Information Risk and Credit Contagion

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Abstract

This paper demonstrates a positive relationship between information risk and the credit contagion effect. We use abnormal changes in the Credit Default Swaps (CDS) spreads to measure the contagion effect, and the dispersion of analyst forecasts as a proxy for information risk. We find that firms with higher information risk suffer a greater contagion effect that occurs in advance to the credit default events. This finding is robust under controls of key firm-specific characteristics and general condition of stock and credit markets.

Keywords: Contagion effect, Information risk; Credit Default Swaps

JEL classifications: G14; G32; G15

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1. Introduction

Credit risk management requires robust risk modeling, including the possibility of credit contagion: the process by which a credit event for one institution negatively impacts the risk valuations of its peers. In order to accurately model the possible credit loss distribution of a portfolio, precise measurement of the credit default correlation is needed, and the dynamics of credit contagion must be fully explored.\(^1\) Existing research has studied the credit contagion effect by examining its correlation with types of default events, industry attributes, or firm-specific characteristics.\(^2\) The present paper extends this line of research, documenting for the first time a link between credit contagion and information risk.

Following Jorion and Zhang (2007; 2009), this study employs the spreads of Credit Default Swaps (CDS) as a direct measurement of corporate credit conditions. We quantify credit contagion as the reaction in a firm’s CDS spreads due to downgrades in the credit ratings of its peers. Due to the complexity of credit quality monitoring and pricing, most market participants of credit derivatives are institutional traders. Therefore, information advantage is naturally priced in CDS spreads. Norden and Wagner (2008) show that CDS spreads are strongly related to the spreads on new syndicated loans, suggesting that not only

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\(^1\) For example, the pricing of Collateralized Debt Obligations (CDO) relies on a specific correlation between the underlying credits. For another instance, the Basel agreements require banks to maintain a level of capital sufficient to prepare for extreme credit loss. The proper level can be accurately estimated only with precise credit correlations.

\(^2\) Jorion and Zhang (2007) demonstrate that the bankruptcy of a firm leads to either credit contagion or competitive effect of its industry peers, depending on the type of default. The authors also show that the contagion effects are significantly correlated with several firm characteristics including size, leverage ratio, and the closeness of stock returns between the bankrupt firm and its peers. Huang et al. (2012) show that the contagion effect dominates the competitive effect during the late period of the 2008-2009 financial crisis, because public confidence is generally destroyed by unexpected major defaults.
do banks play an active role in CDS markets, but any information possessed by the banks relevant to lending decisions is also incorporated in CDS prices. Acharya and Johnson (2007) show that the magnitude of information flow from credit derivatives to the equity market is positively related to the underlying entity’s number of bank relationships. This relationship is particularly strong for information from negative credit shocks.

When a major credit default occurs, CDS market participants naturally use this event and their private information to adjust their credit evaluations of other firms, and trade CDS to improve the outlook of their portfolios. The participants often have precise knowledge regarding the credit conditions of some firms, but ambiguous information for others. Therefore, the effects of credit contagion should vary across firms with different levels of information risk. Specifically, we expect the magnitude of credit contagion to be positively correlated with information ambiguity. In addition, the informed participants should take actions prior to public announcements of the default events, and that would lead to an anticipated contagion effect. This intuition is formalized in following hypothesis.

**Hypothesis:** The anticipated credit contagion effect should be stronger for firms with higher information risk, i.e., greater ambiguity of the information possessed by market participants.

Prior studies have used several financial indicators as proxies for information uncertainty such as firm size, stock return volatility, book-to-market ratio, and leverage ratio;
see Zhang (2006) for an example. Most of the indicators, however, are generated using the firm’s stock prices, whose dynamics are largely affected by herding investors with little or no valuable information of the firms. Instead, this research adopts the analyst forecast dispersion (AFD) as the primary proxy of information ambiguity. AFD is computed as the standard deviation in analyst EPS forecasts for the next quarter. This proxy, which is composed only with judgments of financial analysts, should provide a better idea of the firm’s information risk, from the point of view of institutional participants in the CDS market.

Detailed descriptions of our methodology and data are provided in Section 2. Section 3 presents empirical results, and Section 4 concludes the paper.

2. Data and Methodology

Our sample consists of daily corporate CDS spreads (five-year contracts) in the U.S. between January 1, 2004 and December 31, 2010. More than 400 corporate CDS series covering the entire period are extracted from Thomson DataStream. Stock return series are extracted from CRSP, firm-specific characteristics are obtained from Compustat, and analyst reports and forecasts are obtained from I/B/E/S. We collect all corporate downgrade announcements during the sample period, omitting cases that overlap with other downgrades within a 5-day window to avoid contamination. We are left with 56 downgrade events. When studying the effect of a given downgrade event, we exclude firms that also have rating
changes within one month. This criterion leaves an average of 200 non-event firms for each downgrade event.

Following Norden and Weber (2004) and Jorion and Zhang (2007; 2009), this paper quantifies reactions in the CDS spreads of non-event firms with the abnormal CDS spread change (ASC) defined as follows.

\[
ASC_{ij} = (CDS_{i,t} - CDS_{i,t-1}) - (Index_{r,t} - Index_{r,t-1}),
\]

where \(CDS_{i,t}\) is the CDS spread for firm \(i\) on day \(t\), and \(Index_{r,t}\) is the CDS market index for rating class \(r\) on day \(t\). The CDS market index has two rating classes: high-grade (AAA–BBB-) and low-grade (BB+ or below). For each class, the index value is the moving average of all CDS spread series within the grade. Thus, the ASC shows the price change of a CDS in excess of general CDS market conditions. The cumulative abnormal CDS spread change (CASC) can then be obtained for a selected time interval \((t_1\) to \(t_n)\):

\[
CASC(t_1, t_n) = \sum_{t=t_1}^{t_n} ASC_{ij}.
\]

Hull et al. (2004) and Norden and Weber (2004) document significant change in a firm’s CDS spread prior to downgrade announcements of its own credit rating. This result suggests that CDS participants anticipate credit rating changes, which implies that credit contagion very likely occurs right before a downgrade is announced. Therefore, to investigate such anticipated effect, this paper represents the magnitude of credit contagion by calculating \(CASC\) for the time interval \([-5, -1]\). In the spirit of Jorion and Zhang (2009), we perform a
cross-sectional regression with $CASC$ as the dependent variable:

$$
CASC_i = \alpha_0 + \beta_1 \text{Leverage}_i + \beta_2 \text{Return}^{Market}_i + \beta_3 \text{Return}_i + \beta_4 \text{Size}_i + \beta_5 \text{BM}_i + \\
\beta_6 \text{Volatility}_i + \beta_7 \text{CORR}_i + \beta_8 \text{AC}_i + \beta_9 \text{AFD}_i + \beta_{10} \text{SpecGrade}_i + \\
\beta_{11} \text{Momentum}^{6M}_i + \beta_{12} \text{Winner}_i + \epsilon_i. \tag{3}
$$

Here, $\text{Leverage}$ is the average leverage ratio over the previous four quarters, $\text{Return}^{Market}$ is the return of the CRSP value-weighted index of $[-5, -1]$, $\text{Return}$ is the firm stock return of $[-5, -1]$, $\text{Size}$ is the median firm size in natural log over the previous four quarters, $\text{BM}$ is the median book-to-market ratio over the previous four quarters, $\text{Volatility}$ is the 30-day historical volatility, $\text{CORR}$ is the correlation of stock returns between the event firm and non-event firm over the last 250 trading days, and $\text{AC}$ is the number of analyst coverage during the month of the event. The $\text{AFD}$ is the analyst forecast dispersion measured by the standard deviation of analyst EPS forecast that refer to the next quarter, at the month of event day. $\text{SpecGrade}$ is a dummy variable equal to one if the firm’s rating is BB+ or below, and zero otherwise. Two momentum control variables are also included: $\text{Momentum}^{6M}$ is the stock return over the last 125 trading days, and $\text{Winner}$ is a dummy equal to one if the firm’s past 125-day stock return is positive and zero otherwise.\(^3\)

\(^3\) Year and industry dummies are also included in the regressions to control for time and industry fixed effects. Industry dummies are assigned based on the one-digit SIC code.
3. **Empirical Outcomes**

Table 1 presents the regression outcomes. Model 1 includes conventional explanatory variables from the literature, and we find that all estimated coefficients are statistically significant at the 10% level or better. All the coefficient signs are consistent with intuitions and finding of existing research. For example, the coefficient of *Leverage* is positive, implying that firms with a higher ratio of leverage suffer greater credit contagion. The coefficient of *AC* is also positive, showing that firms with more analyst coverage experience a greater cumulative abnormal spread increase in their CDSs when downgrades of their peers will be announced in the next 1 to 5 days. This finding supports the scenario where informed participants in the CDS market are able to anticipate near-future downgrades.

Model 2 replaces the key variable *AC* with the forecast dispersion *AFD*, and uses the same control variables as Model 1. The coefficient of *AFD* is positive and significant. This outcome shows that non-event firms with a higher dispersion in analyst forecasts experience greater CDS jumps when downgrade events of their peers are about to be announced. That is, when the information regarding a firm is more ambiguous, the credit contagion effect (based on the flow of information not yet available to public) is stronger. This positive relationship between information risk and credit contagion is direct evidence supporting our research hypothesis, and represents a new finding in the finance literature.

<Insert Table 1 about here>
Model 3 includes both AC and AFD, and the estimates of both coefficients remain positive and statistically significant. The result suggests that the number of analysts covering a firm and information ambiguity are independent factors that both contribute to the contagion effect. Model 4 adds the dummy SpecGrade to Model 3, and its coefficient is highly significant. The coefficient of AFD, on the other hand, becomes insignificant, showing that the impact of AFD on the CASC might be partially driven by the firm rating class. This result implies that information risk leads to greater contagion only for firms with worse credit ratings.

To further evaluate the interaction between AFD and SpecGrade, we add control variables of momentum (Momentum$^{6M}$ or Winner) to Models 5 to 6. This modification is justified by recent results from the literature: Avramov et al. (2007) document a quadratic relationship between momentum effects and credit condition, and Huang (2012) demonstrates a significant link between information ambiguity, credit condition, and momentum effect. The outcomes of models 5 and 6 confirm that momentum also plays a role in credit contagion. When either Momentum$^{6M}$ or Winner is included as a control, the coefficients of AFD and SpecGrade are both significantly estimated. In Model 5 for example, the estimates of AFD, SpecGrade, and Momentum$^{6M}$ are all significant, and the coefficient of AFD is positive. This outcome suggests that when past return patterns are taken into consideration, firms with higher analyst forecast dispersion experienced an increase in their abnormal CDS changes.
within the 5 days before a downgrade is announced for one of their peers. This conditional positive relation between information ambiguity and credit contagion is observed with SpecGrade being controlled in the regression.

<Insert Figure 1 about here>

To illustrate the key finding of this paper, Figure 1 plots the average CASC of all firms in our sample around the Lehman Brothers’ bankruptcy (day 0 of the series), which is probably the most unforgettable event of the 2008-2009 financial crisis. Figure 1 also plots the average CASCs for two separate groups: firms whose monthly analyst forecast dispersions are higher than the average (high AFD firms) and those with AFDs lower than the average (low AFD firms). We see that the CASC trend for all firms dropped below zero just before event day, due to some positive news such as the rescue action of Fannie Mae and Freddie Mac by the U.S. government on September 6, 2008 (9 days before the event day). After the bankruptcy, the average CASC of all firms declined and stayed below zero. On the same day, investors received some positive news: it was announced that Merrill Lynch would be bought out by Bank of America and that the U.S. government would establish a secured credit facility of $85 billion to bailout AIG, who was suffering a serious liquidity crisis at the time. By looking at the CASC trend of all firms, it appears that the positive and negative shocks of the event day offset each other, and there is no apparent evidence of credit contagion.

\[\text{Figure 1 about here}\]

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4 Lehman Brothers filed chapter 11 bankruptcy at 1:45AM, September 15, 2008. It was the largest bankruptcy in U.S. history at the time.
Now we focus on the CASC trend of high AFD firms. From day –20 to –9, the CASC increased and stayed above zero. From day –9 to –5, CASC dropped below zero, presumably due to the rescue plan of Fannie Mae and Freddie Mac, and from day –9 to –1, the trend mildly increased; showing anticipated reaction to the default event. From day –1 to day 4, a sharp jump was observed followed by a quick drop back to near zero. From day 5 to 10, CASC trended up by 30 basis points. These movements clearly demonstrate the contagion effect, in that the Lehman Brothers bankruptcy triggered a large jump in CDS spreads, which was then temporarily eased by the Merrill Lynch buyout and AIG’s rescue action. As the general condition of the credit market continued to deteriorate, the contagion effect led to a significant, sustained increase in the CASC of high AFD firms.  

The CASC trend of low AFD firms follows a completely opposite pattern and demonstrates a reverse contagion effect. When a major default event occurs, the abnormal CDS spreads for firms with low information ambiguity should drop. When market participants have a clear understanding of the firms’ operations and credit conditions (that is, the firms have low information risk), defaults of their peers would not cause unnecessary panic. Consequently, the default enhances informed participants’ faith in the competing firms’ strength and leads to a lower evaluation of the relative credit risk.

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5 Note that CASC represents the movement in CDS spreads over and above movement of a related CDS index.
4. Concluding Remarks

This paper documents positive correlation between anticipated credit contagion effect and the firms’ information risk. We find that firms with higher information ambiguity suffer from a greater contagion effect, where the magnitude of the anticipated effect is measured as an abnormal jump in CDS spreads prior to downgrades of peers’ credit ratings. This exercise shows that the CDS participants make different adjustments to the credit risk evaluation for firms, depending on their levels of information risk before credit default events. This paper contributes to the literature by demonstrating an information channel contagion effect, and therefore improves our understanding of credit risk evaluation. The new finding is also a valuable reference in credit modeling and financial risk management.
References


Table 1
Determinants of Credit Contagion

This table presents regression outcome with $C^{ASC}$ of non-event firms in interval of [-5, -1] as dependent variable. $t$ statistics are reported in paranetheses. *, **, and *** show statistical significance at 10, 5, and 1 percents, respectively.

<table>
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<tr>
<th>Explanatory Variables</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>20.42 ***</td>
<td>22.24 ***</td>
<td>15.16 ***</td>
<td>18.99 ***</td>
<td>14.85 ***</td>
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<td></td>
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<td>(3.79)</td>
<td>(4.11)</td>
<td>(2.78)</td>
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<td>(2.73)</td>
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<td>4.61 **</td>
<td>4.76 ***</td>
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<td>(4.61)</td>
<td>(4.11)</td>
<td>(4.64)</td>
<td>(2.35)</td>
<td>(2.38)</td>
<td>(2.62)</td>
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<td>Return$_{Market}$</td>
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<td>156.62 ***</td>
<td>156.32 ***</td>
<td>156.00 ***</td>
<td>155.58 ***</td>
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<tr>
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<td>(8.53)</td>
<td>(8.52)</td>
<td>(8.50)</td>
<td>(8.50)</td>
<td>(8.18)</td>
<td>(8.33)</td>
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<td>(-7.86)</td>
<td>(-7.89)</td>
<td>(-9.18)</td>
<td>(-8.22)</td>
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<td>Size</td>
<td>-1.42 ***</td>
<td>-0.97 ***</td>
<td>-1.38 ***</td>
<td>-0.65 **</td>
<td>-0.94 ***</td>
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<td>(-12.38)</td>
<td>(-13.07)</td>
<td>(-12.69)</td>
<td>(-13.28)</td>
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<td>(-13.21)</td>
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<td>Volatility</td>
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<td>1.55 ***</td>
<td>1.51 ***</td>
<td>1.47 ***</td>
<td>1.87 ***</td>
<td>1.55 ***</td>
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<td>CORR</td>
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<td>-2.82 *</td>
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<td>-3.52 **</td>
<td>-2.63 *</td>
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<td>0.16 ***</td>
<td>0.11 **</td>
<td>0.12 ***</td>
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<td>(2.40)</td>
<td>(2.77)</td>
<td>(2.29)</td>
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<td>7.86 **</td>
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<td>5.66 *</td>
<td>5.66 *</td>
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<td>(2.28)</td>
<td>(1.74)</td>
<td>(1.74)</td>
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<tr>
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<td></td>
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<td>(10.79)</td>
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<tr>
<td>Winner</td>
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<td></td>
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<td></td>
<td></td>
<td>3.12 ***</td>
</tr>
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<td></td>
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<td>(6.59)</td>
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<tr>
<td>Adjusted $R^2$ (%)</td>
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<td>1.94</td>
<td>1.97</td>
<td>2.28</td>
<td>2.65</td>
<td>2.42</td>
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Figure 1
Trends of Cumulative Abnormal CDS Spread Changes

This figure presents the CASC trends of time interval [-20,10] for all firms, low AFD firms, and high AFD firms using Lehman Brothers’ bankruptcy (September 15, 2008) as event day.