consider a two-state world where informed traders have information about the probabilities of the up and down states. The informed traders are risk averse, share the same log utility function, and have homogeneous expectations about market movements and price changes. They are interested in understanding how the informed traders would trade to maximize their expected utility if they choose to trade on their information in the options markets. Within this framework, informed traders' cash flows are summarized as follows.

	Long Call	*Long Put*
Cash flow at time 0	$-Q_C \times P_C$	$-Q_P \times P_P$
Payoff at time T		
$\text{Prob}(S = S_U) = \pi_U$	$Q_C \times (S_U - X_C)$	0
$\text{Prob}(S = S_D) = \pi_D$	0	$Q_P \times (X_P - S_D)$

where S stands for stock price and Q_C (Q_P) is the call (put) trading volume. $\text{Prob}(S = S_U)$ and $\text{Prob}(S = S_D)$ are the probabilities that the stock price will increase to S_U and decrease to S_D at some time T in the future, respectively. The magnitudes of price up-movement and down-movement are assumed to be the same. π_U (π_D) denotes the probability that stock price increases (decreases). X_C (X_P) is the exercise price for call (put) options and P_C (P_P) refers to the call (put) premium.

Given their private information and subject to an initial wealth constraint of W_0, informed traders will select optimal quantities of calls and puts to purchase to maximize their expected utility. It is found that the ratio of the probability of a price increase (π_U) to the probability of a price decrease (π_D) is equal to the ratio of the call trading value ($Q_C P_C$) to the put trading value ($Q_P P_P$).

When the call–put option trading VR, $(Q_C P_C)/(Q_P P_P)$, is greater (smaller) than unity, stock return is more likely to be positive (negative). Thus, VR is a credible measure for discerning good and bad news information embedded in options trades, because it considers information reflected in both options trading volumes and premia. The equation above confirms that option volume alone does not fully reflect market expectations and implies that stock returns should be positively related to VR.

Thus, we utilize the Chicago Board Options Exchange (CBOE) total equity put-to-call trading volume ratio as the representative measure of sentiment in the options market. This ratio is defined as the aggregate trading volume of put options to the aggregate trading volume of call options.

3.2.5. *Long-short S&P 500 futures*

Following studies that investigate long-short S&P 500 futures (Chen & Wang, 2010; Han, 2008), Long-short S&P 500 futures (*SentLS*) is the net position of large speculators in S&P 500 futures, which is released weekly by the Commodity Futures Trading Commission. It is derived from the open interest of short large speculators divided by the sum of the open interest of long large speculators and the open interest of short large speculators. As it is derived from futures trading data, we consider this sentiment proxy as representative of sentiment in futures markets.

Figure 2 illustrates the time series of changes in five sentiment measures for the entire period, January 2006 to August 2009. It shows the relationship between the movement of changes in CDS spread and that of individual sentiment proxies. Among the five graphs, the option-derived sentiment proxy shows the most identical movement with the CDS spread changes.

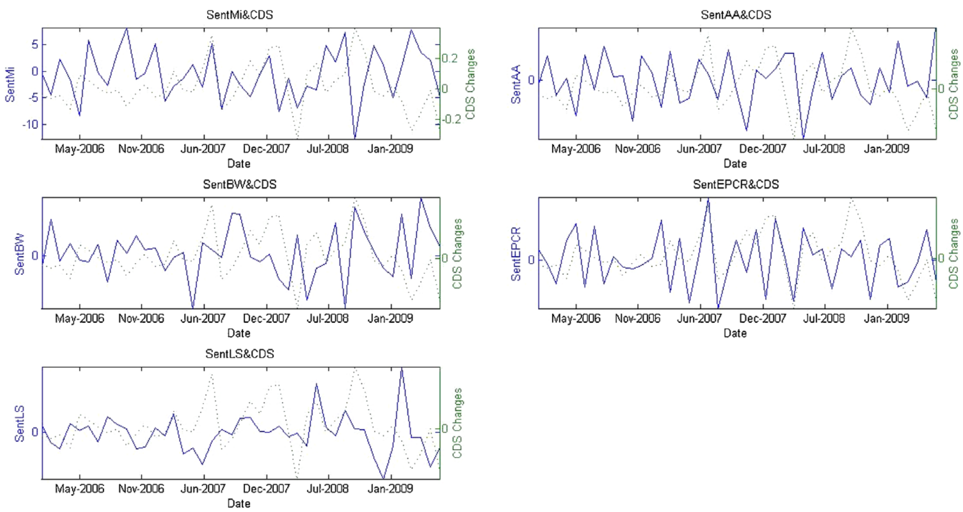

FIGURE 2

Trend of Average Sentiment Proxies and Average CDS Spreads

The five figures represent the time series of change in CDS spreads and of each of the five sentiment measures, $\Delta SentMi$, $\Delta SentAA$, $\Delta SentBW$, $\Delta SentEPCR$, and $\Delta SentLS$ for the entire period, January 2006 to August 2009. The dashed line shows the movement of CDS spread changes and the solid line shows that of each sentiment proxy. [Color figure can be viewed at wileyonlinelibrary.com].

3.3. Theoretical Factors

3.3.1. *Leverage ratio*

According to a prior model (Merton, 1974), as Leverage ratio (*Lev*) increases, the distance to default barrier becomes narrower. Thus, default probability will be higher. We use the CRSP to obtain the market value of firm equity and Compustat to collect the quarterly book value of firm debt and preferred stock. *Lev* is calculated as follows:

$$\text{Leverage ratio } (Lev) = \frac{[\text{book value (debt + preferred stock)}]}{[\text{book value (debt + preferred stock) + market value (equity)}]} \quad (2)$$

3.3.2. *Stock return volatility*

As a number of studies show a strong link between corporate bond spreads and stock return realized volatility or stock option implied volatility through empirical analysis, we implement stock return volatility (*Vol*) as the substitute for firm value volatility, while Collin-Dufresne, Goldstein, and Martin (2001) use S&P 500 Index option implied volatility.

Very recent literature documents that realized volatility can serve as a better measure for the true latent volatility (see, e.g., Fernandez-Perez, Fuertes, & Miffre, 2016). By summing sufficiently finely sampled high-frequency returns, it is possible to construct ex post realized volatility measures for integrated latent volatilities that are asymptotically free of measurement error. From Andersen, Bollerslev Diebold, and Ebens (2001), Andersen, Bollerslev, Diebold, and Labys (2000a,b, 2001, 2003), and Andersen, Bollerslev, Diebold, and Vega (2003), the realized volatilities are generally estimated using intraday data, for example, 5-minute interval data. However, in the present paper, it is difficult to use intraday data for all individual stocks. Instead, we use exponentially weighted moving average (EWMA) volatilities as an alternative to realized volatilities. The exponentially weighted average of daily squared returns over the preceding 3 months is calculated with decay factor 0.94. We adopt the JP Morgan risk-metrics decay factor of 0.94. The data source for stock price time series for each firm is CRSP.

3.3.3. *Risk-free rate*

The ten-year maturity Treasury bond yield collected from the Federal Reserve Economic Data (FRED) set is used for the Risk-free rate (*Rf*). Longstaff and Schwartz (1995) report a negative association between *Rf* and credit spread or default probability, since a high reinvestment interest rate will increase future firm value.

3.4. Controlling Variables

3.4.1. *Term spreads*

The term spread (*Term*) of the yield curve is computed basically by deducting the two-year maturity Treasury yield from the ten-year maturity Treasury yield. As Collin-Dufresne et al. (2001) show that term spread has a negative relation with bond credit spread, we also use term spread as the controlling variable.

3.4.2. *S&P 500 index*

S&P 500 index prices (*SP*) obtained from the CRSP are used to proxy business climate. It is well known that bull stock markets represent a good business environment and increase the expected recovery rates of companies, which lowers CDS spreads.

3.4.3. *Smirk*

Collin-Dufresne et al. (2001) insist that, since a negative jump, which can be detected by option implied volatility smiles, can increase the probability of default in a corporation, a downward jump is expected to result in an increase in credit spreads. Zhang, Zhou, and Zhu (2009) report that the volatility and jump risks of individual corporations using high-frequency equity prices predict a large portion of CDS premia. Likewise, we include smirk as the controlling variable.

Smirk is calculated as follows. First, we select the options from standardized S&P 500 Index options, of which a delta of puts and of calls exceed -0.5 and 0.5, respectively, and of which the remaining maturities are longer than 1 month. With the selected data and implied volatility curves from OptionMetrics, a linear regression of implied volatility on strike price is fitted as follows:

$$imvol\ (K) = a + bK \tag{3}$$

where K is the strike price and $imvol\ (\cdot)$ is an implied volatility function. The slope of smirk is generated as follows:

$$imvol\ (0.9S) - imvol\ (1.1S) \tag{4}$$

where S is current stock price.

Panel A of Table I sets forth the variables defined in this study and their descriptions, including the specific data used in their estimation. The last column shows the expected results of the regression for differences in the natural logarithm of CDS. In addition, as a stationary check for the variables employed in the regression analysis, the unit root test is implemented before conducting the regression. We first generate the averages of CDS, *Lev*, and *Vol*, and test whether the data are stationary or non-stationary.

The null hypothesis is that time series is non-stationary; $H = 0$ means failing to reject the null hypothesis and $H = 1$ means rejecting the null hypothesis. In Panels B and C of Table I, we present the results with the test statistic, including corresponding p-values and t-statistics. Panel B represents the Augmented Dickey Fuller Test for the raw time series data of all variables. Except sentiment variables, *SentAA* and *SentLS*, the variables are non-stationary. Panel C indicates that the logarithm of CDS spread, theoretical variables, and a battery of market sentiment proxies are all stationary in first differences. The statistics for the theoretical variables coincide with the result of Greatrex (2008) that the variables suggested by the structural model are stationary in the first differences.

Panel A of Table II summarizes descriptive statistics of the log difference of CDS spreads and the explanatory variables in first difference used in the multiple regressions. For the firm-specific variables and CDS spread, cross-sectional averages are reported. The first four columns are for the basic statistics and the last three columns (skewness, kurtosis, and J-Q test) are for information on the distributions. With the exception of *Rf*, no variables are skewed. However, several variables, especially the three theoretical variables and *SentLS*, show fatter tails than the normal distribution. As expected, these variables reject the J-Q test, for which the null hypothesis is that the data are normally distributed.

Panel B of Table II shows the correlation of all independent variables. The maximum correlation is -0.4351 between *Rf* and term spread, which is not substantially large correlation. The correlation coefficients among sentiment variables are relatively low (the highest correlation coefficient is 0.28 between *SentBW* and *SentMi*), which means it is worthwhile to examine all our sentiment measures.

4. ANALYTICAL FRAMEWORK

4.1. Structural Model (Merton Model)

As we utilize differences in logarithm CDS spread as the proxy for credit risk, we test the model of Ericsson et al. (2009) by replacing differences in CDS spread with this new proxy and investigate the validity of the structural model. The regression equations are as follows:

$$\Delta log\ (\mathrm{CDS}_i) = a_i + \beta_{lev} \Delta lev_i + \varepsilon_i \tag{5}$$

TABLE I

Expected Signs for Variables and Unit Root Test

Panel A: Expected Signs for the Variables

Variables	*Description*	
Δ*Lev*	Change in leverage ratio	+
Δ*Vol*	Change in exponentially weighted moving average of squared stock returns	+
Δ*Rf*	Change in yield on ten-year Treasury	−
Δ*SentMi*	Sentiment proxy, change in consumer sentiment	−
Δ*SentAA*	Sentiment proxy, change in individual investment sentiment	−
Δ*SentBW*	Sentiment proxy, change in Baker and Wurgler sentiment measure derived from stock market sentiment	−
Δ*SentEPCR*	Sentiment proxy, change in equity put-to-call ratio	+
Δ*SentLS*	Sentiment proxy, change in net position of long-short S&P 500 futures	?
Δ*Term*	Change in difference between ten- and two-year Treasury yield	?
Δ*SP*	Change in S&P 500 index	−
Δ*Smirk*	Change in slope of one-month volatility curve across strike prices	+

Panel B: Unit Root Test Before Differencing the Time Series Data

	H	*P-value*	*t-value*
log (CDS)	0	0.6304	−0.0429
Lev	0	0.9176	1.0288
Vol	0	0.4973	−0.4071
Rf	0	0.4174	−0.6259
SentMi	0	0.2666	−1.0389
SentAA	1	0.0010	−4.4105
SentBW	0	0.4702	−0.4818
SentEPCR	0	0.4158	−0.6305
SentLS	1	0.0184	−2.3808
Term	0	0.8916	0.8595
SP	0	0.3887	−0.7047
Smirk	0	0.3969	−0.6821

Panel C: Unit Root Test After Differencing the Time Series Data

	H	*p-value*	*t-value*
Δ*log (CDS)*	1	0.0010	−4.2832
Δ*Lev*	1	0.0010	−5.2250
Δ*Vol*	1	0.0010	−4.8916
Δ*Rf*	1	0.0010	−5.8083
Δ*SentMi*	1	0.0010	−7.1424
Δ*SentAA*	1	0.0010	−8.7327
Δ*SentBW*	1	0.0010	−7.6195
Δ*SentEPCR*	1	0.0010	−10.9810
Δ*SentLS*	1	0.0010	−5.7828
Δ*Term*	1	0.0010	−5.7436
Δ*SP*	1	0.0010	−4.9821
Δ*Smirk*	1	0.0010	−10.6090

Panel A represents the description and expected signs from regressions of important variables employed in various models. Panel B indicates the results of unit root tests before differencing the time series data, while Panel C represents the results after differencing the time series data. Significance tests are conducted at the 5% level. As stationarity is determined by the existence of unit root, Augmented Dickey Fuller Test is implemented. Lags are selected according to the Schwarz Information Criterion. The null hypothesis is that the variable has unit root.

TABLE II
Summary Statistics and Correlation Coefficients of Variables

Panel A: Summary Statistics

	Mean	*Min*	*Max*	*Std*	*Skew*	*Kurtosis*	*J-Q*
Δ*log* (CDS)	0.0172	−0.3248	0.3997	0.1526	0.3280	3.4947	0
Δ*Lev*	0.0026	−0.0361	0.0539	0.0178	0.5333	4.9140	1
Δ*Vol*	0.0052	−0.3065	0.3670	0.0970	0.5986	8.1295	1
Δ*Rf*	−0.0002	−0.0124	0.0053	0.0029	−1.5186	8.5911	1
Δ*SentMi*	−0.5930	−12.7000	8.2000	4.6765	−0.1461	2.7502	0
Δ*SentAA*	0.0036	−0.4137	0.3707	0.1736	−0.2438	2.7114	0
Δ*SentBW*	0.0995	−1.4998	1.6997	0.7411	−0.0579	2.8573	0
Δ*SentEPCR*	0.0019	−0.2700	0.3500	0.1491	0.0549	2.2941	0
Δ*SentLS*	−0.0017	−0.0717	0.1025	0.0303	0.8677	5.8325	1
Δ*Term*	0.0570	−0.6900	0.5600	0.2432	−0.1397	4.0061	0
Δ*SP*	−6.1900	−194.7600	115.5900	66.7387	−0.7291	3.4711	0
Δ*Smirk*	0.0000	−0.0675	0.0986	0.0332	0.3076	3.5460	0

Panel B: Correlation Coefficients

	Δ*log* (CDS)	Δ*Lev*	Δ*Vol*	Δ*Rf*	Δ*SentMi*	Δ*SentAA*	Δ*SentBW*	Δ*SentEPCR*	Δ*SentLS*	Δ*Term*	Δ*SP*	Δ*Smirk*
Δ*log* (CDS)	1.0000											
Δ*Lev*	0.3170	1.0000										
Δ*Vol*	0.2345	0.2683	1.0000									
Δ*Rf*	−0.2768	−0.1531	−0.0945	1.0000								
Δ*SentMi*	−0.1299	−0.2453	−0.1822	0.1136	1.0000							
Δ*SentAA*	−0.1245	−0.0851	0.0800	0.1952	0.0783	1.0000						
Δ*SentBW*	−0.0285	−0.0406	0.0324	−0.1688	−0.1235	0.1825	1.0000					
Δ*SentEPCR*	0.2494	0.2899	0.1193	−0.1175	−0.1216	−0.2173	−0.0659	1.0000				
Δ*SentLS*	0.0857	−0.0495	0.2603	−0.2028	−0.0500	0.1984	0.0449	−0.1322	1.0000			
Δ*Term*	0.1276	0.0770	0.2098	0.4351	0.0037	−0.0375	−0.1088	−0.0071	−0.0096	1.0000		
Δ*SP*	−0.4423	−0.6129	−0.4206	0.2390	0.3176	0.1729	0.1160	−0.4831	−0.0193	−0.2359	1.0000	
Δ*Smirk*	−0.0392	0.0644	0.0571	0.2235	−0.2399	−0.3785	−0.0913	0.1986	−0.0627	0.1306	−0.1046	1.0000

Panel A shows summary statistics of differences for all variables. The first row shows statistics for log CDS premia in first difference and the next three rows show changes in theoretical factors, which are the time series statistics of cross-sectional means of the data. The rest of the table shows time series statistics of the other explanatory variables. Panel B reports means of the correlation coefficients between the time series changes in all the regression variables used in sentiment models.

$$\Delta log\ (\mathrm{CDS}_i) = a_i + \beta_{vol}\Delta vol_i + \varepsilon_i \tag{6}$$

$$\Delta log\ (\mathrm{CDS}_i) = a_i + \beta_{rf}\Delta Rf + \varepsilon_i \tag{7}$$

$$\Delta log\ (\mathrm{CDS}_i) = a1_i + \beta 1_{lev}\Delta lev_i + \beta 1_{vol}\Delta vol_i + \beta 1_{rf}\Delta Rf + \varepsilon 1_i \tag{8}$$

Regression Equations (5–7) verify that each theoretical variable can explain the credit spread, and model (8) tests the explanatory power of the theoretical variables as a whole. We report the average of 285 coefficients and the Mean Group (MG) *t*-statistic of Pesaran and Smith (1995), which is computed by dividing the mean of individual coefficients by the standard deviation of coefficient values, scaling by the square root of the number of firms. The MG estimation is employed in many other studies, such as Collin-Dufresne et al. (2001), Ericsson et al. (2009), and Brun-Aguerre, Fuertes, and Phylaktis (2012).

4.2. Sentiment Model

4.2.1. Firm level

To be consistent with previous studies, such as Collin-Dufresne et al. (2001), Ericsson et al. (2009), and Kim et al. (2017), we implement the following regression equations, adding the sentiment variable to their variables:

$$\Delta log\ (\mathrm{CDS}_i) = a2_i + \beta 2_{sent}\Delta Sent + \varepsilon 2_i \tag{9}$$

$$\Delta log\ (\mathrm{CDS}_i) = a3_i + \beta 3_{lev}\Delta lev_i + \beta 3_{vol}\Delta vol_i + \beta 3_{rf}\Delta Rf + \beta 3_{sent}\Delta Sent + \varepsilon 3_i \tag{10}$$

$$\begin{aligned}\Delta log\ (\mathrm{CDS}_i) = a4_i &+ \beta 4_{lev}\Delta lev_i + \beta 4_{vol}\Delta vol_i + \beta 4_{rf}\Delta Rf + \beta 4_{sent}\Delta Sent + \beta 4_{term}\Delta term \\ &+ \beta 4_{sp}\Delta sp + \beta 4_{smirk}\Delta smirk + \varepsilon 4_i\end{aligned} \tag{11}$$

To examine whether each sentiment variable can predict spread variations, we use univariate regression analysis for each sentiment variable as Equation (9). Then we perform the regression of CDS spread on the three theoretical factors for each individual firm and sentiment variable *i*, as represented in Equation (10). To test the robustness, we also add the sentiment variable to the base regression of Collin-Dufresne et al. (2001) in Equation (11). For the *t*-statistics, we divide the mean of each beta by the standard error of 285 firms, as adopted previously (Pesaran & Smith, 1995).

4.2.2. Portfolio level

We also conduct a portfolio-level regression to examine whether each sentiment variable can predict spread variations after the idiosyncratic risk is controlled (Kim et al., 2017). We first use a univariate regression for each sentiment variable, as in Equation (12). Then, we regress CDS spread on the three theoretical factors and the sentiment variable for each of the 25 portfolios, as represented in Equation (13). We also add the sentiment variable to the base independent variables of Collin-Dufresne et al. (2001), as in Equation (14).

$$\Delta log\ (\mathrm{CDS}_p) = a_p + \gamma_{sent}\Delta Sent + \varepsilon_p \tag{12}$$

$$\Delta log\ (\mathrm{CDS}_p) = a1_p + \gamma 1_{lev}\Delta lev_p + \gamma 1_{vol}\Delta vol_p + \gamma 1_{rf}\Delta Rf + \gamma 1_{sent}\Delta Sent + \varepsilon 1_p \tag{13}$$

$$\Delta log\ (\mathrm{CDS}_p) = a2_p + \gamma 2_{lev}\Delta lev_p + \gamma 2_{vol}\Delta vol_p + \gamma 2_{rf}\Delta Rf + \gamma 2_{sent}\Delta Sent + \gamma 2_{term}\Delta term + \gamma 2_{sp}\Delta sp + \gamma 2_{smirk}\Delta smirk + \varepsilon 2_p \qquad (14)$$

5. EMPIRICAL RESULTS

5.1. Structural Factors

Table III presents the results of the regression analysis between variations of CDS spread and traditional structural variables according to Merton (1974) and validated by Ericsson et al. (2009). The first three columns display the coefficients of univariate regressions. *Lev*, *Vol*, and *Rf* are statistically significant in predicting CDS spread changes and the adjusted R^2s are 12%, 5%, and 7%, respectively. The last column of the table displays the results of the multivariate regression incorporating all three factors. Based on the information from the adjusted R^2, the structural model predicts only about 20% of log CDS spread differences. This result agrees with the finding of Ericsson et al. (2009), who report that these three determinants explain 23% of the CDS spread difference. Our result on the explanatory power of the variables is about 3% lower compared to Ericsson et al. (2009). This difference may reflect the method of differencing CDS spreads, that is, a statistical difference between naïve difference in CDS premia and difference in logarithm of CDS premia, and from the sample period.

5.2. Investor Sentiment Factors

5.2.1. Firm-level regression results

Table IV reports the results of basic regressions between each selected sentiment measure and individual firm CDS spread changes. Overall, sentiment proxies for diverse markets are significant. Δ*SentMi*, Δ*SentAA*, and Δ*SentBW* are negatively significant, while Δ*SentEPCR* and Δ*SentLS* are positively significant. Only Δ*SentMi* loses significance, showing altering

TABLE III
Regression Results of Theoretical Variables

Constant	0.0097	0.0153	0.0135	0.0072
	(0.5840)	(0.8221)	(0.6987)	(0.4219)
Δ*Lev*	4.0606			3.5379
	(9.2348)			(3.8109)
Δ*Vol*		0.4537		0.3089
		(19.1668)		(13.4200)
Δ*Rf*			−22.2381	−17.8554
			(−30.6138)	(−24.4826)
R^2	14.18%	8.16%	9.61%	25.73%
A-R^2	12.09%	5.92%	7.41%	20.02%

This table represents the result from univariate and multivariate regression of CDS spread changes on the changes in structure variables suggested by Ericsson et al. (2009) from January 2006 to August 2009, or 44 months. The coefficient estimates and the *R*-squared values are the average of the result of regressions of each CDS spread change of individual firms, and the *t*-statistics are calculated by dividing the mean of individual coefficients by the standard deviation coefficient values scaling by the square root of number of firms, as in Collin-Dufresne et al. (2001).

TABLE IV
Regression Results of Sentiment Proxies

Constant	0.0133	0.0071	−0.0033	0.0178	0.0078	−0.0027	0.0181	0.0093	−0.0026	0.0165	0.0077	−0.0039	0.0183	0.0073	−0.0034
	(0.6935)	(0.4169)	(−0.1578)	(0.9238)	(0.4565)	(−0.1330)	(0.9166)	(0.5315)	(−0.1214)	(0.8494)	(0.4491)	(−0.1875)	(0.9521)	(0.4333)	(−0.1682)
Δ*Lev*		3.5497	1.2624		3.3230	1.1859		3.3756	1.2874		2.9860	1.3094		3.4033	1.0920
		(3.8626)	(1.0129)		(3.8423)	(0.9781)		(3.7056)	(0.9601)		(3.1984)	(1.0603)		(4.0719)	(0.9438)
Δ*Vol*		0.3141	0.0709		0.3322	0.0981		0.3220	0.0788		0.2949	0.0814		0.3032	0.0521
		(13.4449)	(3.4775)		(13.9648)	(4.8556)		(13.7099)	(3.9278)		(13.3298)	(4.0884)		(12.5602)	(2.4788)
Δ*Rf*		−17.7934	−19.9416		−16.7057	−18.6019		−18.7990	−20.4057		−17.0768	−20.2061		−17.6860	−19.6186
		(−24.4242)	(−27.0411)		(−23.4159)	(−25.3938)		(−24.9487)	(−27.0856)		(−23.7524)	(−27.1322)		(−23.6974)	(−26.3228)
Δ*SentMi*	−0.0066	−0.0001	0.0008												
	(−16.9886)	(−0.2825)	(2.2195)												
Δ*SentAA*				−0.1721	−0.1023	−0.0667									
				(−16.7662)	(−10.1166)	(−5.7766)									
Δ*SentBW*							−0.0086	−0.0212	−0.0098						
							(−3.9123)	(−9.4953)	(−4.3932)						
Δ*SentEPCR*										0.3984	0.2248	0.1422			
										(25.0340)	(15.6630)	(9.4887)			
Δ*SentLS*													0.6368	0.0630	0.1068
													(12.8721)	(1.1175)	(1.8971)
Δ*Term*			0.1509			0.1445			0.1524			0.1672			0.1521
			(18.2004)			(17.4104)			(18.3087)			(19.4944)			(18.3661)
Δ*SP*			−0.0010			−0.0010			−0.0010			−0.0008			−0.0010
			(−19.4697)			(−19.4095)			(−18.7546)			(−15.8220)			(−19.6508)
Δ*Smirk*			−0.2838			−0.4634			−0.3190			−0.4070			−0.3051
			(−6.5271)			(−8.3999)			(−7.2486)			(−8.7053)			(−6.9069)
R^2	3.32%	27.19%	39.05%	3.13%	27.69%	39.37%	1.44%	27.51%	39.11%	8.64%	29.51%	40.13%	2.03%	27.10%	39.10%
A-R^2	0.97%	19.52%	26.86%	0.76%	20.08%	27.25%	−0.97%	19.87%	26.93%	6.41%	22.09%	28.15%	−0.36%	19.43%	26.92%

This table represents the result from linear regression of CDS spread changes on the other variables from January 2006 to August 2009, or 44 months. The coefficient estimates and the *R*-squared values are the average of the result of regressions of each CDS difference of individual firms, and the *t*-statistics are calculated by dividing the mean of individual coefficients by the standard deviation coefficient values scaling by the square root of number of firms, as in Collin-Dufresne et al. (2001).

sign from negative to positive when the controlling variables are added to the regression. Among the valid factors, $\Delta SentEPCR$ displays a significantly positive effect on the variations in CDS spread changes, which indicates that larger changes in the ratio of trading volume of puts to the trading volume of calls are associated with larger changes in CDS spreads. Univariate regression indicates that $\Delta SentEPCR$ is a superior predictor than volatility, a firm-specific factor; the adjusted R^2s of volatility and $\Delta SentEPCR$ are 5.92% and 6.41%, respectively. Moreover, $\Delta SentEPCR$ enhances the explanatory power by 2% compared to that of the three-factor theoretical model.

5.2.2. *Firm-level regression results for investment-grade firms versus non-investment-grade firms*

To examine whether sentiment affects CDS premium variations more precisely, CDS is categorized by ratings into two groups: investment-grade firm CDS, ranging from AAA to BBB, and non-investment-grade firm CDS, below BBB, as previously described (Chen & Wang, 2010; Kim et al., 2017). Table V presents the results of the regression model that examines the explanatory power of sentiment on the investment-grade firms' CDS for 44 months from January 2006 to August 2009. Except for $\Delta SentMi$, sentiment proxies are significant and align with the expected signs. However, their magnitudes of coefficient and t-statistics markedly decrease compared to the basic regression; most of the adjusted R^2s are either negative or nearly zero in univariate regression, except for $\Delta SentMi$. Only the coefficient resulting from $\Delta SentMi$ is statistically significant. Its adjusted R^2 is as high as the theoretical factors, but its coefficient shows opposite signs in the model with controlling variables. Overall, sentiment barely explains high-grade CDS spread changes.

Table VI presents the results of the regression model that examines the explanatory power of sentiment on the non-investment-grade firm CDS for the entire sample period. Comparing the results of two divided CDS ratings, unlike the results from other studies (Chen & Wang, 2010; Greatrex, 2008), there is no evidence that theoretical variables can explain CDS premium changes for speculative firms better than for investment-grade firms. However, one sentiment model performs better in predicting differences in speculative CDS by showing markedly higher R^2 in models on speculative CDS than investment-grade CDS. For non-investment-grade CDS, the univariate regression of $\Delta SentEPCR$ predicts about 8% of CDS premium differences, and this result is much better than results from the univariate regression on theoretical variables of *Vol* and *Rf*, of which the adjusted R^2 for both are only about 5%.[11]

5.2.3. *Portfolio-level regression results*

A 5×5 portfolio is constructed based on five leverage ratios and five stock return volatilities, as previously described (Kim et al., 2017). Table VII presents summary statistics for each portfolio and the cross-sectional mean of correlation coefficients of all variables employed in the portfolio models. CDS spread grouped by rankings of leverage ratio and volatility is highly correlated (about 80%) to the portfolio leverage ratio.

Table VIII reports linear regression results for 25 portfolio matrixes by quintiles based on leverage ratio and stock volatility, each with 44 monthly CDS spread quotes over the full sample period. Overall explanatory power increases in the firm-level regression by

[11]The univariate regression results on theoretical variables for non-investment grade firms are not reported in Table 6, but are available on request.

TABLE V
Regression Results for Investment-Grade CDS

Constant	0.0070	0.0133	0.0068	−0.0044	0.0182	0.0077	−0.0032	0.0185	0.0094	0.0094	0.0168	0.0077	−0.0047	0.0188	0.0074	−0.0040
	(0.3978)	(0.6825)	(0.3844)	(−0.2056)	(0.9344)	(0.4404)	(−0.1532)	(0.9258)	(0.5162)	(0.5162)	(0.8564)	(0.4346)	(−0.2214)	(0.9762)	(0.4247)	(−0.1917)
Δ*Lev*	4.1245		4.1285	1.3499		3.8442	1.2478		3.9147	1.3933		3.4811	1.4098		3.9630	1.1461
	(3.8340)		(3.3360)	(0.8019)		(3.3001)	(0.7621)		(3.1906)	(0.7693)		(2.7664)	(0.8453)		(3.5226)	(0.7335)
Δ*Vol*	0.3592		0.3639	0.0749		0.3897	0.1130		0.3766	0.0866		0.3463	0.0887		0.3468	0.0484
	(14.2148)		(12.2020)	(2.8165)		(12.9077)	(4.3170)		(12.6193)	(3.3197)		(12.3200)	(3.4193)		(11.1781)	(1.7721)
Δ*Rf*	−20.1010		−20.0242	−22.3907		−18.7182	−20.5675		−21.1361	−23.0136		−19.3239	−22.7391		−19.7139	−21.8824
	(−27.4659)		(−23.4620)	(−27.0951)		(−22.4468)	(−25.0355)		(−23.9984)	(−27.2585)		(−22.9730)	(−27.2520)		(−22.3835)	(−25.7912)
Δ*SentMi*		−0.0072	−0.0003	0.0003												
		(−16.5106)	(−0.7435)	(0.6585)												
Δ*SentAA*					−0.1979	−0.1240	−0.0937									
					(−16.4958)	(−10.2774)	(−6.8975)									
Δ*SentBW*								−0.0096	−0.0234	−0.0113						
								(−3.7290)	(−8.7249)	(−4.2170)						
Δ*SentEPCR*											0.3961	0.2206	0.1385			
											(22.0512)	(14.0097)	(8.0309)			
Δ*SentLS*														0.7570	0.1862	0.2088
														(13.5089)	(2.8610)	(3.1956)
Δ*Term*				0.1713			0.1611			0.1721			0.1869			0.1711
				(17.9359)			(16.9341)			(17.9210)			(18.7048)			(17.9403)
Δ*SP*				−0.0011			−0.0011			−0.0011			−0.0009			−0.0011
				(−18.0166)			(−18.1622)			(−17.4317)			(−14.5390)			(−18.4510)
Δ*Smirk*				−0.3505			−0.5728			−0.3694			−0.4541			−0.3525
				(−7.2524)			(−9.1535)			(−7.4263)			(−8.6921)			(−7.0734)
R^2	25.68%	3.46%	27.15%	39.09%	3.56%	27.86%	39.57%	1.40%	27.54%	39.21%	8.07%	28.97%	39.99%	2.24%	27.09%	39.24%
A-R^2	19.96%	5.83%	21.49%	27.99%	−1.00%	19.91%	27.05%	1.20%	20.26%	27.48%	1.11%	19.48%	26.91%	−0.15%	19.41%	27.08%

This table represents the result from linear regression of investment-grade CDS spread changes on the other variables from January 2006 to August 2009, or 44 months. CDS are divided into two credit rating categories: investment-grade, from AAA to BBB, and non-investment-grade, below BBB. The coefficient estimaites and the *R*-squared values are the average of the result of regressions of each CDS spread change of individual firms, and the *t*-statistics are calculated by dividing the mean of individual coefficients by the standard deviation coefficient values scaling by the square root of number of firms, as in Collin-Dufresne et al. (2001).

TABLE VI
Regression Results for Non-Investment-Grade CDS

Constant	0.0078	0.0133	0.0080	0.0000	0.0166	0.0080	−0.0013	0.0169	0.0093	0.0093	0.0155	0.0079	−0.0015	0.0168	0.0072	−0.0017
	(0.5002)	(0.7230)	(0.5265)	(−0.0002)	(0.8893)	(0.5071)	(−0.0700)	(0.8860)	(0.5807)	(0.5807)	(0.8247)	(0.4943)	(−0.0792)	(0.8802)	(0.4597)	(−0.0926)
Δ*Lev*	1.8656		1.8993	1.0130		1.8369	1.0091		1.8385	0.9853		1.5742	1.0229		1.8073	0.9376
	(18.3027)		(9.3369)	(5.9173)		(9.6866)	(5.8666)		(9.0208)	(5.8766)		(8.4908)	(5.7711)		(9.3337)	(5.3085)
Δ*Vol*	0.1654		0.1720	0.0596		0.1683	0.0558		0.1662	0.0566		0.1483	0.0606		0.1791	0.0626
	(14.7838)		(7.6367)	(2.8760)		(7.4851)	(2.5762)		(7.3609)	(2.6967)		(6.9602)	(2.9854)		(7.6133)	(2.8256)
Δ*Rf*	−11.4524		−11.4327	−12.9583		−10.9672	−12.9972		−12.1351	−12.9697		−10.6692	−12.9835		−11.9037	−13.1638
	(−19.8900)		(−10.3139)	(−10.1040)		(−9.5705)	(−9.3727)		(−10.5507)	(−10.1449)		(−9.8162)	(−10.1570)		(−10.1904)	(−10.2558)
Δ*SentMi*		−0.0051	0.0005	0.0024												
		(-6.1180)	(0.7400)	(3.3847)												
Δ*SentAA*					−0.0985	−0.0406	0.0101									
					(−5.7086)	(−2.4756)	(0.5221)									
Δ*SentBW*								−0.0057	−0.0150	−0.0057						
								(−1.3576)	(−3.8592)	(−1.4233)						
Δ*SentEPCR*											0.4047	0.2369	0.1526			
											(11.9541)	(7.3086)	(5.0265)			
Δ*SentLS*														0.2941	−0.2882	−0.1839
														(3.1456)	(−2.7928)	(−1.7597)
Δ*Term*				0.0926			0.0971			0.0961			0.1113			0.0981
				(6.2645)			(6.1663)			(6.4403)			(7.4002)			(6.4951)
Δ*SP*				−0.0009			−0.0009			−0.0009			−0.0007			−0.0009
				(−8.0730)			(−7.8317)			(−7.6691)			(−6.6046)			(−7.8354)
Δ*Smirk*				−0.0937			−0.1513			−0.1754			−0.2726			−0.1699
				(−1.0160)			(−1.4005)			(−1.9198)			(−2.7225)			(−1.8404)
R^2	25.89%	2.93%	27.29%	38.95%	1.90%	27.21%	38.82%	1.53%	27.41%	38.82%	10.27%	31.04%	40.51%	1.43%	27.13%	38.71%
A-R^2	20.19%	0.56%	19.63%	26.74%	−0.49%	19.55%	26.58%	−0.87%	19.77%	26.58%	8.08%	23.79%	28.61%	-0.97%	19.46%	26.45%

This table represents the result from linear regression of non-investment-grade CDS spread changes on the other variables from January 2006 to August 2009, or 44 months. CDS are divided into two credit rating categories: investment-grade, from AAA to BBB, and non-investment-grade, below BBB. The coefficient estimates and the *R*-squared values are the average of the result of regressions of each CDS spread change of individual firms, and the *t*-statistics are calculated by dividing the mean of individual coefficients by the standard deviation coefficient values scaling by the square root of number of firms, as in Collin-Dufresne et al. (2001).

TABLE VII
Summary Statistics of Individual Portfolios and Correlation Coefficients of Variables

Panel A: Summary Statistics of Individual Portfolios

	Vol1	*Vol2*	*Vol3*	*Vol4*	*Vol5*
Lev1	[0.36]	[0.43]	[0.81]	[0.65]	[1.08]
	(7.03)	(5.83)	(6.00)	(6.11)	(9.22)
	{23.34}	{30.91}	{37.35}	{45.11}	{54.80}
Lev2	[0.37]	[0.59]	[0.75]	[1.16]	[1.06]
	(13.25)	(13.97)	(13.54)	(14.82)	(14.31)
	{23.07}	{31.39}	{38.55}	{44.30}	{55.36}
Lev3	[0.73]	[0.65]	[1.06]	[1.5]	[2.93]
	(21.27)	(20.46)	(21.24)	(21.28)	(21.13)
	{24.76}	{31.64}	{37.43}	{45.40}	{59.49}
Lev4	[0.79]	[1.10]	[1.15]	[2.09]	[3.48]
	(31.63)	(32.14)	(32.41)	(32.67)	(32.07)
	{25.39}	{31.79}	{37.42}	{45.50}	{60.47}
Lev5	[0.93]	[1.63]	[1.86]	[3.44]	[7.19]
	(46.75)	(46.22)	(51.00)	(52.31)	(57.22)
	{23.65}	{30.79}	{37.55}	{46.29}	{65.81}

Panel B: Correlation Coefficients of Variables

	Δlog (CDS)	ΔLev	ΔVol	ΔRf	$\Delta SentMi$	$\Delta SentAA$	$\Delta SentBW$	$\Delta SentEPCR$	$\Delta SentLS$	$\Delta Term$	ΔSP	$\Delta Smirk$
Δlog (CDS)	1.0000											
ΔLev	0.8020	1.0000										
ΔVol	0.4601	0.4842	1.0000									
ΔRf	−0.3746	−0.2665	−0.2954	1.0000								
$\Delta SentMi$	−0.2644	−0.3399	−0.1618	0.1136	1.0000							
$\Delta SentAA$	−0.0875	−0.1663	0.1128	0.1952	0.0783	1.0000						
$\Delta SentBW$	−0.0307	−0.0628	−0.0214	−0.1688	−0.1235	0.1825	1.0000					
$\Delta SentEPCR$	0.4408	0.5055	0.1031	−0.1175	−0.1216	−0.2173	−0.0659	1.0000				
$\Delta SentLS$	0.0565	−0.0030	0.4415	−0.2028	−0.0500	0.1984	0.0449	−0.1322	1.0000			
$\Delta Term$	0.1653	0.1168	0.1778	0.4351	0.0037	−0.0375	−0.1088	−0.0071	−0.0746	1.0000		
ΔSP	−0.7633	−0.8922	−0.5379	0.2390	0.3176	0.1729	0.1160	−0.4831	−0.1100	−0.2359	1.0000	
$\Delta Smirk$	0.0058	0.1152	−0.0490	0.2235	−0.2399	−0.3785	−0.0913	0.1986	−0.0793	0.1306	−0.1046	1.0000

Panel A reports the summary statistics of CDS and firm-specific data for individual portfolios sorted by leverage ratio scale and volatility scale. The statistics are listed following the order of low leverage ratio and volatility (lev1vol1) to high leverage ratio and volatility (lev5vol5). Panel B reports means of 25 portfolio correlation coefficients between the time series changes in all the regression variables. The values within [], (), and {} in each portfolio indicate the averages of CDS spread, leverage ratio, and volatility, respectively.

TABLE VIII
Results for Basic Portfolio Regressions

Constant	0.0040	0.0045	−0.0026	0.0049	−0.0017	0.0062	−0.0020	0.0054	−0.0030	0.0043	−0.0023
	(0.4674)	(0.5288)	(−0.2654)	(0.5752)	(−0.1726)	(0.7191)	(−0.1997)	(0.6045)	(−0.2915)	(0.5060)	(−0.2189)
Δ*Lev*	3.5814	3.7129	−1.7081	3.2943	−1.7137	3.3959	−1.5447	2.7727	−1.4432	3.7085	−1.6412
	(31.2516)	(31.6402)	(−9.4019)	(33.6978)	(−9.6007)	(32.9187)	(−9.0746)	(30.1987)	(−8.2301)	(30.8093)	(−8.5896)
Δ*Vol*	0.3383	0.3507	0.0462	0.3802	0.0902	0.3558	0.0585	0.3515	0.0757	0.3007	0.0045
	(22.1166)	(22.1434)	(4.1546)	(23.9432)	(7.6949)	(21.9087)	(5.3173)	(23.5119)	(7.0010)	(19.3081)	(0.3560)
Δ*Rf*	−17.1568	−17.2908	−20.1748	−15.9332	−18.8487	−18.1854	−20.5949	−16.6923	−20.4272	−16.7114	−19.6054
	(−54.9812)	(−54.7973)	(−77.6872)	(−53.5786)	(−88.9529)	(−55.5008)	(−77.9139)	(−53.5033)	(−78.3856)	(−49.9336)	(−69.0418)
Δ*SentMi*		0.0015	0.0004								
		(8.7380)	(2.9999)								
Δ*SentAA*				−0.1121	−0.0596						
				(−32.8161)	(−13.5769)						
Δ*SentBW*						−0.0212	−0.0077				
						(−21.3369)	(−9.3447)				
Δ*SentEPCR*								0.2051	0.1419		
								(29.8804)	(19.8349)		
Δ*SentLS*										0.2119	0.2166
										(8.8284)	(7.4516)
Δ*Term*			0.1465		0.1386		0.1476		0.1622		0.1453
			(47.1589)		(47.2362)		(46.7305)		(46.5972)		(46.7490)
Δ*SP*			−0.0014		−0.0014		−0.0014		−0.0012		−0.0014
			(−43.8240)		(−43.8126)		(−44.0340)		(−39.5596)		(−43.7427)
Δ*Smirk*			−0.3176		−0.4759		−0.3403		−0.4330		−0.3315
			(−18.7747)		(−21.8631)		(−17.3545)		(−19.6438)		(−16.5900)
R^2	38.95%	39.46%	53.56%	40.43%	53.85%	40.19%	53.64%	42.11%	54.78%	39.44%	53.91%
A-R^2	34.26%	33.09%	44.28%	34.16%	44.62%	33.89%	44.37%	36.02%	45.74%	33.06%	44.69%

This table represents the result from linear regression of CDS spread changes assigned in 5 × 5 portfolios on the other variables from January 2006 to August 2009, or 44 months. The coefficient estimates and the *R*-squared values are the average of the result of regressions of each CDS spread change of individual firms, and the *t*-statistics are calculated by dividing the mean of individual coefficients by the standard deviation coefficient values, scaling by the square root of the number of firms, as in Collin-Dufresne et al. (2001).

approximately 13% points, from about 20% to about 33% in the theoretical model. The coefficients of sentiment proxies in all sentiment models are statistically significant. In particular, the magnitude of the coefficient of Δ*SentEPCR* is highest among five proxies and the coefficient of Δ*SentEPCR* is economically and statistically significant. Moreover, the adjusted R^2 is increased by 3% over that of the Merton (1974) model. Nevertheless, Δ*SentMi* is significantly positive, with an opposite sign to the expected signs derived from Tang and Yan (2010), which reports that the CBCC Index shows similar movement with Δ*SentMi*, and is negatively correlated with CDS. This discrepancy reflects the regression results, which are characterized by the periods shown in Tables XI and XII.

For portfolio-level regressions, the adjusted R^2 of individual portfolios is presented in Table IX. For every result from the regression of the sentiment model at the portfolio level, the most stable portfolio in which CDS spread with the lowest *Lev* and *Vol* are assigned has the lowest adjusted R^2 and shows a general ascending trend when *Lev* and *Vol* grow. In other words, the most volatile portfolio having the highest leverage ratio and volatility is explained best by the models. The difference in the adjusted R^2 between the lowest and highest *Lev–Vol* portfolios ranges from 41.33% in the *SentAA* model to 47.20% in the Merton (1974) model.

The average adjusted R^2 for each of the five *Lev* and five *Vol* values of structural and extended models are determined, including controlling variables, in Table X. Similar to Table IX, the explanatory power increases when the firm's *Vol* and *Lev* increase. More specifically, we examine the ability of models to predict CDS spread change by the *Lev* and *Vol* criteria. The steadily ascending pattern in explanatory power by portfolio order is obtained by dividing by *Lev*, especially after controlling the independent variables of Collin-Dufresne et al. (2001), only with the exception of results from Δ*SentBW* and Δ*SentLS* regressions. In the sentiment models, the gap between the adjusted R^2 of two polarized portfolios by *Lev* is larger than for two polarized portfolios by *Vol*.

We have three main conclusions from portfolio-level analysis. First, when idiosyncratic risk is eliminated, explanatory power increases, in agreement with Kim et al. (2017). Second, Δ*SentEPCR* shows excellent predictive power compared to the structural model. Finally, the 5×5 portfolio has a large adjusted R^2 gap between the lowest and highest *Lev–Vol* portfolios, with the portfolio better organized under the *Lev* criterion, rather than the *Vol* criterion. This is an intuitive result indicating that CDS spread changes reflect default risk by the degree of *Lev* and not by the degree of the firm's *Vol*, which contains both the credit risk and other risk factors including market and operational risks. This line of reasoning echoes Cesare and Guazzarotti (2010), who report that *Lev* explains CDS spread variances better than *Vol*.

5.2.4. *Portfolio-level regression results for the pre-crisis period versus the crisis period*

We separate the sample period into two parts: prior to the Global Financial Crisis, from January 2006 to August 2007, and the Global Financial Crisis, from September 2007 to August 2009.[12] Table XI reports the result of various models that examine the relationship between each selected sentiment measure and CDS spread changes grouped by five *Lev* and

[12]The global crisis period is somewhat inconsistently defined in the literature concerning corporate CDS spreads. For example, Coro et al. (2013) designate the crisis subsample as April 2007 to July 2009, and Galil et al. (2014) designate it as August 2007 to June 2009. Tang and Yan (2013) set the crisis period as July 2007 to March 2009, and Kim et al. (2013) set it as September 2007 to August 2009. Particularly for splitting subsamples, Kim et al. (2013) conduct a volatility break test of Inclan and Tiao (1994) on unit recovery claims extracted from U.S. corporate CDS spreads. As their division is based on econometric methodology, different from the other literature, we define the crisis period as in Kim et al. (2013).

TABLE IX
Adjusted R^2 Coefficients for Basic Portfolio Regressions

Panel A: Structural Variables

	Lev1 (%)	*Lev2 (%)*	*Lev3 (%)*	*Lev4 (%)*	*Lev5 (%)*
Vol1	18.65	33.90	32.62	37.16	39.00
Vol2	27.96	37.95	49.02	36.44	14.13
Vol3	55.41	50.06	49.76	44.90	35.02
Vol4	35.85	33.62	56.95	46.59	46.00
Vol5	42.33	10.69	61.13	60.76	75.49

Panel B: SentMi Model

	Lev1 (%)	*Lev2 (%)*	*Lev3 (%)*	*Lev4 (%)*	*Lev5 (%)*
Vol1	14.20	30.30	28.90	33.73	35.76
Vol2	23.96	35.60	46.54	32.92	11.37
Vol3	53.67	48.75	48.56	42.24	31.90
Vol4	32.31	31.49	54.75	46.73	44.34
Vol5	41.41	6.29	59.67	59.66	74.48

Panel C: SentAA Model

	Lev1 (%)	*Lev2 (%)*	*Lev3 (%)*	*Lev4 (%)*	*Lev5 (%)*
Vol1	33.60	36.29	35.91	48.77	29.89
Vol2	37.99	45.57	47.34	40.99	32.80
Vol3	54.24	51.30	51.24	47.80	30.56
Vol4	47.13	40.57	51.41	46.16	54.44
Vol5	58.26	5.48	67.21	54.75	65.79

Panel D: SentBW Model

	Lev1 (%)	*Lev2 (%)*	*Lev3 (%)*	*Lev4 (%)*	*Lev5 (%)*
Vol1	20.73	33.27	31.27	36.35	36.61
Vol2	27.49	35.94	46.85	34.78	26.38
Vol3	53.66	48.72	47.73	42.11	33.17
Vol4	39.92	35.10	55.59	43.94	43.10
Vol5	20.73	33.27	31.27	36.35	36.61

Panel E: SentEPCR Model

	Lev1 (%)	*Lev2 (%)*	*Lev3 (%)*	*Lev4 (%)*	*Lev5 (%)*
Vol1	19.68	38.00	35.36	34.57	37.11
Vol2	26.00	38.92	48.64	43.29	29.40
Vol3	56.69	47.57	50.12	45.69	36.30
Vol4	37.15	33.81	59.24	44.97	43.74
Vol5	44.02	5.77	59.49	59.59	74.13

Panel F: SentLS Model

	Lev1 (%)	*Lev2 (%)*	*Lev3 (%)*	*Lev4 (%)*	*Lev5 (%)*
Vol1	15.49	32.39	32.16	34.89	36.11

continued

TABLE IX
(Continued)

Panel F: SentLS Model

	Lev1 (%)	*Lev2* (%)	*Lev3* (%)	*Lev4* (%)	*Lev5* (%)
Vol2	24.67	36.47	49.11	34.32	15.42
Vol3	52.95	51.84	47.72	44.47	32.35
Vol4	32.47	30.49	54.82	45.64	43.06
Vol5	39.56	5.98	58.99	58.90	74.39

This table represents the matrix of coefficients of adjusted R^2 by each portfolio from linear regression of each sentiment model, which examines the relation between CDS spread changes assigned in 5×5 portfolios and the theoretical variables and sentiment proxy.

five *Vol* values during the pre-crisis 20-month period from January 2006 to August 2007. The explanatory power is lower compared to the aggregate period regressions. The structural model performance is disappointing, reporting an adjusted R^2 of only 5.9%, and other models embedding sentiment variables show no more differentiation, except for the regression on Δ*SentEPCR*. The *SentEPCR* model has an explanatory power of approximately 15%, which is almost three times higher than that of the theoretically structured model. This is a highly significant and large magnitude of coefficients, which are also consistent with the expected signs. This result implicates Δ*SentECPR* as the best candidate among various sentiment measures derived from different markets. On the other hand, other sentiment factors perform poorly in predicting CDS spread changes. Δ*SentMi* and Δ*SentAA* show opposite coefficient signs to the expected signs and Δ*SentBW* has very low explanatory power at 1.2%.

Table XII presents the results of regression models that study the relationship between each selected sentiment proxy and CDS spread changes grouped by five *Lev* values and five stock price *Vol* values during the 24-month crisis period from September 2007 to August 2009. Although the overall explanatory power of variables is lower and inconclusive signs are observed in the stable period, the result for the turbulent term supports our hypothesis. All five sentiments are economically significant with consistent signs. However, unlike previous results in the aggregate and stable periods, the four factor model with Δ*SentAA* predicts 48.77% of changes in CDS premium, which is the best prediction among the models, including proxies for sentiment, and is 7.5% higher than the theoretical model. During the crisis period, even Δ*SentBW*, which is insignificant in another stage, displays a strongly significant negative coefficient. We conclude that sentiment models perform better in a crisis period than in a stable period.

Our results are consistent with an existing explanation. Stambaugh et al. (2012) insists that when sentiment exists widely in the market, short-sale limitations play a major role in increasing the severity of asset mispricing. The authors further opine that a higher level of sentiment, in turn generally considered as an indicator of a downturn, fuels overpricing. On the other hand, due to the absence of short selling in a bullish market, sentiment does not provide a convincing explanation in this period. Based on the argument of Stambaugh et al. (2012), we interpret that in bad economic states, overpricing renders the hedging of CDSs by equity or equity options difficult and increases CDS spreads. Thus, sentiment better explains CDS spreads in a turbulent period.

There are two main findings. First, and most notably, even though both stock return and the implied volatility of equity options are effective factors in explaining CDS spread, Δ*SentBW* derived from the stock market performs poorly in predicting CDS spread, whereas Δ*SentEPCR* is superior among the several sentiment candidates, with the exception of

TABLE X
Average Adjusted R^2 Values for Portfolio

	Before Controlled		*After Controlled*	
	By Lev (%)	*By Vol (%)*	*By Lev (%)*	*By Vol (%)*
Structural Model				
Low	30.18	25.59		
	27.79	27.78		
	42.63	39.14		
	37.01	36.91		
High	33.68	41.86		
SentMi Model				
Low	24.01	28.71	36.00	46.06
	27.27	26.17	40.32	34.88
	37.77	41.44	47.04	50.12
	35.55	35.75	47.44	47.71
High	40.84	33.37	50.58	42.62
SentAA Model				
Low	25.76	30.73	36.89	46.24
	28.53	27.84	40.94	35.84
	38.53	42.46	47.03	50.62
	36.59	36.12	47.94	47.69
High	41.41	33.66	50.30	42.70
SentBW				
Low	30.86	25.19	45.88	36.11
	27.72	28.02	35.29	40.56
	41.62	38.29	50.12	46.85
	35.68	36.94	48.04	47.76
High	33.57	41.01	42.53	50.59
SentEPCR Model				
Low	30.77	26.88	37.23	45.77
	28.33	31.89	43.60	35.77
	43.41	41.11	48.71	51.39
	39.95	37.24	47.91	50.20
High	37.64	42.99	51.22	45.55
SentLS Model				
Low	24.12	28.76	36.59	45.77
	26.48	26.18	40.68	35.34
	37.94	41.95	47.46	50.75
	35.90	35.71	48.09	48.37
High	40.52	32.36	50.16	42.77

This table shows average R^2 by leverage ratio and volatility throughout the period resulting from structural regression and sentiment regression on the 5×5 portfolio. The "before controlled" column includes theoretical variables and designated sentiment proxy, and controlling variables are additionally embedded in the "after controlled" column.

predicting CDS spread changes for investment-grade firms. This may indicate that the sentiment in options markets predicts CDS spread variation rather than sentiment in stock markets, because the options market is also sensitive to the volatility of asset returns, just as is CDS spread, but the stock market is sensitive to the direction of asset values. Moreover, this finding aligns with results from other studies, which reveal the price discovery role of derivative markets on stock price. As low initial cost and high leverage are more prevalent in derivatives markets, they respond to the information efficiently. Therefore, in terms of information efficiency, the derivatives market performs better than the stock market due to this characteristic.

TABLE XI
Results for Portfolio Regressions During the Pre-Crisis Period

Constant	0.0045	0.0079	0.0353	0.0041	0.0308	0.0047	0.0347	0.0053	0.0286	−0.0001	0.0290
	(0.2567)	(0.4451)	(1.2648)	(0.2349)	(1.2968)	(0.2680)	(1.4547)	(0.3130)	(1.2561)	(−0.0029)	(1.2839)
ΔLev	10.0919	10.6443	3.8243	9.7992	3.7324	10.4539	3.3787	8.7898	4.1113	10.2186	3.3873
	(9.0533)	(9.4886)	(2.6452)	(8.9147)	(2.6723)	(9.3715)	(2.4500)	(8.0189)	(2.9037)	(9.4261)	(2.5035)
ΔVol	−0.2085	−0.2458	−0.4928	−0.0471	−0.2553	−0.1831	−0.3651	−0.6426	−0.6769	−0.2683	−0.4272
	(−4.4282)	(−5.0616)	(−10.9749)	(−0.9799)	(−5.6408)	(−3.8226)	(−8.1768)	(−12.3438)	(−12.7354)	(−5.7896)	(−9.6671)
ΔRf	−3.8752	−5.8846	1.2583	−5.0587	2.3532	−3.9628	0.7093	1.4377	2.3276	−5.5303	−0.2228
	(−6.5211)	(−8.9135)	(2.1014)	(−8.4408)	(4.1705)	(−6.7385)	(1.2820)	(2.7977)	(4.1750)	(−8.7507)	(−0.3860)
$\Delta SentMi$		0.0050	0.0051								
		(14.7576)	(11.8097)								
$\Delta SentAA$				0.1329	0.1233						
				(25.5512)	(22.0838)						
$\Delta SentBW$						−0.0105	−0.0182				
						(−6.7557)	(−14.6261)				
$\Delta SentEPCR$								0.2865	0.1525		
								(26.3745)	(13.6375)		
$\Delta SentLS$										0.0000	0.0000
										(−15.0493)	(−16.7851)
$\Delta Term$			−0.1493		−0.1898		−0.1902		−0.1340		−0.2112
			(−11.6958)		(−15.1484)		(−15.1014)		(−12.4160)		(−16.8748)
ΔSP			−0.0021		−0.0021		−0.0022		−0.0017		−0.0021
			(−26.0227)		(−27.2584)		(−28.8122)		(−20.5158)		(−27.2994)
$\Delta Smirk$			−0.0606		−0.0111		−0.4275		−0.4313		−0.3696
			(−1.9087)		(−0.3700)		(−15.9720)		(−15.7408)		(−13.5387)
R^2	20.76%	26.49%	47.20%	24.55%	44.28%	22.06%	43.82%	32.04%	45.47%	24.28%	44.88%
A-R^2	5.90%	6.88%	16.40%	4.43%	11.78%	1.27%	11.05%	13.92%	13.66%	4.09%	12.73%

This table presents the results from linear regression of CDS spread changes assigned in 5×5 portfolios on the other variables from January 2006 to August 2007, or 20 months. The coefficient estimates and the *R*-squared values are the average of the result of regressions of each CDS spread change of individual firms, and the *t*-statistics are calculated by dividing the mean of individual coefficients by the standard deviation coefficient values, scaling by the square root of the number of firms, as in Collin-Dufresne et al. (2001).

TABLE XII

Regression Results for Portfolio Regressions During the Crisis Period

Constant	0.0078	0.0068	−0.0291	0.0157	−0.0200	0.0125	−0.0237	0.0125	−0.0218	0.0067	−0.0285
	(0.5332)	(0.4680)	(−1.5225)	(1.1403)	(−1.1525)	(0.8661)	(−1.2765)	(0.8725)	(−1.3020)	(0.4442)	(−1.4822)
Δ*Lev*	3.0971	2.9596	−2.9593	1.9068	−1.5698	2.7805	−1.5529	1.6042	−1.7583	3.2633	−1.1760
	(27.3501)	(26.6126)	(−12.6033)	(22.9001)	(−7.7993)	(27.9285)	(−8.0449)	(20.6083)	(−8.1958)	(25.5672)	(−5.4808)
Δ*Vol*	0.4154	0.4096	−0.0714	0.6096	0.1108	0.4384	0.0174	0.4902	0.0804	0.3506	−0.1498
	(24.6147)	(24.0396)	(−5.2278)	(30.5704)	(7.7408)	(24.2340)	(1.4073)	(26.5627)	(5.8507)	(20.6513)	(−10.1686)
Δ*Rf*	−19.7633	−19.8944	−38.9874	−16.2350	−33.5276	−21.1920	−37.1703	−20.6408	−37.5910	−19.1360	−35.4182
	(−47.4786)	(−48.9621)	(−58.7232)	(−38.8492)	(−53.6479)	(−49.4095)	(−57.9247)	(−47.1145)	(−58.7363)	(−43.2510)	(−57.3173)
Δ*SentMi*		−0.0020	−0.0077								
		(−10.8889)	(−33.7001)								
Δ*SentAA*				−0.3350	−0.1001						
				(−53.3272)	(−17.2830)						
Δ*SentBW*						−0.0275	−0.0056				
						(−21.3805)	(−5.1993)				
Δ*SentEPCR*								0.2779	0.1735		
								(27.6060)	(16.8319)		
Δ*SentLS*										0.0000	0.0000
										(7.5719)	(16.9459)
Δ*Term*			0.3035		0.2528		0.2738		0.2840		0.2863
			(64.5034)		(72.3733)		(66.6384)		(65.5206)		(61.9001)
Δ*SP*			−0.0012		−0.0010		−0.0011		−0.0009		−0.0011
			(−25.8759)		(−24.1442)		(−24.5314)		(−23.3591)		(−27.0614)
Δ*Smirk*			1.1128		0.7109		0.9460		0.8649		0.9589
			(17.8024)		(12.6996)		(16.5802)		(14.9264)		(16.7279)
R^2	49.27%	49.91%	74.62%	58.08%	72.70%	51.46%	72.34%	52.52%	73.30%	50.03%	73.44%
A-R^2	41.26%	38.78%	62.78%	48.77%	59.97%	40.67%	59.43%	41.97%	60.84%	38.92%	61.04%

This table represents the result from linear regression of CDS spread changes assigned in 5×5 portfolios on the other variables from September 2007 to August 2009, or 24 months. The coefficient estimates and the *R*-squared values are the average of the result of regressions of each CDS spread change of individual firms, and the *t*-statistics are calculated by dividing the mean of individual coefficients by the standard deviation coefficient values, scaling by the square root of number of firms, as in Collin-Dufresne et al. (2001).

Second, sentiment explains CDS spread changes better in a turbulent period. The multiple-equilibria model, the theoretical background of Saka et al. (2015), explains this result. According to this model, during a crisis period, markets may not always behave optimally and thus may move with no major change in fundamental factors. Further, a self-fulfilling liquidity crisis may be caused by the decisions of panic-driven investors. Therefore, we interpret our result as that sentiment from panic-driven investors may have led to liquidity contraction of the CDS market during the Global Financial Crisis, and thus the sentiment variables explain CDS spread changes better during the Global Financial Crisis period than in the normal period.

6. CONCLUSION

We investigate whether investor sentiment predicts CDS premium changes, using several proxies. We verify our hypothesis that investor sentiment explains CDS spread changes. We explore which sentiment measure is the most effective determinant. In general, most sentiment proxies are valid in explaining CDS spread changes, and the change in equity put–call ratio is the best predictor due to the characteristics of options market.

In portfolio-level regression analysis, overall explanatory power is increased compared to individual-level regression analysis, as Kim et al. (2017) document. In addition, the change in equity put–call ratio shows outstanding explanatory power, nearly three times greater than the structural model. When precisely observing the results for each portfolio, we find that sentiment explains changes in CDS spread best in the group whose *Lev* and *Vol* are highest and vice versa. Also, the gap in the ability to explain the two polarized portfolios is dramatically large, ranging from 41.33% to 47.20%.

We divide the sample period into two stages: the pre-crisis period from January 2006 to August 2007, and the crisis period from September 2007 to August 2009, to test the explanatory power of sentiment by business cycle. We find that our suggested models explain CDS spread changes much better in a turbulent period than in a stable period.

The results align with the hypothesis that sentiment explains mispriced CDS spreads better in turbulent periods. Stambaugh et al. (2012) insist that when sentiment exists widely in the market, the limitation in short selling plays a major role in increasing the severity of asset mispricing. The period of higher levels of sentiment, generally considered the downturn, is characterized by more overpricing. This can be interpreted as that in bad economic states overpricing renders the hedging of CDSs by equity or equity options difficult and increases CDS spreads. Thus, sentiment explains CDS spreads better in turbulent periods. On the other hand, due to the absence of short selling impediments in bullish markets, sentiment cannot explain well in such periods.

In addition, the results support the multiple-equilibria theory. In this theory, markets may not always show optimal behavior during crisis periods, and a self-fulfilling liquidity crisis may be led by panic and investor fear, with no significant change in fundamental factors. Therefore, sentiment from panic-driven investors may cause liquidity contraction of the CDS market during crisis periods, and the sentiment variables can explain CDS spread changes better during the Global Financial Crisis period than in the normal period.

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