The Impact of News Sentiment and Investor Attention on Credit Default Swaps and Equity Markets

Preliminary and Incomplete

Lara Cathcart[‡] **Yining Shi**[‡] **Lina El-Jahel**[‡]

January 30, 2017

[‡]Imperial College London, email: l.cathcart@imperial.ac.uk
[‡]Imperial College London, email: yining.shi09@imperial.ac.uk.
[‡]University of Auckland, email: l.eljahel@auckland.ac.nz

The Impact of News Sentiment and Investor Attention on Credit Default Swaps and Equity Markets

Abstract

We study the impact of firm-specific news sentiment on credit default swaps (CDS) and equity returns of 31 U.S. financial firms. We construct a news score variable for each firm using a linguist analysis algorithm on news articles published by the Wall Street Journal (WSJ). Using panel and panel VAR regressions, we firstly find CDS returns exhibit a delay in responding to news sentiment in comparison to equity returns. Secondly, CDS returns respond to news sentiment more quickly during the financial crisis than the non-crisis period. The improvement in the news reaction of CDS return during the financial crisis is accompanied by a simultaneous increase in market liquidity risk. The empirical findings support explanations related to the investor inattention theory. If a CDS trader has specific liquidity preferences, and if an investors attention is a scare resource, the CDS trader would pay less attention to news development than an informed equity trader. During the financial crisis when the liquidity risk is high, the CDS trader is forced to monitor market liquidity conditions by paying more attention to news development in order to avoid extreme losses.

Keywords: News Sentiment, Credit Default Swaps, Equity Returns, Investor Attention.

JEL Classification: G12; G15.

1 Introduction

Several studies have demonstrated that sentiment analysis has wide implications for understanding the nature of financial transactions, volumes and price movements, and predicting future returns (Tetlock, 2007; Jegadeesh and Wu, 2013; Garcia, 2013; Cathcart, Gotthelf, Uhl, and Shi, 2016; Loughran and McDonald, 2011). In this paper, we aim to explore the relationship between media content, equity and corporate credit risk. To do so, we construct a sentiment score variable by using the 'bag-of-words' linguist textual analysis algorithm (Loughran and McDonald, 2011; Liebmann, Orlov, and Neumann, 2016). For companies, we focus on the most liquid U.S. financial firms in the S&P 500 financial sector index. We collect the news articles for each firm from the Wall Street Journal (WSJ). The choice of the WSJ is simply because it is a New York City based mainstream business-oriented newspaper, which is published by the Dow Jones & Company. Furthermore, it is the journal that is used in various studies, such as Tetlock (2007); Tetlock, Saar-Tsechansky, and Macskassy (2008); Dougal, Engelberg, Garcia, and Christopher (2012). To measure the corporate credit risk, we use the single-name CDS contract.

Standard financial theory suggests that in a perfectly efficient financial market, all derivatives based on the same underlying assets are exposed to the same fundamental risks. Therefore, any new information about the underlying assets would be reflected in all relevant markets. In practice, due to reasons such as regulations, trading conventions, leverage constraints and transaction costs, it is often that specific investors have particular preferences for certain types of securities. Various studies has highlighted the potential price discovery dynamics among different markets, such as stock, bond and CDS markets (e.g., Norden and Weber, 2004; Forte and Peña, 2009; Acharya and Johnson, 2007, 2010). We explore this issue by investigating the reactions of different assets to the same news sentiment. Specifically, we focus on the CDS and equity markets. Important corporate news influences capital markets across different asset classes. The literature of price discovery suggests that equity returns tend to be the primary market where new information is discovered, in comparison to the CDS and bond markets (e.g., Marsh and Wagner, 2012; Norden and Weber, 2009, 2004; Forte and Peña, 2009; Hilscher, Pollet, and Wilson, 2015). We follow the same logic and propose the following hypothesis. If the price discovery process is led by the equity market and lagged in the CDS market, we would observe a faster response to news sentiment in a firm's equity return than its credit return. We find significant price reactions in the equity market on the day of news release. Furthermore, the impact of news sentiment on equity returns reverses within two days. However, CDS returns illustrate a significant delay in responding to news sentiment. The CDS spread reactions do not occur until the second day. It takes another two to three days for CDS returns to absorb the information and fully reverse. Robustness checks confirm that the superior reactions to news illustrated by equity returns over CDS returns are consistent over different regression settings, and are unaltered when we separate the sample into crisis and non-crisis periods. One possible explanation is the inattention of CDS traders. Studies have shown that human attention is a scare resource. Furthermore, limits of human attention affect market prices (DellaVigna and Pollet, 2007; Barber and Odean, 2008; Cohen and Frazzini, 2008; Mamaysky and Glasserman, 2016). The study by Hilscher, Pollet, and Wilson (2015) suggests that informed traders prefer to trade in the equity market, while CDS traders are uninformed traders with liquidity preferences. [1] Since the CDS traders are predominantly trading for nonfundamentals-based reasons, they may not be as attentive to the news development as equity market traders. This helps to explain the slower response to news sentiment for CDS returns.

Our second finding is directly linked to Garcia (2013). We find the impact of news sentiment on the CDS and equity returns increases substantially during the crisis period, in

[1] The specific liquidity preferences and the underlying reasons are assumed to be exogenous in the original theoretical model of Easley, O'hara, and Srinivas (1998).

comparison to the non-crisis period. Furthermore, we compare the news reaction patterns of CDS returns for the crisis versus non-crisis periods. We observe a significant improvement in the impact of media sentiment on the credit returns during the crisis period, statistically and economically. In addition, the results show that during the crisis period, liquidity risk factor becomes significant in explaining CDS returns, which is not the case during the non-crisis period. The simultaneous improvements in the impacts of the news content and the liquidity risk on the CDS returns provide evidence to a separate equilibrium market setting, which is proposed by Easley, O'hara, and Srinivas (1998). In their model, there are two types of investors: the informed traders, who decide to trade either in the equity or the option market, and the uninformed liquidity traders.[2] The presence of the latter would allow the informed traders to benefit from their superior private information without exposing their identities. In this setting, the informed trader can either choose to 'pool' and trade in both markets, or to 'separate' and trade in only one market. The choice of the informed traders on which market to trade depends on whether the market 1) is highly sensitive to information; 2) has low transaction costs and 3) has a large proportion of uninformed traders. Hilscher, Pollet, and Wilson (2015) show that high bid-ask spreads of the CDS market deter informed traders from joining the credit market despite of a large fraction of uninformed traders. The informed traders opt for the equity market due to its low bid-ask spreads and large transaction volume, whereas the CDS market is filled with uninformed traders who have liquidity preferences. The authors also find that the credit protection returns respond more quickly during salient news events such as corporate earnings announcement, which presumably both CDS and equity traders are more likely to pay attention to (Greatrex, 2009; Frazzini and Lamont, 2007). Therefore, we argue, during the financial crisis, the rise of liquidity and funding risks force the uninformed liquidity traders to carefully monitor market liquidity conditions, resulting in increasing attention to market news from the CDS traders and improved news reactions.

[2] The option market extends for any alternative derivative market.

2 Literature Review

Our work is related to various strands of the literature. Firstly, it is related to studies that investigate the impact of news sentiment on asset market performance. Tetlock (2007) documents the evidence that news media content can predict movements in broad indicators of stock market activity. The author uses a quantitative content analysis programme to study the daily variation in the WSJ 'Abreast of the Market' columns from 1984 to 1999, and to construct a simple measure of media pessimism.[3] Tetlock, Saar-Tsechansky, and Macskassy (2008) explore the same research question but focus on the predictability of negative words. Their findings suggest that linguistic media content captures otherwise hard-to-qualify aspects of firms' fundamental, which would be incorporated quickly into the stock prices. Garcia (2013) shows that the predictability of stock returns using news content is concentrated in recessions. Furthermore, the study by Dougal, Engelberg, Garcia, and Christopher (2012) distinguishes a reflective and a causal role of financial media by using the exogenous rotation scheduling of the WSJ columnists. They find that financial reporting has a causal impact on the stock market performance. Engelberg and Parsons (2011) disentangle the causal impact of the content of media reporting from the impact of the event. The authors use 19 mutually exclusive trading regions in U.S. and study the reactions of local investors to the same information event. They find that local media coverage strongly predicts local trading, and that local trading is strongly related to the timing of local reporting. A rather ambitious study is conducted by Hillert, Jacobs, and Müller (2014). The paper uses 2.2 million articles from 45 national and local U.S. newspapers between 1989 and 2010 to study the impact of media coverage on cumulative stock returns. They find that firms particularly covered by media exhibit stronger momentum and that this effect depends on media tone. Intensive media coverage exacerbates investor biases. Unlike traditional studies that focus on stock returns, Mamaysky and Glasserman (2016) study the impact of news unusualness

[3] The content analysis programme used is the General Inquirer.

on predicting realised and implied volatilities of individual stocks and the aggregate market.

More recent studies explore the impact of news sentiment on the price of credit products. Tang and Yan (2010) find that investor sentiment is the most important determinant of credit spreads. The study by Tang and Yan (2016) uses the VIX index as a measure of market 'fear' sentiment and finds it significantly explains changes in CDS spreads. Cathcart, Gotthelf, Uhl, and Shi (2016) use advanced news sentiment sequences from Reuters and find that media content significantly impacts the sovereign CDS movements, as well as the expected default component. It is worth mentioning that our work is closely linked to the study by Liebmann, Orlov, and Neumann (2016). We both use sophisticated linguist content analysis programmes to build a news sentiment measure, and study its impact on the CDS and equity returns. However, our focus is rather different. Their purpose is to study how traders of different markets interpret and react to the same news texts. In particular, two filtered news series are constructed: the corporate event news and the debt news. Our focus is on the speed and magnitude of the news reaction process in each market, and on any differences in the patterns between the two markets. Especially, we study the causal relationship between news sentiment and the stock returns (and between news sentiment and CDS returns). We document a delayed response of the credit market to news sentiment, in comparison to the equity market.

Secondly, we contribute to the literation that studies the price discovery process between the CDS market and equity market. Acharya and Johnson (2007, 2010) show that insider trading activity occurs in the CDS market. Such private information is then slowly incorporated into the stock price. On the other hand, various studies suggest the opposite lead-lag relationship. That is, the stock market leads the CDS market in exploring new information about market condition and firm fundamentals. Forte and Peña (2009) study the price discovery across stock, CDS and bond markets with a sample of 17 North American and

European non-financial firms from 2001 to 2013. Norden and Weber (2009) extend the same empirical framework to a lager cross sectional data set, which contains 58 firms from 2000 to 2002. Both studies draw the same conclusion that the stock market leads the CDS market and the bond market in price discovery. Daily lead-lag relationship between the CDS and equity markets is studied by Marsh and Wagner (2012). The paper of Hilscher, Pollet, and Wilson (2015) find that equity returns lead credit protection returns at daily and weekly frequencies, whereas credit protection returns do not lead equity returns. Our study provides aligned evidence that the equity market illustrates a more rapid response to news sentiment, in comparison to the CDS market.

Thirdly, we link our findings to the investor inattention theory (Easley, O'hara, and Srinivas, 1998; DellaVigna and Pollet, 2007, 2009; Cohen and Frazzini, 2008; Barber and Odean, 2008; Duffie, 2010). The theory claims that limits of human attention affect market prices. For example, DellaVigna and Pollet (2007) show that investors are inattentive to information with long-term consequences. DellaVigna and Pollet (2009) find that reduced investor attention causes less immediate responses to earnings announcements on Friday. An interesting study by Ehrmann and Jansen (2012) finds that traders were distracted during the World Cup matches in 2010. When the national teams were playing, the trading volumes of the corresponding countries' stock markets dropped substantially. Hirshleifer, Hou, Teoh, and Zhang (2004) construct an accounting measure, the cumulative difference between operating income and free cash flow, which quantitatively captures the investors' inattention. This measure is based on the assumption that investors with limited attention tend to neglect information about cash profitability, and focus on accounting profitability. They find that this inattention measure significantly predicts long-run stock returns. The study by Mamaysky and Glasserman (2016) suggests that inattentive investors pay less attention to the short-term volatility, but focus more on the long-term market pressure. Hilscher, Pollet, and Wilson (2015) find that CDS traders are liquidity traders and are inattentive to news development, in comparison to the informed traders in the equity market. Furthermore, they find credit traders respond more quickly during the salient news events, such as earnings announcements (Frazzini and Lamont, 2007; Greatrex, 2009). Similar finding is also documented in Norden and Weber (2004) that the CDS spreads react faster than the equity returns only during negative rating announcements. Our findings provide evidence that supports the investor inattention explanation. As suggested by Easley, O'hara, and Srinivas (1998); Hilscher, Pollet, and Wilson (2015), CDS traders have preferences for liquidity and pay less attention to news about fundamentals, leading to a delay in the response of credit returns to the news sentiment. Furthermore, we find credit returns react faster during the crisis period than the non-crisis period. Simultaneously, the explanatory power of the liquidity risk becomes significant during the crisis period. The Great Recession was highlighted as a liquidity induced crisis, higher liquidity risk forces CDS traders to pay more attention to relevant market news, which causes a more rapid reaction of CDS returns during this period.

3 News, Data and Other Variables

This section starts with a description of the filtration steps for the financial firms selection. It is followed by a detailed elaboration of the news articles collection process, as well as the news sentiment score construction. In the end, we summarise the relevant information on the CDS data, equity price, and other explanatory variables.

3.1 The Financial Firms

First, we download the constituent name list of the S&P financial sector index. We use the list which was published by the S&P Dow Jones Indices in February 2016.[4] The full name list contains 90 financial firms. Second, we cross check the firm names against the Markit CDS reference entity name list. We filter out firms that have not underwritten any CDS contract. The updated name list contains 64 firms. We use news articles published by the Wall Street Journal. The total number of news observations on an individual firm is rather limited, especially during the period 2001-2003. Therefore, in the third step, we exclude firms which have less than 100 relevant news articles over the sample period.[5] After these steps, 31 U.S. financial firms are selected for the empirical study.[6] Table 1 lists the companies used in our sample.

[4] http://us.spindices.com/indices/equity/sp-500

[5] The third step of firms filtration would not be necessary once we enrich the news articles entries. We plan to include news articles from Reuters, Bloomberg and Financial Times etc.

[6] The majority of our firms also are the constituents for the CDX.NA.IG index.

3.2 The News

Our data set of news consists of Wall Street Journal news articles about the 31 S&P 500 financial firms. The news articles are extracted from Factiva. The only additional search criterion we used is the language as English. We then set the company criteria as the subjective firm name, and download all articles in the displayed search results for each firm in the list. The raw data contains over 28,000 news articles from January 2001 to June 2016. Various reports occur multiple times for reasons such as rewriting of the same original story, or repeated releases in different versions of the journal (i.e., the WSJ U.S. versus the WSJ Europe). For these cases, we keep only the first presence of such articles in the data set. This leaves us with 15,827 news articles which we use to construct the news score. There are many articles that mention more than one firm. This distinguish our study from Liebmann, Orlov, and Neumann (2016) as our news sample contains all relevant news of a company as long as its name is shown or tagged in the article, whereas their paper focuses on two specific categories of news articles: the corporate event news and the debt news.

For each news article we collected, we perform linguist textual analysis. We analyse the text content of each news release in order to determine its sentiment direction. In particular, the analysis we conduct is the traditional sentiment evaluation process, which calculates the fraction of words in a given article that have negative or positive connotations (Mamaysky and Glasserman, 2016; Loughran and McDonald, 2011; Jegadeesh and Wu, 2013). This score-based algorithm is also known as the "bag-of-words" approach and requires word dictionaries and corpus. The Harvard IV-4 psychosocial dictionary is used in the studies such as Tetlock (2007) and Tetlock, Saar-Tsechansky, and Macskassy (2008). The recent work by Loughran and McDonald (2011) creates the Laughran-McDonald word list, which is based on sophisticated analyses on the 10-K SEC filing documents of the U.S. corporations.[7]

[7]The list is downloaded from $http://www3.nd.edu/ mcdonald/Word\_Lists.html$

Research by (Loughran and McDonald, 2011; Heston and Sinha, 2014; Sinha, 2016) show such word list has a superior accuracy for sentiment analysis in the financial field than the Harvard dictionary. For this reason, we use the Laughran-McDonald word list. Furthermore, we extend our dictionary with the MPQA Lexicons, including the Opinion and Emotional-based Subjectivity Sense Annotations lexicon and the goodFor/badFor corpus.[8] For each news article, the algorithm produces a sentiment score. A positive score indicates investors are optimistic about the future market growth, while a negative score suggests investors are pessimistic about the market movement. Sometime, multiple news reports occur in one day. For each company and for each day, we calculate the average scores over all articles which are published on that day. Once the series of the news score is constructed, we standardise it at firm level. The corresponding score is the ultimate sentiment news variable used in the empirical regression.

3.3 The CDS and Equity Data

We use the single-name CDS contract as a proxy for firm-specific credit risk. We prefer CDS spreads to corporate bond yields for several reasons. Firstly, the CDS contract is typically traded on standardised terms, and its spread provides a relatively pure measure of the default risk of the underlying entity. This is because bond yields are very sensitive to contract specifications such as coupon rate, debt seniority, embedded option, convention and corporate guarantees (Zhang, Zhou, and Zhu, 2009). Studies by Longstaff, Mithal, and Neis (2005) and Chen, Lesmond, and Wei (2007) suggest that a large proportion of cross sectional variations in corporate bond yields are linked to the market liquidity risk, instead of specific firm default risk. Secondly, Marsh and Wagner (2012) and Zhu (2006) find that the CDS market leads the bond market in price discovery, especially for the information that reflects

[8]MPQA resources is sponsored by the University of Pittsburgh on annotated corpus, subjectivity lexicon, political debate data: *http://mpqa.cs.pitt.edu/*.

changes in credit conditions.

We download the corresponding CDS spreads of the 31 firms we selected from Markit. The sample period ranges from 3rd January, 2001 to 14th June, 2016. We choose single-name CDS contracts with five-year maturity, because they are the most traded and most liquid maturity in the CDS term structure. Furthermore, we include the CDS observations that are underwritten on senior debt issued by these firms. It is because the market for CDS contracts written on senior debt is more liquid than the market for subordinate bonds.[9] Furthermore, the recovery criteria on the underlying bond is set as 'Modified Restructuring', since such default definition clause is the most common restructuring convention used for U.S. firms (Hilscher, Pollet, and Wilson, 2015; O'Kane, 2011). The notional of all CDS contracts is expressed in US dollars. For any missing data points, we bootstrap the data by using the credit term structure, including CDS contracts with maturity of one, two, three, five, seven, and ten year. The summary statistics for the five year CDS spreads on the 31 firms are reported in Table 2.[10]

For the dependent variables, we use CDS protection return (phrases such as credit return or CDS return are used interchangeably) and equity return on each firm. The CDS protection return is used in the studies of Hilscher, Pollet, and Wilson (2015); Cathcart, Gotthelf, Uhl, and Shi (2016). Since the release of the CDS Big Bang on 8th April, 2009, the trading convention for CDS contracts has been changed. Originally, the single-name corporate CDS contract was quoted in its par spread, which sets the discounted present value of a CDS contract to be zero for both protection buyer and seller at the outset of the trade (i.e., it is the standard CDS spread definition in a CDS pricing model).[11] The new protocol

[9]Senior debt entitles the bond holder to seniority (over subordinate debt) when claiming losses, given that the bond issuer defaults on both senior and subordinate bonds. Senior debt contains less credit risk and has a better recovery rate.

[10]It is based on raw observations downloaded from Markit

[11]See: http://www.isda.org/bigbangprot/bbprot_faq.html#cdi14

standardises the single-name CDS trading with a fixed coupon, which is 100 basis points or 500 basis points, plus an upfront fee. The upfront fee would be equal to the discounted present value of the CDS, which compensates the difference between the fixed coupon and the actual premium for the trade. Consider an investor purchases a CDS contract at time t with upfront points of s_t and at time $t+1$, the investor sells an offsetting CDS contract with upfront points of s_{t+1}. The cash flow associated with such a trade would be $s_{t+1} - s_t$. Hence the expected return of the investor at time t is $r_{t,cds} = \frac{s_{t+1} * D^{1/360} - s_t}{s_t}$, where D is the annuity discount factor. Since we are using daily observations, this annuity factor is always close to 1. Therefore, we calculate the percentage changes in the credit spread as the CDS return in the empirical analysis.

The equity return of each firm is the percentage changes of its closing stock price. The data is extracted from Bloomberg. Furthermore, all returns data (both the CDS and the equity returns) are winsorised at the 1% and the 99% levels. That is, extreme outliers which exceed the cut-off points are replaced with the observation value in the 1st and 99th percentile.

3.4 Explanatory Variables

For control purposes, we also include a list of explanatory variables to capture global, financial and firm-specific risk factors. Three macro-economic and financial variables are used to capture the overall condition of the economy and the financial market. The 'US stock market' variable is the daily excess return of the S&P 500 index. The 'volatility premium' is the difference between CBOE VIX index and the realised 30-day volatility of the S&P 500 stock index. We also consider the market 'liquidity risk' because the CDS market demands a mark-to-market margin system and requires investors to post collaterals. The liquidity risk is calculated as the difference between 3-month Libor rate and the USD OIS rate. The standard Merton (1974) default risk framework builds a direct link between a firm's default risk and the volatility of such firm's asset value. We use the past 30-day realised volatility of the firm's equity return as a firm-specific risk factor. We also construct other standard structural factors, such as dividends payout ratio and leverage ratio (Zhang, Zhou, and Zhu, 2009). In addition, we construct two corporate credit market variables, the investment grade spread and the high yield spread. Interestingly, we find these two factors are highly correlated with the realised volatilities of individual firms. Therefore, we do not include these two variables in our empirical framework.[12] All aforementioned data are extracted from Bloomberg.

[12]The correlations are as high as 97 percent on levels, and 11 percent on changes. The correlations are significant at 0.00001 percent level.

4 Pooled Vector Autoregression

Before moving to the formal regression analyses, we perform a preliminary test on the cross-predictability between the CDS and equity returns as in Hilscher, Pollet, and Wilson (2015). We adopt the same econometric tool, the simplest pooled vector autoregression (VAR). Besides running pooled VAR on the full sample period, we also run it on two sub-sample periods. That is, the exact same period as in Hilscher, Pollet, and Wilson (2015) from 2001 to 2007, and the crisis period from 2008 to 2009.[13] The coefficient statistics for the full sample period regression are reported in Table 3, and the results for the two sub-sample periods are reported in Table 4. The t-statistics are based on standard errors that are clustered by firm id, and are adjusted for heteroskedasticity.

The study of Hilscher, Pollet, and Wilson (2015) finds that equity returns can significantly predict the credit protection returns, but not vice versa. Furthermore, in comparison to the autoregressive credit protection return itself, the equity returns show a superior forecasting power to the credit returns. Our findings of the sub-sample period from 2001 to 2007 are aligned with these discoveries. The top panel of Table 4 shows that the one-day lagged equity returns can significantly predict the CDS returns at the time t, whose statistical significances are much stronger than the lagged CDS returns. On the other hand, the one-day lagged credit returns have no forecasting power on the equity returns. This suggests that the informed trading occurs in the equity market first.

However, the findings from the crisis period (as well as the full-sample period) show a different story. As shown in the lower panel of Table 4, we observe enhanced statistical significance illustrated by the autoregressive CDS returns in predicting the credit returns.

[13]The pooled VAR is also performed on the entire no-crisis period, the regression results stay consistent as the results shown in the sum-sample 2001-2007.

Furthermore, the lagged credit returns also significantly forecast the movements in the equity returns at time t. These findings suggest, during the financial crisis period, the equity returns predict credit protection returns, and vice versa. It is, therefore, hard to determine the direction of information flow, neither the location of informed traders. These preliminary tests document similar behaviour patterns to the one reported in the existing literature but also highlight new results pertaining to the crisis period.

5 Regression Analyses

As the purpose of this study is to examine and compare price reactions to news media content of the equity and CDS markets, it is essential to establish the explanatory power of our news score variable. We perform simple OLS panel regressions of the equity and CDS returns on the news score. In addition, we separate our sample into crisis and non-crisis periods. The crisis period is the U.S. financial crisis from January 2008 to December 2009. We also investigate the interaction between the CDS (and equity) return and the news media content via a panel vector autoregressions (Panel VARs) and the corresponding impulse response functions.

5.1 Panel Regression

We perform panel regression as shown in equation (1) across the 31 financial firms. $Y_{i,t}^{k}$ stands for the CDS protection return, and the equity stock return, respectively. We control for heteroskedasticity by clustering the standard error at firm level. A firm specific fixed effect is included to control for unobserved average cross section differences. We also include a year effect to capture the influence of aggregate time-series trends in the sample. We ensure all variables are stationary at the panel setting. The regression is performed on the daily observations of the CDS protection return and the equity return.

$$\begin{aligned} Y_{i,t}^{k} &= \alpha_i^k + \beta_{i,1}^k NewsScore_{i,t} + \beta_{i,2}^k Volatility\ premium_t \\ &\quad + \beta_{i,3}^k Equity\ volatility_{i,t} + \beta_{i,4}^k US\ stock_t \\ &\quad + \beta_{i,5}^k Liquidity\ risk_t + \epsilon_{i,t}^k \\ &\quad k \in \text{CDS return},\ \text{equity return}; \quad \forall i \in 1, ..., 31; \end{aligned} \tag{1}$$

The regression results of equation (1) are reported in Table 5. Columns 1, 3 and 5 report the coefficient statistics of the explanatory variables for the CDS returns. Columns 2, 4 and 6 are the regression coefficients for the equity returns. Columns 1 and 2 are based on the full sample observations. Columns 3 and 4 are based on the observations of the U.S. financial crisis, and columns 5 and 6 report the results for the non-crisis period. The adjusted R squared and the number of observations are also reported in the table. The t-statistics are in the parentheses.

There are several interesting findings that emerge from the panel regressions. Firstly, the news score variable has a significant impact on the equity returns for the entire sample regression, as well as the ones for the sub-sample periods. However, the news media content only impacts the CDS returns significantly during the Great Recession. Secondly, focusing on the crisis period, the news score has a negative impact on the CDS returns, while a positive impact on the equity returns. One standard deviation increase in the news score decreases CDS returns by 16.5 percent while increases equity returns by 31.5 percent. This finding is in line with the existing literature that positive news depresses credit returns but improves equity returns (Liebmann, Orlov, and Neumann, 2016). It also confirms the negative relationship between the CDS and the equity returns (Zhang, Zhou, and Zhu, 2009; Cremers, Driessen, Maenhout, and Weinbaum, 2008). Thirdly, comparing the coefficients of the news sentiment on the equity returns across the two different sub-samples, we observe substantial increases in the magnitude and the significance level of the coefficient, from 0.036 at a significance level of 5 percent of the non-crisis period, to 0.315 at a significance level of 1 percent of the crisis period. The coefficient of the non-crisis period is consistent with the result based on the full sample observations. Such improvement in the magnitude and statistical importance of the news media score confirms the findings in Garcia (2013): the impact of news sentiment tend to concentrate during recessions. The same logic also applies to the CDS returns. During non-crisis period, the news score is insignificant and with inappropriate sign (and the full sample period). During the crisis period, the news sentiment becomes significant at 5 percent level and with the correct sign.

Hilscher, Pollet, and Wilson (2015) suggest the inattention theory would help to explain the changing responses of credit returns to the news. The theory suggests that CDS traders are less attentive than equity traders to events of common concerns because CDS traders are motivated by liquidity considerations. Therefore, we do not observe a significant impact of the news on credit returns during the non-crisis period. However, during the crisis period, both liquidity and funding risks increase. Risk averse CDS traders need to pay more attention to the market sentiment in order to gather information on market liquidity conditions. This explains the significance of news score variable on CDS returns during the crisis period. This explanation could be further supported by the coefficients of the liquidity risk across different samples. There is no significant impact of liquidity risk on the CDS returns before or after the financial crisis. However, during the financial crisis, the liquidity risk factor starts to impact CDS returns significantly. One basis point relative increase in the 3 month Libor rate over the OIS rate increases CDS returns by 8.9 percentage points, at 1 percent significance level. This increasing explanatory power of the liquidity risk factor, presumably, suggests an increase of the attention from CDS traders on the market liquidity condition during the Great Recession. With respect to the other control variables, the U.S. equity market return remains the most important global risk factor (Longstaff, Mithal, and Neis, 2005; Longstaff, Pan, Pedersen, and Singleton, 2011), which significantly impacts both CDS and equity returns, in the full period and both sub-sample periods. One percentage increase in the U.S. stock market return decreases CDS returns by 4.81 (column 1) percentage points, while increase equity returns by 134.1 (column 2) percentage points. The realised volatility of a firm's equity return has a significant impact on the CDS returns in the non-crisis (and full period) sample. A higher volatility of the stock price implies a higher risk of the CDS's underlying firm, and hence a higher CDS spread. The insignificant impact of the equity volatility on the firm's equity return can be explained by the inclusion of the firm fixed effect.[14] The volatility premium of the U.S. VIX index has explanatory powers on both return series, but for different sample periods. The volatility premium significantly impacts CDS returns during the non-crisis period, while critically influences equity returns in the crisis period.

Regarding the explanatory power of the overall model, the adjust R squared for CDS returns is not as promising as for equity returns. For the entire sample, our model explains 3.5 percent variations in the cross sectional CDS returns, but 42.6 percent variations in the equity returns. The low adjusted R squared for CDS returns could be caused by the lack of debt level information, such as leverage and other balance sheet factors. Indeed, we observe a higher adjusted R squared for CDS returns when we include the balance sheet variables such as leverage ratio, dividend payout ratio, return on equity, etc. Inclusion of these variables does not change our findings on the news score. Due to the different frequency between these balance-sheet variables and our dependent variables, we do not include them in the main regression.[15]

For robustness purposes, we also include three lags of the dependent variables in the regressions. The results are reported in Table 6. Our findings on the news score remain robust. However, we lose the explanatory power of the liquidity risk variable when we include the lagged CDS returns. This is reasonable given the direct relationship between CDS spreads and market funding and liquidity risk.

[14]The equity volatility is significant on equity returns when we exclude the fixed effect.

[15]Relevant regression results are available upon request.

5.2 Panel Vector Autoregression (Panel VAR)

The panel regressions have established the significant explanatory power of our WSJ based news score on capturing the cross sectional variations in equity returns, as well as CDS returns during the crisis period. The different reaction patterns between the equity and CDS returns, as well as between the crisis versus non-crisis periods motivate us to explore further the causal (predictive) relationship between the media content variable and the returns (both CDS and equity). For this, we adopt the panel vector autoregression (panel VAR) model.

The standard time-series vector autoregression (VAR) model has been widely used in macro-econometrics to explore the interactions among various endogenous but interdependent variables.[16] Holtz-Eakin, Newey, and Rosen (1988) is the first attempt to introduce VAR in a panel data setting. Such setting allows for non-stationary individual effects. The key difference between the traditional VAR versus the panel VAR is that the latter introduces a cross sectional dimension, which takes into account the individual heterogeneity. Such feature makes the panel VAR to be preferred to the VAR model in micro studies in order to capture cross sectional heterogeneity (Canova and Ciccarelli, 2013; Abrigo and Love, 2015).

Equation (2) displays the panel VAR regression setting. The endogenous variables are the news score and the CDS return, $Y_{i,t}^k$ when $k =$ CDS (and the equity return when $k =$ equity). Five lags of the endogenous variables are included. This lag length is chosen in accordance with the Bayesian Information Criteria. We also control for both heteroskedasticity and autocorrelation.

$$Y_{i,t}^k = \alpha_i^k + \sum_{l=1}^{5} \delta_{i,l}^k Y_{i,t-l}^k + \sum_{l=1}^{5} \gamma_{i,l}^k News_{i,t-l} + \epsilon_{i,t}^k \tag{2}$$

[16] Exogenous variables could be included as well

$$k \in \text{CDS return}, \ \text{equity return}; \quad \forall i \in 1, ..., 31;$$

The hypotheses are as follows. First, if the price discovery happens in the equity market first, we should expect a faster reaction of equity returns to the news sentiment than the reaction of CDS returns. Any significance in the coefficients of the news score for equity returns should materialise prior to any significance in the news score for CDS returns. However, if the information flows from the CDS market to the equity market, we should expect to observe the opposite. Second, if the CDS market is filled with inattentive traders who have preferences for liquidity, it is reasonable to expect that the explanatory power of the news score improves for CDS returns during the crisis period. This is because there is higher liquidity risk during the crisis. A risk averse CDS trader who trades for liquidity pays more attention to the news over this period in order to avoid losses. Hence, the reaction of CDS traders to news sentiment would be faster and stronger during the crisis than the non-crisis period.

Table 7 reports the coefficient statistics for equation (2). The first two columns report the results of full sample. Columns 3 and 4 are the results of crisis period, and the last two columns are the findings of non-crisis period. Column 1, 3, and 5 (2, 4, and 6) are the coefficient statistics for CDS (equity) returns. For the full sample, the reaction of CDS returns to the media news occurs on the second day. One standard deviation increase in the news score significantly decreases the credit return by 4.9 percentage points. On the fourth day, CDS returns rebound back with a 5.4 percentage points increase. For the equity returns, the reaction happens much earlier than credit returns. We observe an immediate reaction of equity returns to the media content at the first lag (The impulse response function shows that the reactions actually happen on the news event day). With one standard deviation increase in the news score, stock returns increase on average by 12.1 percentage. The impact of the news is absorbed on the following day when stock returns drop by 13.7 percentage. The coefficients of both lags are significant at 5 percent level. The sufficient large scales of the coefficients also suggest that the news score has a considerable economic impact on the equity returns. Figure 1 plots the impulse response functions. Each impulse is a one standard deviation shock to the news score. The direct effect of such shock on the CDS returns is plotted in Figure 1a, and the effect on the equity returns is plotted in Figure 1b. It is clear that CDS returns react significantly to the news from day 1 to day 2, and recover back from day 2 to day 4. After day 4, the impact of the news starts to diminish. From day 6, the news impact on CDS returns reverses back to zero. The impulse response function of equity returns shows a more rapid and stronger reaction than the credit returns. The equity returns increase significantly on the day of news release. The absorption of such news impact is much faster (day 5) as well. Furthermore, comparing the crisis and non-crisis periods, equity returns always react on the first lag (and the second lag in the non-crisis period), while credit returns react on the second lag and the fifth lag (crisis period) or the fourth lag (the non-crisis period). This is in line with our assumption that equity returns react to media news much faster than credit returns if the information flow is led by the equity market. Our results are supportive of Hilscher, Pollet, and Wilson (2015): equity returns lead credit protection returns.

Next, we examine the behaviour of the credit protection returns in and out of the crisis period. Column 3 of Table 7 suggests that CDS returns start to react significantly to the news at the second lag, during the U.S. Great Recession. The reversal then happens at the fifth lag. Furthermore, the impact of the news sentiment during the crisis has a high economic significance, in comparison to the news impact in the non-crisis period. One standard deviation increase in the news score depresses credit protection returns by 19.4 percentage points two days after the news release. Credit returns recover back to normal levels after another three days with a 17.7 percentage points increase. In the non-crisis period, CDS returns exhibit a much weaker reaction to the news score. The news sentiment only affects CDS returns at the fourth lag. The magnitude of such coefficient is also small (i.e., 6 percentage points). Overall, the empirical findings suggest that traders in the CDS market tend to respond to media news in a more rapid fashion during the crisis.

In the lower part of Table 7, we report the χ^2 statistics of the panel VAR-Granger Causality Wald test. The null hypothesis is that excluding all news score variables does not Granger-cause the changes in the dependent variable (i.e., the CDS and equity returns). In all cases, we reject the null with statistically significance, and conclude that the news sentiment Granger-causes the movements in returns. Furthermore, we also perform an F-test on the panel VAR regressions with a null hypothesis that the sum of the coefficients corresponding to the five lags of news sentiment is equal to zero. In all cases, we fail to reject the null and conclude that there is full price reversal across all of the six empirical settings.

For robustness purposes, we run the panel VAR regression of equation (2) with control variables. We include exogenous risk factors (with one day lag). The risk factors are the ones used previously in the panel regression. We include the volatility premium, the equity volatility of individual firm, the U.S. stock market excess return, and the liquidity risk factor. The regression results are reported in Table 8. First, the main results on the equity and the credit returns do not change. The equity return illustrates a faster and more economic significant reaction to the news than the credit return, for the full sample, the crisis and non-crisis periods. Second, credit returns respond to the news at a more rapid speed and with a higher economic significance during the financial crisis than the non-crisis period.

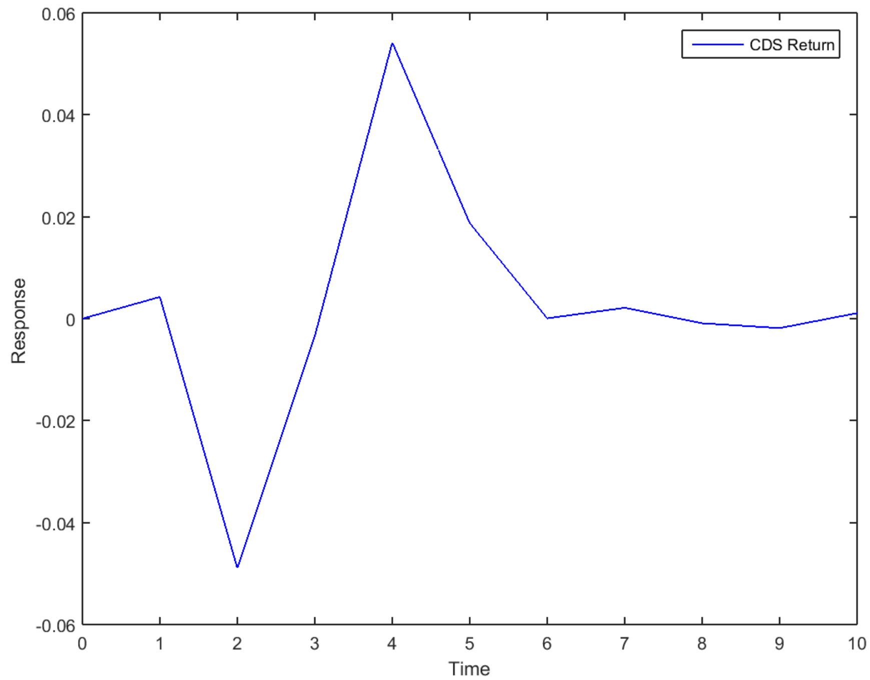
With respect to the control variables, the U.S. stock market remains the most important global risk factor. It is statistically and economically significant for both credit and equity returns, except for equity returns during the non-crisis period. Furthermore, the signs are consistent with the negative relationship between the CDS and equity returns. That is, an increase in the stock market return decreases CDS returns and increases equity stock returns.

The behaviour of the liquidity risk is also worthy of a mention. We observe a significant influence of the liquidity risk on CDS returns during the financial crisis period, but not during the non-crisis sample. This result confirms that the CDS market is sensitive to the deterioration of market liquidity conditions during the Great Recession. The increasing significance of the liquidity risk, together with the simultaneous improvement of CDS traders' attention to news, tend to support the inattention theory proposed in the literature. The inattention of the CDS traders causes the delay in the CDS returns' response to new information releases, in comparison to the equity market. During the financial crisis, the preferences for liquidity of credit traders force them to pay more attention to market news, which leads to a more rapid reaction to news sentiment in the CDS market.

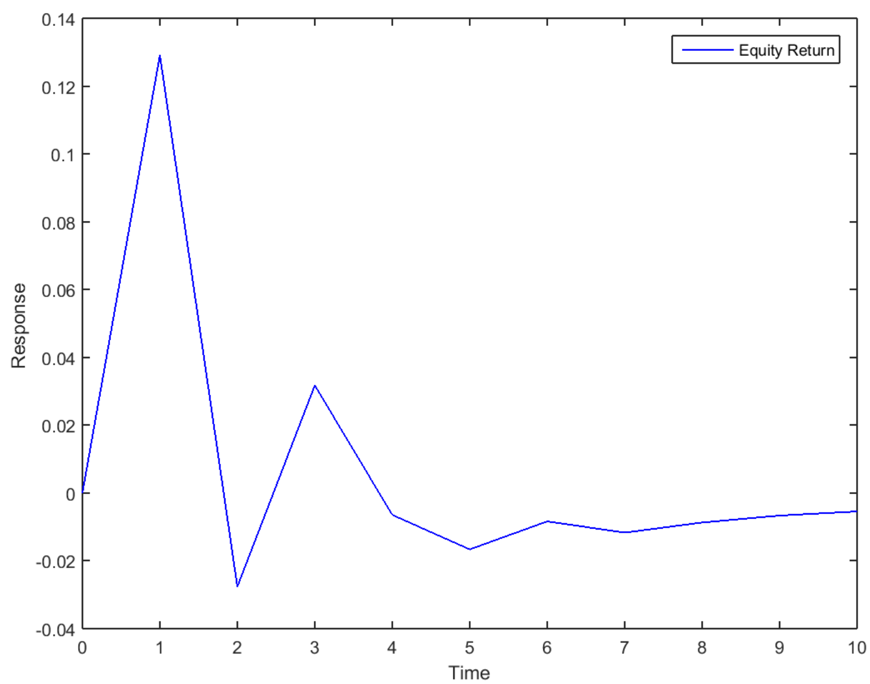
6 Conclusion

In this paper, we study the impact of firm-specific news sentiment on the credit and equity returns of 31 U.S. financial firms. We perform a standard linguist analysis algorithm on news articles published by the Wall Street Journal and construct a news score variable for each firm. We then examine the reactions of credit and equity returns to the news score by using the panel and panel VAR regressions. We find that CDS returns exhibit a delay in responding to the news, in comparison to equity returns. We further separate the sample into crisis and non-crisis periods. The regression results based on the sub-samples suggest that CDS returns respond to the news more quickly during the financial crisis than the non-crisis period. The improvement in the news reaction of CDS returns is accompanied by a simultaneous increase in the significance of the market liquidity risk.

Our results are supportive of the findings of Garcia (2013). News sentiment impact tends to concentrate during recessions. We provide evidence showing that such phenomenon also exists in the credit derivative market. Furthermore, this paper is closely linked to Hilscher, Pollet, and Wilson (2015) and Mamaysky and Glasserman (2016). In particular, our empirical findings suggest an explanation related to investor inattention. Hilscher, Pollet, and Wilson (2015) argue that informed traders would prefer to trade in the equity market due to high transaction costs in the CDS market, whereas credit market is used by liquidity traders for non-fundamentals based reasons. Therefore, the CDS traders pay less attention to news development than the equity traders, which explains the delayed response in the credit returns. During the financial crisis, the credit market liquidity deteriorates, which causes risk averse CDS traders to become more attentive to news information in order to avoid potential losses. This explains the faster response of CDS returns to news sentiment during the crisis period, and the increasing significance of the liquidity risk factor.



(a) CDS returns



(b) Equity Return

Figure 1: Impulse Response Function: CDS and Equity Returns

Table 1: Financial Firms included in the Wall Street Journal News Sample

	S&P 500 Financial Firms	Markit CDS Ticker
1	American Express Co	AXP
2	American International Group Inc	AIG
3	Aon PLC	AOC
4	Bank of America Corp	BACORP
5	Bank of New York Mellon Corp	BNYMEL
6	BB & T Corp	BBT
7	Berkshire Hathaway Inc	BRK
8	Capital One Financial Corp	COF
9	Charles Schwab Corp	SCH
10	Citigroup Inc	C
11	Fifth Third Bancorp	FITB
12	Goldman Sachs Group Inc	GS
13	JPMorgan Chase & Co	JPM
14	KeyCorp	KEY
15	Legg Mason Inc	LM
16	Loews Corp	LTR
17	Marsh & McLennan Cos Inc	MMC
18	MetLife Inc	MET
19	Morgan Stanley	MWD
20	PNC Financial Services Group Inc	PNC
21	Prudential Financial Inc	PRU
22	Simon Property Group Inc	SPG
23	State Street Corp	STT
24	SunTrust Banks Inc	STI
25	The Allstate Corp	ALL
26	The Hartford Financial Services Group Inc	HIG
27	Travelers Cos Inc	TRV
28	US Bancorp	USB
29	Vornado Realty Trust	VNO
30	Wells Fargo	WFC
31	Weyerhaeuser Co	WY

Table 2: Summary Statistics

The tables reports the summary statistics of the single-name 5-year CDS spread on the 31 financial firms.The statistics include mean, standard deviation (SD), minimum, maximum and Number of observations (N). All measures are in basis points. The sample period ranges from 3rd January 2001 to 14 June 2016.

Firm Name	Mean	SD	Minimum	Maximum	N
American Express Co	78.02	91.57	8.07	700.07	3884
American International Group Inc	202.24	392.00	8.25	3647.57	3836
Aon PLC	69.50	55.27	23.45	446.87	3793
Bank of America Corp	121.41	90.09	8.09	498.33	2629
Bank of New York Mellon Corp	69.51	31.54	10.02	143.40	2254
BB&T Corp	72.78	47.44	12.62	254.00	3707
Berkshire Hathaway Inc	89.79	82.07	6.80	526.80	3162
Capital One Financial Corp	150.64	139.74	21.75	1051.67	3667
Charles Schwab Corp	50.22	25.91	15.73	141.19	3597
Citigroup Inc	101.76	101.68	6.83	662.86	3846
Fifth Third Bancorp	245.71	45.67	175.38	325.01	1598
Goldman Sachs Group Inc	103.47	82.29	17.90	595.84	3885
JPMorgan Chase	72.86	40.18	11.33	237.91	2997
KeyCorp	132.25	144.38	12.00	618.80	3490
Legg Mason Inc	70.08	45.87	14.50	203.33	3350
Loews Corp	58.94	31.49	10.82	178.26	3835
Marsh & McLennan Cos Inc	59.46	30.80	16.51	277.53	3134
MetLife Inc	133.76	148.33	10.54	996.19	3603
Morgan Stanley	124.39	125.20	17.30	1438.59	3880
PNC Financial Services Group Inc	71.26	49.67	18.27	307.65	3172
Prudential Financial Inc	138.89	172.91	10.56	1323.77	3511
Simon Property Group Inc	102.85	114.01	14.80	900.00	3761
State Street Corp	138.51	78.89	14.30	250.50	2891
SunTrust Banks Inc	90.92	80.90	9.58	422.95	3821
The Allstate Corp	60.71	55.48	8.92	411.25	3613
The Hartford Financial Services Group Inc	139.26	166.93	9.53	1161.54	3546
Travelers Cos Inc	66.81	33.51	16.73	169.94	2342
US Bancorp	58.81	43.18	7.50	249.64	3581
Vornado Realty Trust	129.91	136.72	29.15	982.50	3240
Wells Fargo	60.14	45.69	6.22	315.26	3827
Weyerhaeuser Co	105.76	59.36	23.03	354.21	3826

Table 3: Pooled Vector Autoregression: Full Sample

The following table reports the coefficient statistics from pooled Vector Autoregression for daily equity and CDS protection returns. All regressions include year effect. It also controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The sample period ranges from 3rd January 2001 to 14 June 2016. The t-statistics are reported in parentheses. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

			CDS Return (t)			**Equity Return (t)**	
CDS Return	**Y (t-1)**	0.128***	0.115***	0.113***	-0.028***	-0.025***	-0.025***
		(7.871)	(6.975)	(6.823)	(-3.310)	(-2.960)	(-2.919)
	Y (t-2)		0.070***	0.065***		-0.020**	-0.021**
			(4.271)	(3.914)		(-2.330)	(-2.395)
	Y (t-3)			0.027			-0.015*
				(1.624)			(-1.789)
Equity Return	**Y (t-1)**	-0.243***	-0.241***	-0.240***	0.006	0.006	0.005
		(-7.625)	(-7.581)	(-7.555)	(0.390)	(0.338)	(0.291)
	Y (t-2)		-0.059*	-0.059*		0.000	-0.001
			(-1.827)	(-1.830)		(0.009)	(-0.069)
	Y (t-3)			-0.032			-0.0385*
				(-1.012)			(-1.328)
N		3,883	3,882	3,881	3,883	3,882	3,881

Table 4: Pooled Vector Autoregression: Sub Samples]

The following table reports the coefficient statistics from a pooled Vector Autoregression for daily equity and CDS protection returns. All regressions include year effect. It also controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The sample period on the top panel ranges from 3rd January 2001 to 31 December 2007. The crisis period is the Great Recession of year 2008 and 2009. The t-statistics are reported in parentheses. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

Prior Sample: January 2001 to December 2007							
		CDS Return (t)			**Equity Return (t)**		
CDS Return	**Y (t-1)**	0.042*	0.038	0.036	-0.013	-0.012	-0.011
		(1.756)	(1.572)	(1.477)	(-1.231)	(-1.103)	(-1.040)
	Y (t-2)		0.047**	0.045*		-0.011	-0.011
			(1.975)	(1.854)		(-1.056)	(-1.070)
	Y (t-3)			0.051**			-0.019*
				(2.149)			(-1.809)
Equity Return	**Y (t-1)**	-0.222***	-0.222***	-0.220***	-0.046*	-0.045*	-0.046*
		(-4.032)	(-4.030)	(-3.997)	(-1.895)	(-1.879)	(-1.900)
	Y (t-2)		-0.035	-0.034		0.014	0.012
			(-0.639)	(-0.616)		(0.579)	(0.497)
	Y (t-3)			-0.008			-0.062
				(-0.136)			(-1.354)
N		1,755	1,754	1,753	1,755	1,754	1,753

Crisis Sample: January 2008 to December 2009							
		CDS Return (t)			**Equity Return (t)**		
CDS Return	**Y (t-1)**	0.122***	0.110***	0.107***	-0.026***	-0.023***	-0.023***
		(6.934)	(6.206)	(6.039)	(-3.181)	(-2.787)	(-2.725)
	Y (t-2)		0.067***	0.061***		-0.019**	-0.019**
			(3.794)	(3.396)		(-2.310)	(-2.310)
	Y (t-3)			0.039**			-0.014*
				(2.202)			(-1.733)
Equity Return	**Y (t-1)**	-0.254***	-0.253***	-0.250***	-0.002	-0.003	-0.003
		(-6.749)	(-6.723)	(-6.667)	(-0.132)	(-0.165)	(-0.196)
	Y (t-2)		-0.058	-0.058		0.010	0.009
			(-1.519)	(-1.529)		(0.578)	(0.499)
	Y (t-3)			-0.043			-0.031*
				(-1.144)			(-1.724)
N		505	505	505	505	505	505

Table 5: Panel OLS Regression

The following table reports the coefficient statistics from a panel regression for daily equity and CDS protection returns. The explanatory variables include the media news sentiment, the U.S. volatility premium, 30-day realised equity volatility of each firm, U.S. stock excess return and liquidity risk. The news score measure is based on textural analysis algorithm. All regressions include both year effect and fixed effect. It also controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The sample period ranges from 3rd January 2001 to 14 June 2016. The crisis period is the Great Recession of year 2008 and 2009. The t-statistics are reported in parentheses. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	Full Period		**Crisis Period**		**Non-Crisis Period**	
	CDS Return	**Equity Return**	**CDS Return**	**Equity Return**	**CDS Return**	**Equity Return**
NewsScore	0.003	0.040**	-0.165**	0.315***	0.016	0.036**
	(0.092)	(2.569)	(-2.003)	(3.427)	(0.447)	(2.408)
Volatility premium	0.146***	0.036**	0.052	0.191**	0.177***	-0.021
	(5.810)	(2.573)	(1.568)	(2.419)	(5.051)	(-1.396)
Equity volatility	0.125***	0.001	0.065	-0.064	0.250***	-0.029
	(3.214)	(0.061)	(1.544)	(-1.332)	(3.482)	(-1.050)
US stock market	-0.481***	1.341***	-0.482***	1.872***	-0.521***	1.159***
	(-8.455)	(22.798)	(-6.798)	(16.359)	(-7.969)	(21.296)
Liquidity risk	0.028	0.009*	0.089***	0.011	0.016	0.008*
	(1.574)	(1.698)	(2.667)	(0.141)	(0.891)	(1.815)
Constant	0.115***	-0.012***	0.405***	-0.386***	0.075***	-0.009**
	(16.835)	(-3.018)	(19.216)	(-3.275)	(10.227)	(-2.408)
Adjust R2	0.035	0.426	0.028	0.354	0.044	0.483
N	102,282	102,282	13,978	13,978	88,304	88,304

Table 6: Panel OLS Regression: with Lagged Dependent Variables

The following table reports the coefficient statistics from a panel regression for daily equity and CDS protection returns. The explanatory variables include the media news sentiment, the U.S. volatility premium, 30-day realised equity volatility of each firm, U.S. stock excess return and liquidity risk. Three lags of the dependent variables are included for robustness purpose. The news score measure is based on textural analysis algorithm. All regressions include both year effect and fixed effect. It also controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The sample period ranges from 3rd January 2001 to 14 June 2016. The crisis period is the Great Recession of year 2008 and 2009. The t-statistics are reported in parentheses. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	Full Period		**Crisis Period**		**Non-Crisis Period**	
	CDS Return	**Equity Return**	**CDS Return**	**Equity Return**	**CDS Return**	**Equity Return**
NewsScore	0.009	0.043***	-0.150*	0.267***	0.021	0.037**
	(0.286)	(2.658)	(-1.903)	(2.981)	(0.598)	(2.461)
Y (t-1)	0.039	-0.008	0.046	0.100**	0.033	-0.015***
	(1.215)	(-0.487)	(1.332)	(2.064)	(0.827)	(-2.594)
Y (t-2)	0.042***	-0.007	0.018	0.005	0.054***	0.001
	(3.521)	(-0.981)	(1.112)	(0.270)	(5.335)	(0.321)
Y (t-3)	-0.000	-0.033***	-0.002	-0.043**	-0.001	-0.010***
	(-0.011)	(-7.692)	(-0.231)	(-2.318)	(-0.076)	(-3.220)
Volatility premium	0.154***	0.042***	0.057*	0.200**	0.186***	-0.018
	(5.588)	(2.898)	(1.710)	(2.574)	(5.086)	(-1.171)
Equity volatility	0.118***	-0.001	0.061	-0.063	0.242***	-0.030
	(3.214)	(-0.057)	(1.527)	(-1.319)	(3.434)	(-1.083)
US stock market	-0.475***	1.346***	-0.478***	1.920***	-0.513***	1.161***
	(-8.541)	(22.576)	(-6.808)	(15.836)	(-7.972)	(21.133)
Liquidity risk	0.024	0.010*	0.063	0.085	0.017	0.008*
	(1.332)	(1.821)	(1.443)	(1.057)	(0.952)	(1.712)
Constant	0.105***	-0.011***	0.375***	-0.301**	0.069***	-0.009**
Adjust R2	0.039	0.427	0.030	0.367	0.048	0.484
N	102,189	102,189	13,978	13,978	88,211	88,211

Table 7: Panel Vector Autoregression for CDS and Equity Returns

The following table reports the coefficient statistics from a panel vector autoregression (VAR) for daily equity and CDS protection returns on the news sentiment score variable. The news variable is constructed based on textual analysis algorithm. Regressions controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The t-statistics are reported in parentheses. The full sample period ranges from 3rd January 2001 to 14 June 2016. The crisis period is the Great Recession of year 2008 and 2009. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	Full Period		**Crisis Period**		**Non-Crisis Period**	
	CDS Return	**Equity Return**	**CDS Return**	**Equity Return**	**CDS Return**	**Equity Return**
Y (t-1)	0.038***	-0.065***	0.050**	-0.096***	0.031*	-0.042***
	(2.780)	(-6.113)	(2.283)	(-4.338)	(1.734)	(-7.032)
Y (t-2)	0.044***	-0.015	0.024*	-0.066***	0.057**	0.018***
	(2.831)	(-1.241)	(1.776)	(-3.217)	(2.458)	(3.245)
Y (t-3)	-0.002	-0.032***	-0.003	-0.049***	0.000	-0.013**
	(-0.300)	(-3.090)	(-0.329)	(-2.850)	(0.004)	(-2.403)
Y (t-4)	-0.009	-0.039***	-0.011	-0.083***	-0.009	0.004
	(-1.240)	(-4.033)	(-1.068)	(-5.386)	(-0.830)	(0.873)
Y (t-5)	-0.006	-0.030***	-0.004	-0.021	-0.007	-0.045***
	(-1.150)	(-3.255)	(-0.425)	(-1.361)	(-1.205)	(-9.067)
NewsScore(t-1)	0.004	0.121**	0.094	0.710**	-0.010	0.083**
	(0.176)	(2.495)	(0.989)	(2.422)	(-0.425)	(2.379)
NewsScore(t-2)	-0.049**	-0.137**	-0.194*	-0.513	-0.025	-0.085*
	(-1.988)	(-2.249)	(-2.191)	(-1.327)	(-1.050)	(-1.888)
NewsScore(t-3)	-0.003	0.051	0.128	-0.178	-0.013	0.047
	(-0.170)	(0.852)	(1.504)	(-0.474)	(-0.708)	(1.081)
NewsScore(t-4)	0.054***	0.009	0.026	0.063	0.060***	0.018
	(2.697)	(0.158)	(0.289)	(0.169)	(3.200)	(0.419)
NewsScore(t-5)	0.022	-0.048	0.177*	-0.160	-0.005	-0.028
	(0.931)	(-0.986)	(1.926)	(-0.521)	(-0.202)	(-0.859)
Chi2 (5) [Joint]	11.892	11.068	10.524	10.187	12.146	12.411
p-value	0.036	0.05	0.062	0.07	0.033	0.03
N	105,061	105,061	15,150	15,150	89,911	89,911

Table 8: Panel Vector Autoregression for CDS Return and Equity Return: Robust Control

The following table reports the coefficient statistics from a panel vector autoregression (VAR) for daily equity and CDS protection returns on the news score variable. Additional exogenous variables with one day lag are included: the U.S. volatility premium, 30-day realised equity volatility, U.S. stock excess return and liquidity risk. Regressions controls for outliers as returns are winsorised at 1% and the 99% levels. Standard errors are adjusted for heteroskedasticity and clustered by firm id. The t-statistics are reported in parentheses. The full sample period ranges from 3rd January 2001 to 14 June 2016. The crisis period is the Great Recession of year 2008 and 2009. *** stands for 1% of significance; ** stands for 5% of significance; * stands for 10% of significance.

	Full Period		**Crisis Period**		**Non-Crisis Period**	
	CDS Return	**Equity Return**	**CDS Return**	**Equity Return**	**CDS Return**	**Equity Return**
Y (t-1)	0.023	-0.050***	0.035*	-0.062**	0.012	-0.027***
	(1.629)	(-3.143)	(1.690)	(-2.406)	(0.655)	(-3.291)
Y (t-2)	0.046***	-0.023*	0.025*	-0.049**	0.059**	0.009
	(2.821)	(-1.922)	(1.846)	(-2.357)	(2.442)	(1.581)
Y (t-3)	-0.002	-0.028***	-0.003	-0.036**	-0.001	-0.022***
	(-0.345)	(-2.693)	(-0.331)	(-2.054)	(-0.247)	(-4.144)
Y (t-4)	-0.008	-0.047***	-0.009	-0.076***	-0.009	-0.006
	(-1.006)	(-4.768)	(-0.911)	(-4.642)	(-0.789)	(-1.223)
Y (t-5)	-0.006	-0.028***	-0.006	-0.012	-0.008	-0.055***
	(-1.094)	(-3.065)	(-0.621)	(-0.809)	(-1.255)	(-10.784)
NewsScore(t-1)	-0.001	0.138***	0.070	0.585*	-0.011	0.086**
	(-0.049)	(2.795)	(0.739)	(1.921)	(-0.443)	(2.450)
NewsScore(t-2)	-0.042*	-0.134**	-0.182*	-0.481	-0.024	-0.087*
	(-1.698)	(-2.195)	(-1.806)	(-1.216)	(-0.991)	(-1.919)
NewsScore(t-3)	-0.002	0.033	0.135	-0.136	-0.012	0.048
	(-0.091)	(0.547)	(-1.596)	(-0.357)	(-0.629)	(1.083)
NewsScore(t-4)	0.060***	0.008	0.032	-0.029	0.063***	0.015
	(2.941)	(0.141)	(0.368)	(-0.077)	(3.350)	(0.352)
NewsScore(t-5)	0.016	-0.041	0.158*	-0.152	-0.005	-0.023
	(0.700)	(-0.828)	(1.722)	(-0.483)	(-0.215)	(-0.696)
Volatility premium	0.062***	0.005	0.065**	-0.056	0.066***	0.042***
	(-3.492)	(0.351)	(-2.033)	(-1.522)	(-2.935)	(3.753)
Equity volatility	0.030	0.027**	-0.019	0.042**	0.134**	-0.005
	(1.305)	(1.961)	(-1.208)	(1.986)	(2.297)	(-0.504)
US stock market	-0.437***	0.047*	-0.442***	0.134**	-0.437***	0.002
	(-16.983)	(-1.688)	(-9.509)	(-2.297)	(-14.535)	(-0.136)
Liquidity risk	0.015	0.029***	0.120**	0.067	-0.001	0.021***
	(0.993)	(3.140)	(1.979)	(1.528)	(-0.068)	(2.810)
Chi2 (5) [Joint]	11.726	12.233	9.265	9.205	12.157	11.136
p-value	0.039	0.032	0.099	0.091	0.033	0.049
N	102,097	102,097	13,978	13,978	88,119	88,119

References

Abrigo, M., and I. Love, 2015, "Estimation of Panel Vector Autoregression in Stata: a Package of Programs," working paper, University of Hawaii at Manoa.

Acharya, V., and T. C. Johnson, 2007, "Insider trading in credit derivatives," *Journal of Financial Economics*, 84(1), 110–141.

——— , 2010, "More insiders, more insider trading: Evidence from private-equity buyouts," *Journal of Financial Economics*, 98(3), 500–523.

Barber, B. M., and T. Odean, 2008, "All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors," *Review of Financial Studies*, 21(2), 785–818.

Canova, F., and M. Ciccarelli, 2013, "Panel vector Autoregressive models: A survey," in *VAR Models in Macroeconomics-New Developments and Applications: Essays in Honor of Christopher A. Sims (Advances in Econometrics)*, ed. by F. Tomas, C. Hill, I. Jeliazkov, and J. Carlos. Emerald, Bingley, vol. 32, 205-246.

Cathcart, L., N. Gotthelf, M. Uhl, and Y. Shi, 2016, "Media content and sovereign credit risk," working paper, Imperial Business School.

Chen, L., D. A. Lesmond, and J. Wei, 2007, "Corporate yield spreads and bond liquidity," *Journal of Finance*, 62(1), 119–149.

Cohen, L., and A. Frazzini, 2008, "Economic links and predictable returns," *Journal of Finance*, 63(4), 1977–2011.

Cremers, M., J. Driessen, P. Maenhout, and D. Weinbaum, 2008, "Individual stock-option prices and credit spreads," *Journal of Banking & Finance*, 32(12), 2706–2715.

DellaVigna, S., and J. M. Pollet, 2007, "Demographics and industry returns," *American Economic Review*, 97(5), 1667–1702.

——— , 2009, "Investor inattention and Friday earnings announcements," *Journal of Finance*, 64(2), 709–749.

Dougal, C., J. Engelberg, D. Garcia, and P. Christopher, 2012, "Journalsits and the stock market," *Review of Financial Studies*, 25, 639–679.

Duffie, D., 2010, "Presidential address: Asset price dynamics with slow-moving capital," *Journal of finance*, 65(4), 1237–1267.

Easley, D., M. O'hara, and P. S. Srinivas, 1998, "Option volume and stock prices: Evidence on where informed traders trade," *Journal of Finance*, 53(2), 431–465.

Ehrmann, M., and D. Jansen, 2012, "The pitch rather than the pit: investor inattention during FIFA World Cup matches," working paper, European Central Bank.

Engelberg, J. E., and C. A. Parsons, 2011, "The causal impact of media in financial markets," *Journal of Finance*, 66(1), 67–97.

Forte, S., and J. I. Peña, 2009, "Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS," *Journal of Banking & Finance*, 33(11), 2013–2025.

Frazzini, A., and O. A. Lamont, 2007, "The earnings announcement premium and trading volume," working paper, National Bureau of Economic Research.

Garcia, D., 2013, "Sentiment during recessions," *Journal of Finance*, 68(3), 1267–1300.

Greatrex, C. A., 2009, "The credit default swap market's reaction to earnings announcements," *Journal of Applied Finance*, 19(1-2).

Heston, S. L., and N. R. Sinha, 2014, "News versus sentiment: Comparing textual processing approaches for predicting stock returns," working paper, University of Maryland.

Hillert, A., H. Jacobs, and S. Müller, 2014, "Media makes momentum," *Review of Financial Studies*, 27(12), 3467–3501.

Hilscher, J., J. M. Pollet, and M. Wilson, 2015, "Are credit default swaps a sideshow? Evidence that information flows from equity to CDS markets," *Journal of Financial and Quantitative Analysis*, 50(3), 543–567.

Hirshleifer, D., K. Hou, S. H. Teoh, and Y. Zhang, 2004, "Do investors overvalue firms with bloated balance sheets?," *Journal of Accounting and Economics*, 38, 297–331.

Holtz-Eakin, D., W. Newey, and H. S. Rosen, 1988, "Estimating vector autoregressions with panel data," *Econometrica*, 56(6), 1371–1395.

Jegadeesh, N., and D. Wu, 2013, "Word power: A new approach for content analysis," *Journal of Financial Economics*, 110(3), 712–729.

Liebmann, M., A. G. Orlov, and D. Neumann, 2016, "The tone of financial news and the perceptions of stock and CDS traders," *International Review of Financial Analysis*, 46, 159–175.

Longstaff, F. A., S. Mithal, and E. Neis, 2005, "Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market," *Journal of Finance*, 60(5), 2213–2253.

Longstaff, F. A., J. Pan, L. H. Pedersen, and K. J. Singleton, 2011, "How sovereign is sovereign credit risk?," *American Economic Journal: Macroeconomics*, 3(2), 75–103.

Loughran, T., and B. McDonald, 2011, "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks," *Journal of Finance*, 66(1), 35–65.

Mamaysky, H., and P. Glasserman, 2016, "Does unusual news forecast market stress?," working paper, Columbia University.

Marsh, I. W., and W. Wagner, 2012, "Why is price discovery in credit default swap markets news-specific?," working paper, Cass Business School.

Merton, R. C., 1974, "On the pricing of corporate debt: The risk structure of interest rates," *Journal of Finance*, 29(2), 449–470.

Norden, L., and M. Weber, 2004, "Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements," *Journal of Banking & Finance*, 28(11), 2813–2843.

——— , 2009, "The co-movement of credit default swap, bond and stock markets: An empirical analysis," *European Financial Management*, 15(3), 529–562.

O'Kane, D., 2011, *Modelling single-name and multi-name credit derivatives*, vol. 573. John Wiley & Sons, West Sussex.

Sinha, N. R., 2016, "Underreaction to news in the US stock market," *Quarterly Journal of Finance*, 6(2), 105–165.

Tang, D. Y., and H. Yan, 2010, "Market conditions, default risk and credit spreads," *Journal of Banking & Finance*, 34(4), 743 – 753.

——— , 2016, "Understanding transactions prices in the credit default swaps market," *Journal of Financial Markets*.

Tetlock, P. C., 2007, "Giving content to investor sentiment: The role of media in the stock market," *Journal of Finance*, 62(3), 1139–1168.

Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy, 2008, "More than words: Quantifying language to measure firms' fundamentals," *Journal of Finance*, 63(3), 1437–1467.

Zhang, B. Y., H. Zhou, and H. Zhu, 2009, "Explaining credit default swap spreads with the equity volatility and jump risks of individual firms," *Review of Financial Studies*, 22(12), 5099–5131.

Zhu, H., 2006, "An empirical comparison of credit spreads between the bond market and the credit default swap market," *Journal of Financial Services Research*, 29(3), 211–235.