Accounting Information Releases and CDS Spreads*

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Abstract

We show that accounting information releases generate large and immediate price impacts, i.e. jumps, in credit default swap (CDS) spreads. Our approach is multivariate, which allows for identification of information events under the presence of confounding news, such as credit events and other simultaneous news arrivals. The economic impact of accounting news releases is twice as large as the impact of credit-related news. Good and bad news impact jumps in CDS spreads asymmetrically, and unscheduled announcements are more likely to cause jumps than scheduled ones. The arrival of accounting information is quickly absorbed in CDS spreads, suggesting efficient price discovery in the CDS market.

JEL Classification:

Keywords: Earnings announcements; management guidance; analyst recommendations; credit watch; jumps; CDS.

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1 Introduction

A growing literature investigates the determinants of the yields of credit-risky securities, and part of this literature focuses on the importance of events. However, most studies focus on credit events rather than accounting information events.[1] While the relationship between credit events and credit risky securities is of obvious interest, the study of accounting information events offers unique perspectives for learning about credit risk. Following the intuition in Merton (1974), accounting information events that affect stock prices will affect the pricing of credit risky securities, through their impact on firm leverage and volatility. Importantly, these accounting information events occur much more frequently than credit events, which makes them more important from an economic perspective, and also facilitates identification.

In this study, we investigate the impact of equity accounting information on firm credit risk using Credit Default Swaps (CDS). While the overwhelming majority of existing studies on the cost of debt rely on corporate bond data, CDS contracts may provide a better testing ground for several reasons. First, CDS contract are a cleaner measure of credit risk of the underlying entity. Elton, Gruber, Agrawal and Mann (2001) demonstrate that on average only 25% of corporate bond yield spreads represent compensation for default risk. Second, unlike bond spreads, CDS spreads are not affected by differences in contractual arrangements, such as convertibility, embedded option features, and covenants. Third, the CDS market is relatively more liquid than the corporate bond market, which results in fewer problems with stale data. Fourth, Blanco, Brennan and Marsh (2005) show that in the short run, CDS spreads tend to respond more quickly to changes in credit conditions.

Much of the literature on the determinants of CDS spreads focuses on variables such as interest rates, volatility, and leverage, which are suggested by theory, as well as stock returns and other firm-specific and macro-economic information.[2] A typical approach is to regress CDS spreads or CDS spread changes on these determinants. We use a different approach and investigate the relationship between releases of accounting information and jumps in CDS spreads, rather than the spread levels or the spread changes. Jumps often result from a resolution of uncertainty about a firm's credit risk, and the time series of CDS spread changes

[1] Hull, Predescu and White (2004) document how different types of ratings announcements affect CDS spreads. Hite and Warga (1997) and Dynkin, Hyman, and Konstantinovsky (2002), study the relationship between rating changes and corporate bond yields. See also Katz (1974), Grier and Katz (1976) , and Wansley, Glascock and Clauretie (1992). A related literature studies the relation between ratings changes and stock prices. See for instance Hand, Holthausen and Leftwich (1992), Goh and Ederington (1993), Pinches and Singleton (1978), and Holthausen and Leftwich (1986).

[2] See for instance Blanco, Brennan and Marsh (2005), Ericsson, Jacobs and Oviedo (2009), and Zhang, Zhou and Zhu (2009).

in Figure 1 indicate that much of the variation in CDS spreads is due to large movements that are readily interpretable as jumps. We use a nonparametric jump detection method of Lee and Mykland (2008), which does not require an assumption on the dynamics of CDS spreads. We also confirm the robustness of our results using two parametric specifications.

After identifying jumps in CDS spreads using nonparametric techniques, we examine the impact of equity accounting information releases using logistic regressions. We focus on earnings announcements, analyst recommendation changes, and management guidance, because they are the most studied types of equity accounting information. Existing studies show that these three equity accounting information releases significantly impact equity returns, and they occur more frequently than other types of corporate events. We control for credit-specific news that is known to explain variation in CDS spreads, including credit-rating upgrades and downgrades, firms being put on positive and negative watch, and bond issuance. We also account for Federal Open Market Committee (FOMC) announcements, which explain jumps in the Treasury market (Jiang, Lo and Verdelhan (2010)). Finally, we further attempt to avoid biases by including proxies for other macroeconomic news and jumps in firm-specific credit and equity determinants as explanatory variables.

Existing studies on the association between accounting information events and credit risk rely on an event study methodology, which has two important consequences. First, they exclusively use data around the particular event, whereas we use the entire sample. Second, by focusing on one type of event, it is difficult to separate out the impact of other events that may have occurred at approximately the same time. This is critical in the case of accounting information releases, which tend to be heavily clustered in time, particularly in the case of bad news. Our estimation approach is genuinely multivariate: it analyzes the impact of several different types of news releases simultaneously, and therefore avoids biases due to an omitted variables argument, which may result in wrongly attributing movements in spreads to the one type of event under investigation. It is clear that unbiased assessments of the relative importance of each information event are critically important for risk management purposes.

We find that earnings announcements, analyst upgrades and downgrades, and management guidance all explain jumps in CDS spreads. While an individual credit event, such as credit watch, affects the likelihood of jumps more than an accounting event, it occurs much less frequently. Once we take the frequency of each event into account, we find that the economic impact of the accounting-related news is approximately twice as large as the impact of credit-related news. Moreover, the magnitude of the impact of the accounting releases does not change much after controlling for the credit and macroeconomic events. Unscheduled news releases have a larger impact than scheduled news releases. Management guidance is an unscheduled event by nature and does not happen frequently, but it has a substantial impact on a firm's creditworthiness.

Bad news has a larger impact on return volatility than good news, and prior event studies have identified asymmetric responses to adverse accounting information in equity and bond markets. Using our multivariate approach, we confirm that negative accounting releases, scheduled as well as unscheduled ones, have more impact than positive accounting releases. These results are robust to the inclusion of good and bad news that is not accounting-related. Consistent with existing results, we find that credit upgrades do not have a statistically significant impact on jumps in CDS spreads.[3]

The relatively high liquidity of the CDS market provides an opportunity to investigate how quickly accounting information releases get absorbed in this market. This is harder to ascertain using corporate bond data, due to the relative paucity of data and the presence of stale prices. We regress CDS jumps on the accounting information releases as well as their lagged values. We find very strong evidence that lagged information is much less important than contemporaneous events, although some unscheduled information releases seem to have a longer-lasting impact on CDS premia. Some bad news, notably negative management guidance surprises, credit downgrades and negative watch, impacts the firm's default risk in a more long-lasting way. We conclude that the market for credit risk is informationally efficient.

The paper proceeds as follows. Section 2 outlines the hypotheses under investigation in the empirical work and provides a more detailed discussion of the related literature. Section 3 discusses our empirical methodology, and Section 4 presents the data. Section 5 contains the empirical results, Section 6 presents additional robustness checks, and Section 7 concludes.

2 Background and Hypothesis Development

We analyze three types of accounting information releases: earnings announcements, management guidance, and analyst recommendation changes. The literature on the effects of earnings announcements on equity returns is vast, and largely supports the finding that earnings announcements impact returns.[4] As management guidance is a more recent phenomenon, the available literature on this type of event is much smaller. Anilowski, Feng and Skinner (2007) find that stock returns react to guidance towards the end of the quar-

[3] Holthausen and Leftwich (1986) and Hull, Predescu and White (2004) find that credit watches are more informative than downgrades themselves and that upgrades often provide no additional information to the ones already contained in the credit watch.

[4] See for instance Jennings and Starks (1985), Jennnings and Starks (1986), Patell and Wolfson (1984), and Landsman and Maydew (2002).

ter. Rogers, Skinner and VanBuskirk (2009) find that issuing guidance increases short-term uncertainty. Houston, Lev and Tucker (2010) find that firms that stopped providing guidance experience a decrease in analyst coverage and that the analyst forecast dispersion on these firms increases significantly. Milian (2010) finds that guidance is more informative than earnings. In summary, there is substantial evidence that guidance affects the firm, even though direct evidence on stock returns is relatively limited.

The literature on analyst recommendations is also extensive, but subject to some debate. Most studies confirm the findings of Womack (1996), who documents that, on average, recommendation changes generate a large and statistically significant announcement return.[5] For an alternative view, see Altinkilic and Hansen (2009), Altinkilic, Balashov and Hansen (2010).

In summary, there is substantial evidence that these three types of accounting information releases affect stock returns. It is therefore likely that they will also impact on the firm's credit risk, because state-of-the art credit risk models, following the logic in Merton (1974), predict that the resulting changes in stock prices will affect the pricing of credit risky securities, through their impact on firm leverage and volatility. But the existing literature on accounting information and credit spreads however is rather sparse. Manxi, Maxwell and Miller (2009) investigate the relationship between analyst forecasts and bond prices. Callen, Livnat and Segal (2010) study the relationship between earnings and CDS spreads.

When analyzing the impact of accounting information releases on credit spreads, it is important to control for other credit related events, that have been shown to affect bond spreads. We therefore include credit upgrades and downgrades in the regression.[6] Moreover, Holthausen and Leftwich (1986), Hull, Predescu and White (2004), and Boot, Milbourn and Schmeits (2006) emphasize the importance of considering the process that leads to ratings changes, and especially the importance of the credit watch procedure. We therefore also include indicator variables for positive and negative credit watch in the regression. We also include an indicator variable for bond issuance. Finally, we include jumps in firm-implied volatility as a control variable in the regression, to capture other firm-specific credit events that may not have been captured by the other control variables.

Besides credit-specific events, it is also possible that macroeconomic events affect credit spreads, and it is important to control for this to isolate the effect of accounting information releases. We therefore include an indicator variable for FOMC meeting announcements. To capture omitted macroeconomic effects, we also include an indicator variable for jumps in

[5] See for instance Barber, Lehavy, McNicols and Trueman (2001), and Jegadeesh, Kim, Krische and Lee (2004).

[6] For evidence on the importance of credit upgrades and downgrades for credit spreads, see for instance Hite and Warga (1997), and Dynkin, Hyman and Konstantinovsky (2002)..

the S&P500 return.

This brings us to our first hypothesis of interest. We investigate if jumps in CDS spreads are associated with releases of equity accounting information on the underlying security, and whether results are robust after controlling for releases of credit-risk-related information as well as macroeconomic news.

Our second hypothesis concerns the relative importance of anticipated (i.e. scheduled) or unanticipated (i.e. unscheduled) information events. Ball and Shivakumar (2008), Beyer, Cohen, Lys and Walther (2010), and Milian (2010) document that unscheduled information releases such as management guidance are more likely to affect stock prices compared to regularly scheduled earnings announcements. Although some companies have started providing guidance regularly, usually on the same day as earnings announcements, most guidance is still released irregularly. Furthermore, managers can cease issuing guidance without warning.

There are at least two reasons why unscheduled events are more likely to be associated with jumps. First, from the firm's perspective, managers that choose to issue guidance can time their releases when they perceive the information to be most informative and valuable. Second, it is difficult for informed traders to trade prior to unscheduled announcements; they can therefore only react to the content of the unscheduled announcements once the information is released. This stands in sharp contrast to prescheduled events, such as earnings announcements and bond issuance, where informed traders can trade prior to the news releases. Consequently, price adjustments to these prescheduled events are likely to start prior to the event date and are not necessarily large after the news is released. Our second hypothesis is therefore that unanticipated news releases are more likely to cause jumps in CDS spreads than anticipated news releases.

Prior event studies studying stock markets or corporate bonds have identified asymmetric responses to certain adverse accounting information. Hand, Holthausen and Leftwich (1992) show that credit rating downgrades influence the firm's equity much more than upgrades. Hite and Warga (1997), and Dynkin, Hyman and Konstantinovsky (2002) reach similar conclusions for corporate bonds. It is also well-known that bad news has a larger impact on return volatility than good news. This is sometimes referred to as the leverage effect, after Black (1976). See for instance Engle and Ng (1993), Hentschel (1995), and Glosten, Jagannathan and Runkle (1993) for detailed discussions. We therefore test the third hypothesis that the arrival of unfavorable news is more likely to cause a positive jump in CDS spreads than the arrival of favorable news is to cause a negative jump in CDS spreads.

Our fourth hypothesis concerns the informational efficiency of the CDS market. It has been documented that CDS spreads contain an important liquidity component.[7] However,

[7] See for instance Tang and Yan (2007), and Bongaerts, De Jongs and Driessen (2009).

the CDS market has rapidly grown in size, and it seems to be the foremost channel for incorporating credit risk related information into market prices. Moreover, it has been shown that CDS markets lead bond and equity markets, see for instance Longstaff, Mithal and Neis (2005), and Blanco, Brennan and Marsh (2005). It is therefore worthwhile to investigate how quickly the accounting information regarding the underlying equity gets reflected in CDS spreads. We implement this test by investigating the statistical significance of lagged indicator variables together with the contemporaneous indicator variables.

3 Methodology

We use a two-step procedure.[8] The first step involves detecting jumps in CDS spreads. The second step regresses the time series of jumps on event indicators.

3.1 Detecting Jumps in CDS Spreads

To detect the presence of a jump on a given day, we use a nonparametric test statistic introduced in Lee and Mykland (2008). Daily CDS spread changes are characterized by many outliers, hence it is unrealistic to rely on the standard normality assumption. The nonparametric method does not require an assumption on the distribution of CDS spread changes, and is therefore well suited for this purpose.

The underlying logic of the test is simple: it compares the logarithmic change in CDS spreads to an adequately estimated measure of instantaneous volatility. Sufficiently large observations standardized in this way are deemed to be jumps.

We follow Barndoff-Nielsen and Shephard (2004) and Aït-Sahalia (2004) by measuring instantaneous variance with the realized bipower variation, defined as the sum of the product of consecutive absolute returns

$$\hat{\sigma}_t^2 = \frac{1}{K-1} \sum_{i=t-K+1}^{t-1} |r_i||r_{i-1}| \tag{1}$$

where $r_t = \ln(Spread_t) - \ln(Spread_{t-1})$, and $Spread_t$ is the quoted CDS spread on day t. This estimate is consistent in the presence of jumps. Our test statistic for the presence of a jump on day t is the ratio $L(t) = r_t/\hat{\sigma}_t$.

The window size K affects the test statistic. A longer window attenuates the effect of jumps on the estimation of instantaneous volatility; however an excessively long window makes it difficult to estimate instantaneous volatility dynamics. We use the results in Lee

[8] See Lee (2011) for asymptoptic properties and detailed discussions of the two-stage estimation technique.

and Mykland (2008), who provide comprehensive Monte Carlo simulation tests to show that the optimal window size is $\Delta t^{-1/2}$, where Δt is the size of the detection interval. These results apply to intra-daily returns as well as to returns sampled at a lower frequency. We use daily data of CDS spread changes. Assuming 252 trading days per year, this implies that $\Delta t = \frac{1}{252}$ in annualized terms. We therefore use a rolling window of $K = \left(\frac{1}{252}\right)^{-\frac{1}{2}}$ days, which is about sixteen days.

Lee and Mykland (2008) derive the following criterion for rejecting the null hypothesis that there is no jump over the interval $t-1$ to t

$$\frac{|L(t)| - C_n}{S_n} > 4.6001$$

where

$$\begin{aligned} C_n &= \frac{(2ln(n))^{1/2}}{c} - \frac{ln(\pi) + ln(ln(n))}{2c\,(2ln(n))^{1/2}}, \\ S_n &= \left(c\sqrt{2ln(n)}\right)^{-1}, \quad c = \sqrt{\frac{2}{\pi}}, \end{aligned}$$

and n is the number of observations. This rejection region is based on a 1% significance level. We now discuss the econometric method used for regressing jumps on event indicators.

3.2 Regression Analysis

We want to determine which events affect the probability of a jump in CDS spreads. Logistic regressions are well suited for this type of investigations with a binary dependent variable. We estimate the following panel regression using firms $i = 1, ..., N$:

$$\Pr(J_{i,t} = 1) = (1 + \exp(-(\alpha_i + X_{i,t}\beta)))^{-1}, \tag{2}$$

where $J_{i,t}$ is a jump indicator variable for firm i on day t which takes the value of one if jump is detected and zero otherwise. On the right hand side, $X_{i,t}$ is a $1 \times M$ vector of event indicator variables for firm i on day t, with M being the number of event variables in our study. We estimate the $M \times 1$ parameter vector $\beta = [\beta_1, \beta_2, \cdots, \beta_M]'$ where each element β_j in β determines the likelihood that the event j is associated with a jump in CDS spreads. The parameter α_i is a scalar that is different for each firm and controls for the firm fixed effect; it determines the likelihood of a jump in CDS spread given that none of the events occur, i.e. in case all the indicator variables in $X_{i,t}$ are equal to zero.

Our methodological approach differs from the existing literature on the determinants of

CDS spreads, which uses OLS-type regressions of credit spread levels or differences on a large variety of explanatory variables. Our approach is different because of our focus on information events, which are more likely to be associated with infrequent large movements in CDS spreads. In contrast, other variables analyzed in the literature such as stock returns, interest rates, and volatility, are more likely to be associated with day-to-day and relatively smaller movements in spreads. Another reason for focusing on jumps is that it may be advantageous from an econometric perspective. CDS spreads and credit spreads more in general are nearly integrated, and there is some discussion in the literature about the best way to proceed from an econometric perspective. For instance, Collin-Dufresne, Goldstein and Martin (2001), using bond yields, rightly argue that using differenced data is to be preferred from an econometric perspective. However, Cremers, Driessen, Maenhout and Weinbaum (2008), Doshi, Jacobs and Turnbull (2010), and Jaskowski (2010) argue that in the case of the daily frequency typically used for CDS spreads, differencing may be problematic, essentially because the resulting signal to noise ratio in the data is too low.

Finally, our approach is genuinely multivariate and therefore allows us to contemporaneously investigate the impact of different types of information events. Other studies use an event-type methodology, which may confound the effects of different types of events. Figure 2 explains why this is so important. It depicts events occurring on the release date of three different types of accounting news events: earnings announcements, management guidance, and analyst recommendations. For all three types of events, important other information is typically released on the same day. For instance, approximately 40 percent of earnings announcements are accompanied by management guidance releases on the same day. Moreover, Figure 2 indicates that other events are sometimes released one day later or earlier. Figure 3 depicts the distribution of various information releases around credit events, and it is evident that credit-related news is also characterized by confounding information arrivals. Overall, Figure 2 and 3 confirm that it is necessary to use a multivariate approach to avoid confounding these different effects. Bradley, Clarke, Lee and Ornthanalai (2011) provide a simulation study of the finite-sample performance of multivariate logistic regressions similar to the ones used in this paper. They find that multivariate logistic regression can be used to infer the relative importance of different events in the presence of confounding effects.

4 Data

This section describes our data sources. We first discuss the CDS data. We then describe the databases used to generate the various event indicators.

4.1 Credit Default Swap Spreads

A CDS is a derivative contract that transfers the default risk of an underlying reference entity from one investor to another. The protection seller assumes the default risk of the underlying entity by committing to compensate the protection buyer for the loss suffered in case of a default of the entity. In return, the protection buyer pays a quarterly premium.

While the overwhelming majority of existing studies on the cost of debt rely on corporate bond data, CDS contracts may provide a better testing ground for several reasons. First, a CDS contract provides a cleaner measure of credit risk. Elton, Gruber, Agrawal and Mann (2001) demonstrate that on average only 25% of corporate bond yield spreads represent compensation for default risk. The remaining 75% is due to other systematic risks, such as interest rate risk, taxes, and the default event itself (Driessen (2005)), liquidity risk (Longstaff, Mithal and Neis (2005)), and other priced risk factors specific to the bond market (Berndt, Lookman and Obreja (2006)). Several studies attempt to separate out the interest rate risk from bond yields, but this necessitates an assumption regarding the risk free rate. Different assumptions on the risk free rate can yield different qualitative and quantitative conclusions regarding credit risk (Feldhutter and Lando (2006)). In contrast, no assumption on the riskless rate is required to infer default risk from CDS premia.

Second, the CDS market is more liquid than the corporate bond market, which results in fewer problems with stale data. Furthermore, the higher liquidity makes it easier to investigate how quickly the accounting releases get absorbed in credit markets. Third, unlike corporate bond yields, CDS premia are not distorted by embedded option features such as call options, convertibility, and covenants. For instance, two-thirds of corporate bonds are callable, and it is necessary to correct for this in order to draw conclusions about credit risk and default. Fourth, Blanco, Brennan and Marsh (2005) show that while CDS and bond spread changes are highly correlated in the long run, in the short run CDS spreads tend to respond more quickly to changes in credit conditions. This suggests that the CDS market is more responsive to news arrivals than the bond market, and therefore more suitable for testing how accounting information gets incorporated in credit markets.

We obtain daily 5-year CDS quotes from Markit, a comprehensive data source that assembles a network of industry-leading partners who contribute information across several thousand credits on a daily basis. Based on the contributed quotes, Markit creates the daily composite quote for each CDS contract.

Our sample period is from January 29^{th}, 2002 to March 7^{th}, 2008. We exclusively retain firms that were part of the CDX index at some point during this period, which ensures relatively high liquidity for the contracts in our sample. We only retain contracts written on senior unsecured debt of US firms, and eliminate the subordinated class of contracts because of illiquidity concerns. We focus on CDS contracts with modified restructuring (MR) clauses, as this is the most commonly traded contract type in the US market. Moreover, we only retain prices that were composed using at least three contributors. Finally, we only retain firms for which data are available to construct all event indicators. That is, data must be available for equity price (CRSP), equity accounting information (I/B/E/S and First Call), bond issuance (SDC), credit re-rating (Moody's), and option implied volatilities (Bloomberg). We discuss the data on event indicators in more detail below. The final sample comprises of 87 firms for a total of 132,559 observations. Table 1 lists the firms in the sample, and provides descriptive statistics.

We report firms' credit ratings at the beginning of the sample. At the outset, the sample contains 33 firms with an A rating, 7 firms with an Aa rating, 2 firms with a Ba rating, and 42 firms with a Baa rating. There is only one Ca-rated firm at the beginning of the sample, but changes in creditworthiness during the sample period result in a substantial number of non-investment grade ratings at the end of the sample.

Table 1 indicates substantial cross-sectional differences in the distribution of CDS spreads. For example, the mean and volatility for the CDS spread for WalMart are equal to 16.75 and 7.72 basis points respectively, while for Delphi Corp., the mean and volatility are equal to 664.19 and 1,135.20 basis points respectively. The sample contains firms across a wide variety of industries.

Table 1 also reports the number of jumps detected for each firm. Panel A of Table 2 reports jump statistics aggregated over all firms. On average, there are approximately 47 jumps per firm over the sample period, and we observe 4,132 jumps in the entire sample. Positive jumps, which signal a large increase in the default probability, occur slightly more often than negative jumps, with 26 positive jumps on average versus 22 negative jumps. As a percentage of the total number of days in the sample, we observe jumps on 3.12% of the days, which is approximately 7 jumps per year. This probability can be thought of as the unconditional or long-run jump probability and represents the chance of observing a jump in the daily CDS spread, regardless of the occurrence of news releases. Panel A of Table 2 shows that the unconditional probability of observing a positive jump is 1.68%, while it is 1.44% for a negative jump.

[Table 1 & 2 about here]

4.2 Temporary and Permanent Movements in CDS Spreads

The jumps we detect and investigate in our empirical work are not simply temporary movements in CDS spreads, but instead represent a resolution of uncertainty. Panel B of Table 2 presents the cumulative CDS return around positive and negative jumps. On average, for positive jumps, the CDS level increases the two days before the jump, as well as the two days after the jump. For negative jumps, the opposite conclusion obtains. In other words, jumps on average are not followed by other jumps or changes in the opposite direction, and are therefore not temporary in nature. It could be argued that this finding is due to clustering of jumps. We demonstrate that this is not the case by repeating the analysis for isolated jumps. We define isolated jumps as those that are not preceded by another jump during the two previous days and are not followed by another jump during the two next days. The results are qualitatively similar.

4.3 Earnings Announcements, Management Guidance, and Analyst Recommendations

Information pertaining to management guidance is obtained from First Call, while analysts' recommendations and earnings announcements are collected from I/B/E/S. We create daily indicator variables for each event. For instance, a value of one is assigned to the earnings indicator on the day that an earnings announcement is released, and zero is assigned on other days. Panel A of Table 3 presents the frequency of the events, averaged across firms, on an annualized basis. For instance, each firm experiences on average 3.46 days per year where at least one analyst issues an upgrade recommendation. Changes in analyst recommendations constitute the most frequent news event in our study. There are more than seven changes in analyst recommendations per year for a typical firm in our sample, and recommendations for upgrades and downgrades are, on average, equally likely.[9]

To examine the asymmetry between good and bad news, we further classify earnings announcements into positive and negative surprises. We follow the classification of earnings surprises in Dellavigna and Pollet (2009). First, we divide the difference between the announced earnings and the consensus analyst forecast by the share price five trading days before the announcement date. For each year, we then split these standardized earnings announcements into eleven bins: the first three bins are considered negative earnings surprises, and the last three are considered positive earnings surprises. Using this procedure, positive

[9]Firms issue earnings announcement on a quarterly basis, and hence we expect to find an average of four earnings announcement per firm-year. However, because the time series of CDS data are incomplete for some firms, the number of earnings announcements per firm per year is 3.73 in our sample.

earnings surprises are more frequent: they happen on average 1.24 times a year, compared to 0.30 times for negative surprises.

First Call provides a classification for management guidance forecasts into positive and negative surprises by comparing it to current market expectations. We create dummy variables for management guidance that are qualified as positive and negative surprises. From Table 2, notice that while management guidance forecasts are released on average 3.66 times per year, actual surprises happen in less than half of these cases. Furthermore, different from the case of earnings announcement surprises, positive and negative management guidance surprises are almost equally likely, happening on average 0.72 and 0.68 times per year.

[Table 3 about here]

4.4 Bond Issuance, Credit Ratings, and Credit Watch

Bond issuance information is collected from the Security Database Corporation (henceforth, SDC). SDC collects information from different sources, including regulatory filings, news sources, company releases and prospectuses. Its report contains specific information on all bonds issued by a company, including the issue date, yield-to-maturity (YTM), maturity, proceeds, and ratings. Two firms in our sample issue more than one bond at the same time. We construct an indicator variable that is equal to one for days on which the firm issues any form of debt, and zero otherwise. Alternatively, the firms' filing dates could be used as the debt issuance indicator. However, such information is often not available, and restricting ourselves to firms for which we have this information would greatly reduce our sample size. Therefore, we only investigate the impact of bond issuance on jumps in CDS spreads, and not the impact of firms' filing for a debt issuance. Table 3 indicates that firms in our sample issued debt approximately once a year.

We obtain Moody's credit rating information on firms' senior unsecured debt from Bloomberg. We construct indicator variables for days on which there has been an upgrade or a downgrade in the firm's credit rating. Ratings are often put under review prior to a change, and this period is known as a credit watch. To address this question, we include indicator variables that take the value of one on the day that a credit watch is announced, and zero otherwise. Furthermore, credit watch announcements can be classified as positive and negative news. Positive and negative credit watch are defined by a firm being put on review prior to a credit upgrade and downgrade respectively.

Panel A of Table 3 shows that credit-related events occur much less frequently than equity accounting news releases. Negative credit news occurs more frequently than positive credit news in our sample. Credit downgrades on average occur more than three times as often as a credit upgrade, and we observe a similar pattern for the credit watch variable. Firms in our sample are four times more likely to be put on negative credit watch than on positive credit watch.

Table 3 also presents the jump frequency and the average jump size conditional on a given event happening. Jump frequency conditional on the event is computed as the fraction of the event that is associated with jumps; it represents the univariate expected number of jumps conditional on the event. However, it must be noted that this measure does not take into account the impact of other events, such as confounding news releases. Consequently, we cannot rely on this simple univariate jump frequency to draw inference on the relative importance of each information event in causing jumps.

The average jump size conditional on the event is computed as the average arithmetic return on the CDS spread on event days when we observe a jump. Panel A of Table 3 shows that events signaling negative prospects for a firm, including negative earnings surprises, negative guidance surprises, and analyst and credit downgrades all produce a conditional mean jump size between 10% and 13%. The univariate probability of observing a jump in a firm's CDS for such events ranges from 6% to 14%. This is in sharp contrast with negative credit watch, for which this probability is 29% with an average jump of 27%. The probabilities and jump sizes are typically smaller for the positive indicators, with the exception of positive watch, which has a probability of 18% and an average jump size of -15%. Interestingly, positive watch is the only positive indicator associated with an significantly negative average jump size.

4.5 FOMC Meetings

In Panel B of Table 3, FOMC denotes an indicator variable for days on which the Federal Open Market Committee announces a decision. News released following FOMC meetings may impact the aggregate availability of credit to firms. For instance, if the Federal Reserve announces a low interest rate policy, investors may be encouraged to take on more risk by increasing their lending to individual firms. This in turn may improve liquidity for fixed-income securities and hence decrease individual firms' default probabilities. The FOMC dates are collected from the Federal Reserve website. There are fifty-four FOMC meetings during our sample period. For two-day meetings, we set the indicator variable equal to one only for the second day, when announcements are made.

4.6 Other Controls

The events in Table 3 do not represent an exhaustive list of potential determinants of jumps in CDS spreads. We focus on these events because they are the most studied public events in the finance and accounting literature. However, it is important to investigate if our main results are affected by the exclusion of other events that can cause big changes in CDS spreads. In order to test the robustness of our results, we control for missing macroeconomic and firm-specific events by including in the regression indicators for jumps in the S&P 500 index, as well as indicators for jumps in individual firms' option-implied volatilities. The inclusion of jumps in the S&P 500 index is based on the logic that any market-wide event that can cause a jump in the index should be an important macroeconomic determinant of jumps in the CDS market. We use jumps in option-implied volatility as a control for missing firm-specific news. Equity options are a natural candidate to capture such news; moreover equity options are exchange-traded and hence are not plagued by liquidity issues, and negative news on a firm is likely to surface in put option prices. We therefore expect both negative and positive news to be adequately reflected in option prices, and important public news releases should show up as jumps in the firm's option-implied volatility.

The daily time-series for the S&P 500 index as well as daily individual equity implied volatilities for the one-month maturity are obtained from Bloomberg. We identify jumps in S&P 500 returns and in individual firm's changes in option-implied volatility using the Lee and Mykland (2008) method, as discussed in Section 3.1. Panel B of Table 3 shows that while we detect only one jump in the daily S&P 500 return (-3.47% on February 27^{th}, 2007), we find on average 3.58 jumps per year in the daily changes of firm implied volatility.

5 Empirical Results

5.1 Determinants of Jumps in CDS Spreads

Table 4 reports our basic results, using three logistic regressions. We include firm fixed effects in all regressions. In the first specification, reported in the left-side column, we examine the likelihood that equity accounting news releases, namely earnings announcements, management guidance forecasts, and analyst recommendation changes, are associated with jumps in CDS spreads. We report the logit coefficients β from (2). Next to each estimate, we report the p-value that tests the null hypothesis that the estimate is not statistically significant from zero. The p-values are calculated based on the Wald test statistics, using the gradients of the likelihood at the optimal parameters. The p-values strongly suggest that equity accounting information releases are associated with jumps in CDS spreads. The left-side regressions in Table 4 indicate that among the three equity accounting news events, management guidance is the most likely event to cause a jump in CDS spreads, followed by analyst recommendations, and finally earnings announcements.

To help interpret the results, Table 4 also reports the approximated change in conditional jump probability that is implied by each logit coefficient β. In logistic regressions, the estimated coefficient β_j represents the change in the logarithm of the odds (or odds ratio) of observing a jump conditional on a unit change in the j^{th} element of the explanatory variable vector $X_{i,t}$. Because we exclusively use indicator variables as explanatory variables, β_j can be thought of as the change in the logarithm of the odds of observing a jump when event j happens, *ceteris paribus*. In other words, we can write β_j as

$$\beta_j = \log\left(Odds_j\right) - \log\left(Odds_{-j}\right) \tag{3}$$

where $Odds_j$ is the odds of observing a jump when event j occurs relative to the odds in the absence of the event, $Odds_{-j}$. By definition, the odds ratio of a jump is the ratio of the probability of observing a jump divided by the probability of not observing a jump. For instance, if p is the probability of observing a jump in absence of event j, then $Odds = p/\left(1-p\right)$. When event j occurs, the probability of observing a jump becomes $p + \Delta p_j$, where Δp_j is the change in jump probability when event j occurs. Consequently, the odds of observing a jump when event j occurs is

$$Odds_j = \frac{(p + \Delta p_j)}{(1 - p - \Delta p_j)}. \tag{4}$$

Substituting the above definitions for $Odds_j$ and $Odds_{-j}$ into (3), we can write Δp_j as

$$\Delta p_j = \frac{p \exp(\beta_j)}{1 - p + p\exp(\beta_j)} - p. \tag{5}$$

Equation (5) shows that Δp_j depends on the logit coefficient β_j as well as the probability of a jump in CDS spreads in absence of the event, p. In order to compare the results across different events, we approximate p using the unconditional probability of observing a jump in the overall sample. That is

$$p = Pr(J_t = 1 | X_{i,t}(j) = 0) \approx Pr(J_t = 1).$$

Panel A of Table 2 reports the unconditional jump probabilities. Out of the $132,559$ daily observations, we detect $4,132$ jumps (positive and negative) which translates into an unconditional jump probability of 3.12%.

In the second regression specification of Table 4 (middle columns) we report the likelihood that credit news events as well as FOMC meetings are associated with jumps in CDS spreads. We find that credit watch is the most important determinant of jumps, followed by changes in credit rating. The logit coefficients indicate that being put on credit watch has almost twice the impact of the subsequent rating change announcement. It increases the probability of observing a jump in CDS spreads by 23.02%, which is about three times the change in probability when the subsequent rating change is announced. Hull, Predescu and White (2004) find that being put on credit watch affects CDS spreads, while rating downgrades themselves do not. Our findings are largely consistent with theirs, although in our sample announcements of credit rating changes are also informative, albeit to a lesser degree.

We find that bond issuance is significantly associated with jumps in CDS spreads. This suggests that CDS spreads are affected by increases in firm leverage. The coefficient on FOMC is the smallest among all the news events, suggesting that FOMC meetings on average play a minor role in determining firms' default probabilities.

The third regression specification, in the right-side column, shows that equity accounting news events are associated with jumps in CDS spreads, even after controlling for credit news events as well as FOMC meetings. The coefficients on the indicator variables for earnings announcements, management guidance, and analyst recommendations are largely unaffected by the presence of the credit news events variables in the regression. The same holds for the coefficients on the credit watch and credit risk change indicators. We conclude that equity accounting news as well as credit-related news carry independent information that is relevant for CDS spreads. Credit events occur less frequently than accounting news events, but the conditional probability of a jump conditional on credit events is often much higher.

[Table 4 about here]

5.2 Unscheduled Versus Scheduled News Releases

Table 4 also provides some insight into the relative importance of scheduled and unscheduled news releases. The FOMC indicator has the smallest regression coefficient and hence conditional jump probability among all the event indicators. One reason for this may be that these meetings are regularly scheduled. Moreover, the topics discussed at FOMC meetings are closely watched by various analysts and the media, and hence are often well-anticipated by the market. Consequently, a substantial portion of CDS price reactions to FOMC meetings likely occur prior to the actual meeting date.[10]

The evidence from earnings announcements and management guidance further confirms that scheduled events are less likely to cause jumps in CDS spreads than unscheduled ones. These two types of events carry similar equity information, in that managers issue information regarding earnings per share. However, while earnings announcements are scheduled events, management guidance forecasts are issued at the discretion of the manager. The regression coefficients in Table 4 show that management guidance is much more likely to cause jumps than earnings announcements.

These findings are qualitatively consistent with the existing literature. Shivakumar, Urcan, Vasvari and Zhang (2010) study CDS spread changes over a five-day window around non-bundled earnings announcement and management guidance events. They find that the five-day CDS changes around management guidance forecasts are approximately thirty times larger than those around earnings announcements. Our estimates suggest a smaller difference, but the methodologies are very different, and as a result the estimates are difficult to compare. We use daily CDS spreads for the entire sample, while Shivakumar, Urcan, Vasvari and Zhang (2010) focus on changes over a five-day event window. Moreover, the problem of confounding information arrivals is quite severe in the case of equity accounting news. Figure 2 shows that approximately 45 percent of all earnings announcement are released on the same day as management guidance forecast, and approximately 10 percent of all earnings are released within a day before analysts issue their recommendation changes. Using five-day windows to measure the impact of equity accounting news may therefore bias inference regarding the relative importance of these news events, which we address using our multivariate approach.

5.3 The Economic Impact of the Jump Determinants

The results in Section 5.2 confirm that releases of equity accounting information are associated with jumps in CDS spreads. We further analyze the economic impact of different types of information events by computing how much they contribute to large movements in CDS spreads. The right-most column in Table 4 shows that the probability of observing a jump in CDS spreads increases on average by 2.93% on days when management guidance is released. While this change in jump probability is significant, it is of a smaller magnitude than the jump probabilities due to credit re-rating and credit watch news. However, the change in

[10] Another reason for this finding is that unlike a bond, a CDS is an unfunded security. Interest rates affect the discounting of both legs of the contract, and changes in interest rates typically have a minor impact on spreads. FOMC announcements, which primarily affect interest rates, are therefore not necessarily major determinants of jumps in CDS rates.

conditional jump probability does not take into account the frequency of each information event, and hence does not conclusively determine its economic impact. In order to quantify the economic impact of each type of information event on CDS spreads, we therefore report two additional measures: the expected number of jumps per firm-year due to each event type, and the expected jump size in CDS spreads that can be attributed to each event type. We explain these two measures in more detail below.

The first column of Table 5 reports the conditional jump probability. It is defined as $p_j = p + \Delta p_j$, where p is the unconditional jump probability (3.12%), and Δp_j is the change in jump probability conditional on event j. The value of Δp_j is computed using the right-most logistic regression in Table 4.

The conditional jump probability p_j represents the probability of observing a jump when event j happens. Consequently, we can compute the expected number of jumps per firm-year by multiplying p_j with the average number of observations of event-type j per firm-year. The second column of Table 5 reports the expected number of jumps per firm-year due to each event-type. For instance, Table 3 shows that there are on average 7.04 analyst recommendations per firm-year. The expected number of jumps associated with analyst recommendations is therefore $7.04 \times 5.19\% = 0.37$ per firm-year. Another way to interpret this is that in each year, there is a 37% chance of observing one jump in a firm's CDS spread that is due to analyst recommendation releases.

Table 5 shows that the event that leads to the largest expected number of jumps is analyst recommendation changes, followed by FOMC meetings and management guidance releases. Although the jump probability conditional on analyst recommendation releases is only 5.19%, this type of event occurs relatively often, which makes it the most significant source of jumps in CDS spreads. Overall, Table 5 shows that after taking the frequency of each event into account, equity accounting information causes more jumps in CDS spread than credit-related events.

Table 5 also shows the expected jump size in CDS spreads per firm-year due to each event. This is computed by multiplying the average number of jumps per firm-year due to each event with the average jump size conditional on the event, obtained from Table 3. This measure represents the expected CDS spread that can be attributed to jumps caused by different event types, expressed on a yearly basis. Table 5 shows that analyst recommendations contribute the most to large movements in CDS spreads, followed by credit watch. Combining the sources of equity accounting news, we find that earnings announcements, management guidance, and analyst recommendations account an average for 4.58% in expected jump size per firm-year, which is significantly higher than the expected jump size of 2.58% that can be attributed to credit-related news. In sum, the results in this section confirm the economic importance of equity accounting information. We find that the impact of equity accounting news is about twice as large as the impact of credit-related news, once the frequency of each event-type is taken into consideration.

[Table 5 about here]

5.4 Asymmetries Between Good and Bad News

We now investigate if good and bad news similarly impact jumps in CDS spreads. In Table 6, we further classify events into positive and negative surprises, as well as events that do not contain surprises. The first important finding from this table concerns the relative importance of different information events. We find that earnings announcements that are not considered surprising are not associated with jumps and hence are uninformative to CDS investors. On the other hand, management guidance forecasts that are not surprising are still significantly associated with jumps. This finding confirms our earlier conclusion that management guidance events are on average more informative than earnings announcements for CDS markets.

Regarding the differences between positive and negative surprises, Table 6 indicates that positive news is less likely to be associated with jumps in CDS spreads. We do not find statistically significant evidence that positive earnings surprises and credit upgrades are associated with jumps in CDS spreads. On the other hand, the coefficients on credit downgrade and negative earnings surprises are strongly statistically significant. These findings on the asymmetric news impact of credit downgrades and upgrades on CDS spreads confirm the results of Hite and Warga (1997) and Dynkin, Hyman and Konstantinovsky (2002), who document asymmetries in the bond market's reaction to positive and negative credit re-rating announcements. We find similar evidence of asymmetries in the CDS market's reaction to positive and negative news in the case of management guidance forecasts, analyst recommendation changes, and credit watch announcements, but the coefficients on positive management guidance surprises, analyst upgrade, and positive credit watch remain statistically significant. The asymmetric impact between good and bad news is strongest for earnings announcements. Interestingly, while both negative watch and subsequent credit downgrades are likely to cause jumps in CDS spreads, only positive watch is likely to cause jumps and not the subsequent credit upgrade. This finding suggests that the CDS market reacts strongly to the arrival of negative news, even if such news is partially anticipated or preceded by an early warning sign, i.e. negative watch.

[Table 6 about here]

5.5 Asymmetries for Positive and Negative Jumps

While Table 6 distinguishes between the impact of positive and negative news events, Table 7 further investigates news asymmetries by relating the asymmetric impact of good versus bad news to the sign of the jumps in CDS spreads. A priori, we expect news that carries negative information to increase the firm's default probability, and hence to cause a positive jump in CDS spreads. On the other hand, we expect positive news to decrease the firm's default probability and hence to cause a negative jump in CDS spreads. In Table 7, in the case of positive CDS jumps, the dependent variable is a daily indicator function that is equal to one when a positive jump in CDS spread is detected and zero otherwise. Similarly for the case of negative CDS jumps, the dependent variable is a daily indicator function that is equal to one when a negative jump in CDS spreads is detected and zero otherwise.

Table 7 demonstrates that positive jumps in CDS spreads, which signal an increase in the firm's default probability, are less likely to be associated with positive news. The coefficients on positive earnings surprise, credit upgrade, and positive market watch are not statistically significant. Analyst upgrades and positive management guidance surprise can cause CDS spreads to jump upward, but their estimated coefficients are smaller than their counterparts that are associated with negative news. It is not surprising that we find some types of positive news events are associated with upward jumps in CDS spreads. Schwert (1990) and Engle and Ng (1993) show that the arrival of good news increases stock volatility, though to a lesser extent than the arrival of bad news. This increase in volatility can increase the firm's probability of default, thereby resulting in a positive jump in CDS spreads.

Table 7 shows that credit upgrades are neither associated with positive nor negative jumps in CDS spreads, which confirms our previous finding that credit upgrade news is uninformative. However, all the other positive news releases in Table 7 are significantly associated with a negative jump in CDS spreads. On the other hand, we find no evidence that negative news releases are associated with a downward jump in CDS spreads. Thus, while positive news releases can cause CDS spreads to jump upward and downward, the impact of negative news on CDS spreads is unambiguous: the arrival of bad news, on average, is associated with an increase in the firm's default probability. We do not report the logistic coefficient for positive CDS jumps on positive watch. The reason is that in our sample, we do not observe positive CDS jumps on days with positive watch news releases.

We find that management guidance news that do not contain surprises are associated with negative jumps but not positive jumps in CDS spreads. This finding suggests that guidance forecasts which are in line with market expectations leads to a decrease in the firm's uncertainty, which consequently reduces the firm's default probability. Our result contributes to the recent literature on the impact of guidance on the firm's uncertainty. Rogers, Skinner and VanBuskirk (2009) study changes in option-implied volatility before and after guidance forecasts, and conclude that guidance increases the firm's short-term uncertainty. We find instead that with the exception of negative guidance surprises, the practice of issuing guidance on average reduces information asymmetries, which then results in negative jumps in CDS spreads. This conclusion is consistent with the findings of Houston, Lev and Tucker (2010), who show that firms that stop issuing guidance experience an increase in information asymmetry through decreased earnings, as well as a decrease in analyst coverage.

We find that bond issuance is associated with negative CDS jumps. Bond issuance increases the firm leverage ratio. Following the intuition in Merton (1974), this should increase the cost of debt and subsequently the CDS spread. However, the CDS contracts in our sample are insurance contracts on senior unsecured bonds. To protect bondholders, these bonds often contain covenants that limit any subsequent issuance of debt with higher seniority. Consequently, new bond issuance is likely to have lower seniority, and therefore may provide a buffer in the event of default. Our finding that bond issuance is associated with negative jumps in CDS spreads is consistent with this reasoning.

We find strong evidence that FOMC announcements are associated with positive CDS jumps but not with negative CDS jumps. While changes in interest rates do not greatly impact CDS spreads because discounting affects both legs of the security, it appears that the increase in uncertainty in credit markets following FOMC meetings leads to increases in firms' default probabilities. Interestingly, Table 7 shows that positive earnings surprises are significantly associated with negative jumps in CDS spreads, while Table 6 suggests a weakly significant association between positive earnings surprises and jumps. A similar conclusion obtains for the FOMC indicator. We find strong evidence that FOMC announcements are associated with positive jumps in CDS spreads, but we do not obtain statistically significant results when we do not distinguish between negative and positive jumps in the regression.

In summary, Table 7 convincingly demonstrates that it is important to distinguish between the impact of information events on positive and negative jumps.

[Table 7 about here]

5.6 Informational Efficiency of the CDS Market

We next examine the speed with which information releases are incorporated into CDS spreads. Panel A of Table 8 augments the specification of Table 7 with lagged indicator variables for each information event. For instance, the lagged analyst upgrade variable is an indicator function that takes the value of one if an analyst upgraded her recommendation yesterday and zero otherwise.

The regression coefficients on the contemporaneous indicator variables in Panel A of Table 8 are almost identical to those in Table 7. This demonstrates the robustness of our previous results.

For positive CDS jumps, we find that the coefficients on analyst downgrade lagged and analyst upgrade lagged are not significant, while the coefficients on analyst downgrade and analyst upgrade are highly significant. This suggests that when an analyst issues a recommendation on a stock, the information is quickly transmitted into the CDS market. The bulk of the price adjustment in CDS spreads occurs on the day of the recommendation release, but not on the day after.

We find a significantly positive coefficient for the one-day lagged negative guidance surprise indicator, which suggests that such information has a longer-lasting impact on the CDS spread change. Nevertheless, the coefficient on negative guidance surprise is substantially larger than that of its lag, suggesting that jumps in CDS spreads in response to negative management guidance releases are more likely to occur on the event date rather than on the day after.

We obtain similar conclusions for negative jumps. The coefficients on positive earnings surprise, analyst upgrade, and positive guidance surprise remain highly significant, confirming the robustness of our earlier findings. We find no evidence that equity accounting news released today is associated with a negative CDS jump tomorrow. As for the credit news events, we find the same results as in Table 7. Positive watch and bond issuance are the only two credit risk events that are associated with negative CDS jumps. However, we also find that the one-day lagged variables for positive watch and bond issuance are significant, indicating a longer-lasting impact on negative CDS spread changes.

[Table 8 about here]

In summary, the results in Table 8 demonstrate that jumps are largely associated with contemporaneous information arrivals. Such findings are commonly interpreted in financial markets as evidence for an efficient price discovery process. Perhaps contrary to existing views of the CDS market that emphasize the inefficiency of the over–the-counter trading mechanism, and to evidence of illiquidity during the recent crisis period, we find that the CDS market responds quickly to new information arrivals during our sample period.[11] Our

[11] For evidence of illiquidity in the CDS market, see Tang and Yan (2007) and Bongaerts, De Jong and Driessen (2009).

conclusion of efficient price discovery is strongest in the case of equity accounting information.[12]

6 Robustness

This section further investigates the robustness of our findings. First, we investigate if our results are biased by omitting events. Next we investigate if they are influenced by stale or illiquid quotes. Finally, we employ a parametric jump detection method to confirm that our results are not due to the use of the nonparametric jump detection technique.

6.1 Other Sources of Jumps and Jump Clustering

If important information events are omitted from the regression, it is possible that we obtain biased estimates for our information events of interest due to an omitted variable argument. In order to confirm that our results are robust to the inclusion of other information events, we add two additional information events to our regression. The results are reported in Panel B of Table 8. The first additional control variable is an indicator for daily jumps in the S&P 500 index, which serves as a control for missing macroeconomic news. This variable takes the value of one if we detect a jump in the index and zero otherwise. The second additional control variable is an indicator function for daily jumps in the firm's option-implied volatility. Equity options are traded regularly on the exchange and are generally more liquid than CDS quotes. We therefore expect that omitted events that are important to the firm show up as jumps in its option-implied volatility.

Besides jumps in the index and jumps in implied volatilities, we also include lagged CDS jumps in the regression. We denote this variable as CDS jump lagged, which takes the value of one if we observe a jump (positive or negative) in CDS spreads on the previous day and zero otherwise. Existing studies find that jumps in asset prices tend to arrive in clusters (see Maheu and McCurdy (2004)). We thus expect the likelihood of a jump tomorrow to be higher if we observe a jump in CDS spreads today.

Overall, we find that the estimates in Panel B of Table 8 are almost identical to the estimates in Panel A, confirming that our results are robust to including additional event variables in the logistic regression.[13] Consistent with our earlier findings, we find that equity

[12] Our dataset ends in March 2008 and thus does not cover the crisis period. Including the crisis period in the sample could presumably alter our conclusions on price discovery.

[13] Note that Table **??** does not report results for some logistic coefficients, in cases when we do not observe jumps in CDS spreads on the event days. Nevertheless, we can conclude that these unreported variables are not important determinants of jumps.

accounting news is quickly incorporated into CDS spreads. With the exception of negative guidance surprise, the coefficients on the lagged equity accounting variables are not significant.

We find strong evidence of jump clustering. The coefficient on CDS jump lagged is relatively large and highly significant. Panel B of Table 8 shows that the coefficient on the first lag of the CDS jump is 1.65, which implies that the probability of observing a positive jump in CDS spreads increases by 6.52%. On the other hand, the lagged variables for jumps in implied volatility are not significant, suggesting that information transmission between the option market and the CDS market occurs within one trading day. Moreover, the likelihood that an implied volatility jump is associated with a jump in CDS spreads is strongest for positive CDS jumps.

We observe only one negative jump in the S&P 500 index over our sample period, and Table 8 shows that this event is associated with positive jumps in CDS spreads. The lagged jump in the S&P 500 index is not significant, which suggests an efficient price adjustment process in the CDS market following a market-wide shock.

6.2 Controlling for Stale CDS Quotes

It is important to verify that detected jumps are not simply caused by stale or missing data. The nonparametric jump detection test compares the change in CDS spreads to a measure of instantaneous volatility; stale quotes could bias down the latter and therefore lead to overdetection of jumps.

To investigate the impact of stale quotes, we remove all observations following a gap in the data. Also, we eliminate observations that occur after the CDS quote has not changed for at least three days. There are seventeen quotes on days following a gap in the data, and eleven of these are jumps. There are 5,772 quotes following a string of stale quotes, and 639 of those had been detected as jumps. Overall, we remove 5,781 quotes and re-estimate the model using the remaining 126,778 firm-day observations.

[Table 9 about here]

Although there are some slight changes in the estimated coefficients, our conclusions remain very similar. Table 9 presents results for the constrained sample corresponding to the results in Panel A of Table 8. Some indicator variables that were not significantly different from zero in Table 8 yield different estimates, but the significantly estimated explanatory variables discussed in Section 5.6 do not change by much. The biggest change for a significant event indicator is for bond issuance in the regression for negative jumps, which decreases from 1.09 to 0.89, and remains statistically significant. Overall, our conclusions still hold after removing potentially stale quotes.

6.3 Parametric Jump Detection Methods

Our results have been obtained using the nonparametric jump detection method of Lee and Mykland (2008). While the use of nonparametrics is intuitively appealing in this context, it is possible that the simplicity of this method hides interesting stylized facts that could be uncovered by a fully parametric approach. We therefore investigate the robustness of our results by using a parametric jump detection method to detect jumps in CDS spreads, and compare the results to our findings obtained using the Lee and Mykland (2008) method.

We apply the reduced-form framework of Jarrow and Turnbull (1995) to the pricing of CDS. Under this approach, the risk neutral probability that the firm will not default from now until time t is given by

$$Q\left(\tau > t\right) = E^{Q}\left[\exp\left(-\int_0^t \lambda_s\right) ds\right].$$

This is known as the survival probability, where τ is the time when default occurs, and λ_s is the instantaneous default probability at time s. We assume the following mean reverting dynamic for the risk-neutral instantaneous default intensity

$$\lambda_{t+1} = \left(1-\rho\right)\theta + \rho\lambda_t + \sigma_z\sqrt{\lambda}z_{t+1} + y_{t+1},$$

where $z_{t+1} \sim N(0,1)$, and y_{t+1} is the jump component in the instantaneous default intensity. The parameters ρ and θ represent the mean reversion speed and the long-run level of default intensity respectively. We let the jump component y_{t+1} follow a compound Poisson process $y_{t+1} = \sum_{j=0}^{n_{t+1}} x_{j,t+1}$, where n_{t+1} is the number of jumps that arrive between t and $t+1$. It is distributed as $n_{t+1} \sim \text{Poisson}(\varphi_t)$, where the jump intensity φ_t is linearly related to the default intensity $\varphi_t = \mu + \kappa\lambda_t$. We consider two cases: one in which jumps $x_{j,t+1}$ are normally distributed, and another one where $x_{j,t+1}$ is an exponential random variable. In the former case, there can be positive and negative jumps in the default intensity. The latter model exclusively allows positive jumps in CDS spreads.

In order to detect jumps, we calibrate these fully parametric models to the daily CDS spread changes. The number of jumps, n_{t+1}, is then filtered out daily using a standard filtering algorithm. Table 10 shows summary statistics for jumps detected using the different methods. As the parametric approach allows for multiple jumps on the same day, we set an indicator variable for a jump on days when the filtered value of the number of jumps is above

0.99. Panel A presents the proportion of days on which a jump is detected for each method. The Gaussian specification detects more jumps than the two others, and the exponential specification detects fewer jumps than the two other methods. Most importantly, Panel B shows that more than 96% of detected jumps fall on the same day when comparing the non-parametric method to either parametric method. We therefore conclude that since the vast majority of jump occurrences are corroborated by a fully parametric method, the use of the nonparametric method does not bias the empirical results.

[Table 10 about here]

7 Conclusion

We investigate the relationship between accounting information releases and CDS spreads. Because changes in CDS spreads are dominated by large but infrequent movements, we do not adopt a more conventional least squares approach which regresses spreads or spread changes on the information events of interest; instead we use a nonparametric jump detection technique and subsequently conduct logistic regressions of these jumps in spreads on the accounting information releases. We investigate the importance of accounting information releases after controlling for credit-related events such as changes in credit grades and positive and negative watch, as well as various macroeconomic events.

We find that earnings announcements, management guidance, and analyst recommendations explain a significant fraction of jumps in CDS spreads. Credit upgrades and especially credit downgrades are also independently important for explaining jumps in CDS spreads, and our results confirm the importance of the entire credit rating process, especially the relevance of being put on negative watch. Good and bad news impact jumps in CDS spreads asymmetrically, and unscheduled announcements are more likely to cause jumps than scheduled ones. We demonstrate that the arrival of accounting information is absorbed in CDS spreads on the day of the announcement, suggesting efficient price discovery in CDS markets.

These findings complement the rich literature on the relationship between accounting information and equity returns. They provide additional insight into the impact of accounting information on different investors in the firm, but the findings are also of independent interest because of the increasing importance of credit risk. In particular, our findings suggest that some of the risk associated with credit spread changes can be managed given the fact that accounting releases are frequent and clustered in time.

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Figures and Tables

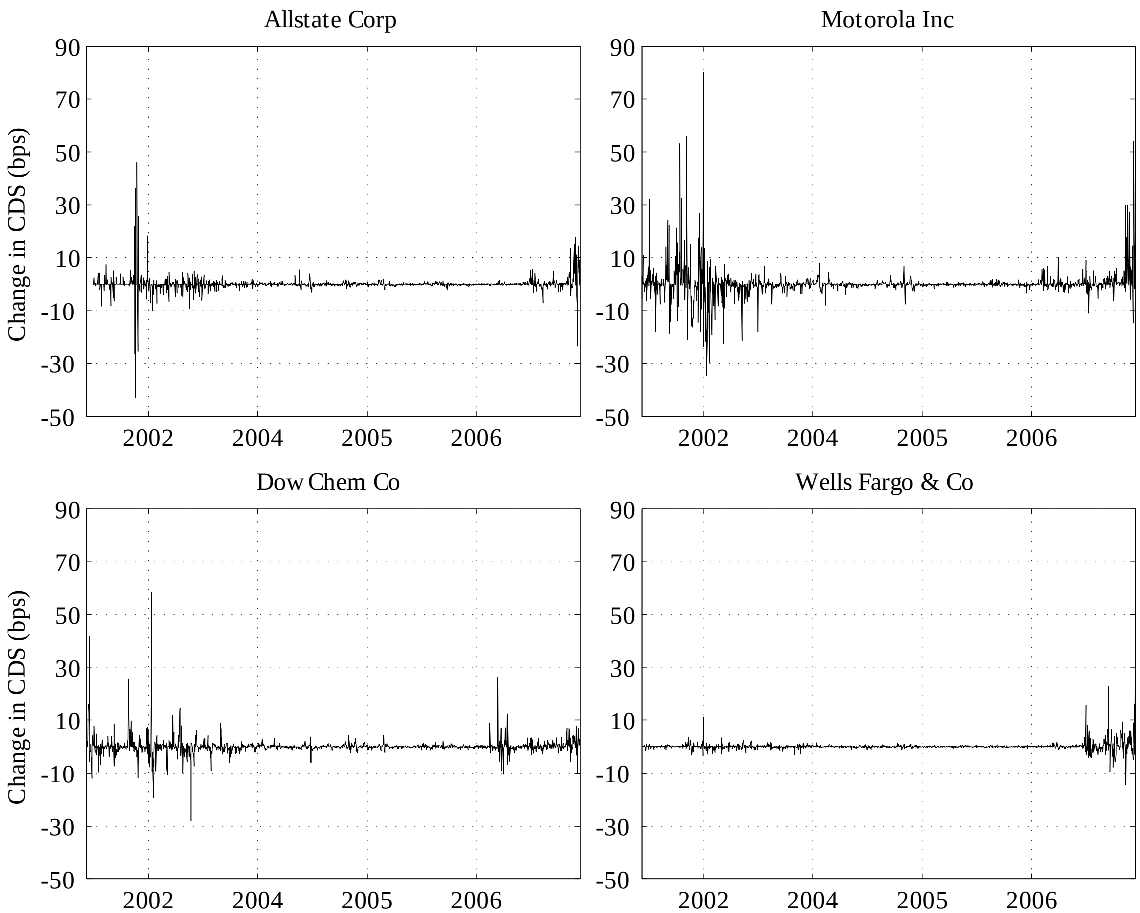

Figure 1. Time Series of CDS Spread Changes for Selected Firms: We graph the time series of daily CDS spread changes for four firms in the sample: Allstate Corporation, Motorola Inc, Dow Chemical Company, and Wells Fargo and Company. The sample period is from January 29^{th}, 2002 to March 7^{th}, 2008.

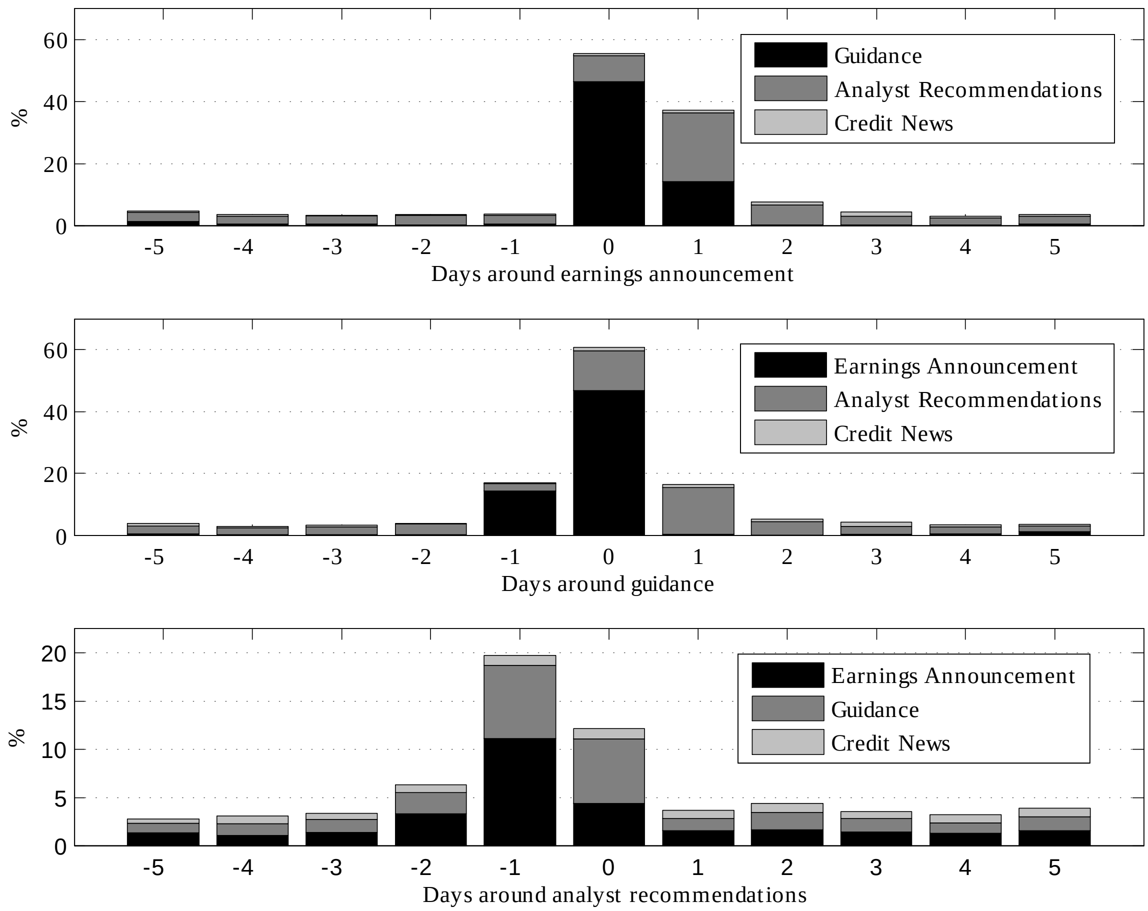

Figure 2. Overlapping events around accounting news releases: We depict events occurring on the release date of three different types of accounting news events: earnings announcements, management guidance, and analyst recommendations. We also depict events occurring up to five days before and after the event date.

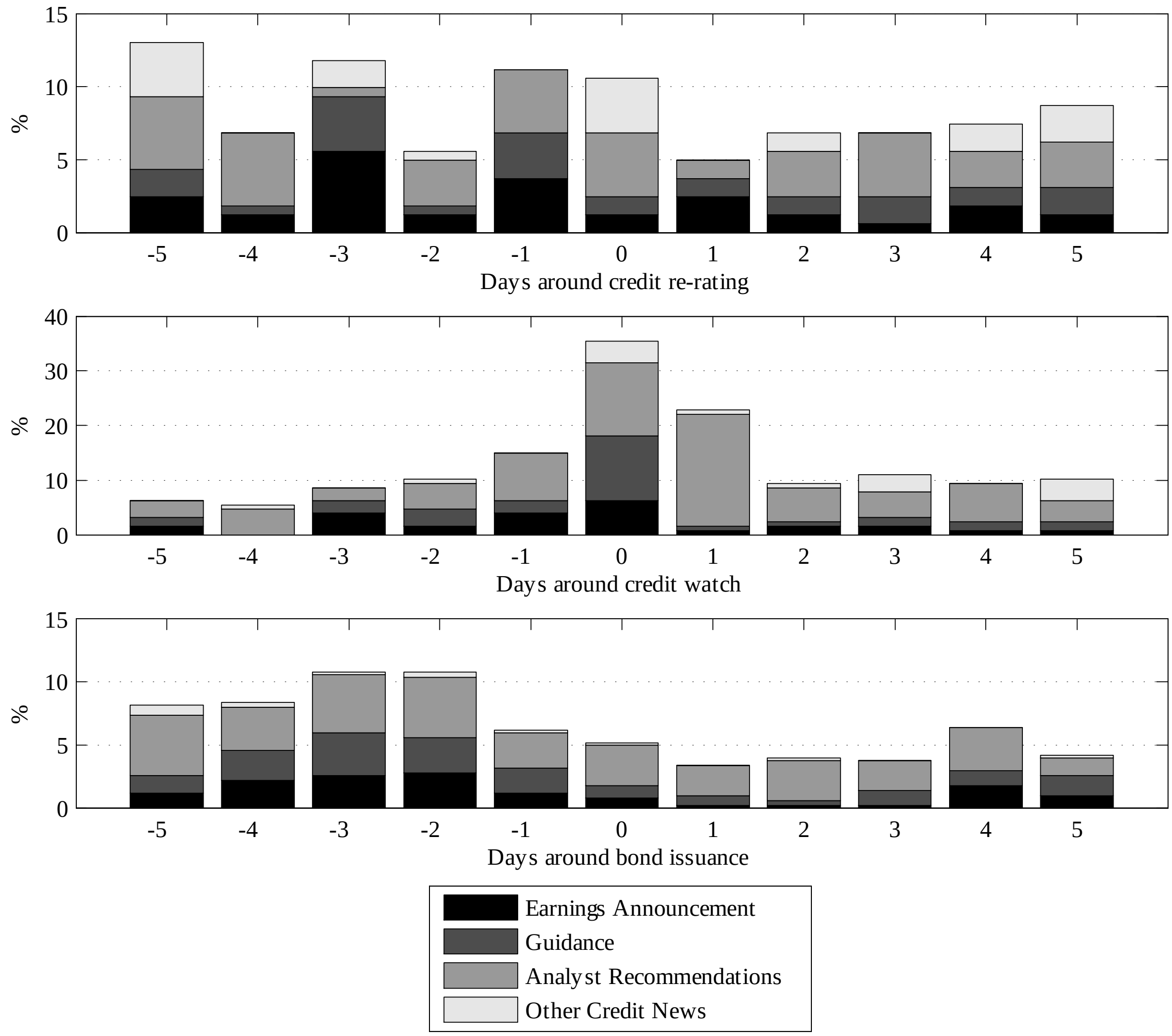

Figure 3. Overlapping events around credit-related news releases: We depict events occurring on the release date of three different types of credit risk news events: credit rating changes, credit watch, and bond issuance. We also depict events occurring up to five days before and after the event date.

Name	Rating	Average Spread	St. Dev Spread	No. of Jumps	No. of Positive Jumps	No. of Negative Jumps	SIC
AT&T Corp.	Aa3	132.95	143.96	35	18	17	4813
Aetna Inc.	Baa3	60.04	56.14	57	29	28	6324
Alcoa Inc.	A1	34.98	18.94	36	20	16	3334
Allstate Corp	A1	31.93	20.70	64	37	27	6331
Altria Gp Inc	A2	114.96	78.92	50	23	27	2111
Amgen Inc.	A2	32.27	27.35	32	16	16	2836
Anadarko Pete Corp	Baa1	41.78	16.39	41	22	19	1311
Arrow Electrs Inc	Baa1	141.83	121.25	54	29	25	5065
Autozone Inc	Baa2	66.37	23.95	63	33	30	5531
Baxter Intl Inc	A3	34.76	18.81	53	27	26	3841
BellSouth Corp	Aa3	39.38	29.47	44	24	20	4813
Burlington Nthn Santa Fe Corp	Baa2	37.06	15.39	68	34	34	4011
CSX Corp	Baa2	51.84	23.15	36	16	20	4011
Campbell Soup Co	A3	26.78	10.40	48	26	22	2032
Cap One Bk	Baa3	138.30	173.09	57	26	31	6022
Cardinal Health Inc	A2	44.24	24.50	60	36	24	5122
Carnival Corp	A2	57.61	43.38	26	17	9	4481
Caterpillar Inc	A2	28.91	15.47	37	19	18	3531
Centex Corp	Baa2	109.58	100.78	32	14	18	1531
Chubb Corp	Aa3	35.15	25.56	48	31	17	6331
Cigna Corp	A3	58.31	43.95	45	28	17	6324
Clear Channel Comms Inc	Baa3	189.20	163.24	38	24	14	-
Computer Assoc Intl Inc	Baa1	231.84	252.11	41	20	21	7372
Computer Sciences Corp	A2	58.52	32.29	52	32	20	7373
ConAgra Foods Inc	Baa1	41.94	14.60	50	30	20	2038
ConocoPhillips	A3	31.93	16.02	72	35	37	2911
Constellation Engy Gp Inc	A3	71.74	75.18	61	35	26	4911
Deere & Co	A2	33.50	19.69	22	10	12	3523
Delphi Corp	Baa2	664.19	1135.20	25	14	11	-
Dominion Res Inc	Baa1	54.93	34.30	52	29	23	4911
Dow Chem Co	A1	55.75	40.45	37	28	9	2821
Expedia Inc	Baa3	174.01	56.71	11	7	4	4789
Eastman Kodak Co	A3	182.31	74.82	49	28	21	3861
Ford Mtr Cr Co	Baa1	325.96	128.16	22	15	7	3711
Gen Mls Inc	Baa1	41.36	20.10	59	31	28	2043
Goodrich Corp	Baa1	80.48	67.45	35	20	15	3728
Halliburton Co	Baa2	116.14	154.51	63	32	31	1389
Hewlett Packard Co	A2	40.39	33.89	36	19	17	3571
Hilton Hotels Corp	Ba1	192.20	154.62	49	29	20	7011
Honeywell Intl Inc	A2	32.14	21.78	41	20	21	3724
Intl Business Machs Corp	A1	28.76	18.19	36	23	13	3571
Intl Paper Co	Baa2	66.13	23.08	31	18	13	2621
Jones Apparel Gp Inc	Baa2	98.27	66.66	63	28	35	2339
Knight Ridder Inc	A2	55.90	53.87	80	32	48	2711
Kraft Foods Inc	A2	39.25	20.10	60	40	20	2099
Lockheed Martin Corp	Baa2	36.86	18.27	56	27	29	3721
Ltd Brands Inc	Baa1	76.01	54.07	54	28	26	5621

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Name	Rating	Average Spread	St. Dev Spread	No. of Jumps	No. of Positive Jumps	No. of Negative Jumps	SIC
MBIA Ins Corp	Aa2	68.72	86.20	55	28	27	6351
MBNA Corp	Baa2	91.04	62.05	34	17	17	6153
Marriott Intl Inc	Ca	61.21	40.51	48	26	22	7011
Marsh & Mclennan Cos Inc	A2	56.05	27.79	43	24	19	6411
May Dept Stores Co	WR	58.41	16.00	42	25	17	-
Maytag Corp	Baa1	91.23	77.10	60	33	27	-
McDonalds Corp	Aa3	26.85	11.92	60	37	23	5812
McKesson Corp	Baa2	56.18	30.12	66	34	32	5122
MetLife Inc	A1	38.57	28.95	44	25	19	6311
Motorola Inc	A3	105.14	112.91	43	24	19	3663
Newell Rubbermaid Inc	A3	48.14	16.48	45	24	21	2591
Nordstrom Inc	Baa1	48.06	32.37	33	18	15	5651
Norfolk Sthn Corp	Baa1	38.92	17.29	53	21	32	4011
Northrop Grumman Corp	Baa3	45.63	33.77	43	18	25	3721
Olin Corp	Baa3	115.43	61.15	71	31	40	2869
Omnicom Gp Inc	A3	60.94	63.59	38	17	21	7311
Progress Engy Inc	Baa1	57.38	41.62	42	23	19	4911
RadioShack Corp	Baa1	100.49	57.50	63	33	30	5731
Raytheon Co	Baa3	61.49	47.68	46	23	23	3812
Rohm & Haas Co	A3	32.72	12.42	52	26	26	2851
Supervalue Inc	Baa3	132.27	70.66	60	32	28	5149
Sabre Hldgs Corp	Baa2	160.79	161.20	54	28	26	4729
Sara Lee Corp	A3	38.75	16.41	91	49	42	2053
Sempra Engy	A2	62.03	54.39	57	32	25	4911
Simon Ppty Gp L P	Baa2	60.97	41.21	71	30	41	6798
Sprint Nextel Corp	Baa2	71.88	87.60	14	10	4	4813
Target Corp	A2	28.26	20.19	54	27	27	5311
Textron Finl Corp	A3	53.20	44.60	47	23	24	3720
The Gap Inc	Baa3	196.70	197.70	46	29	17	5651
The Kroger Co.	Baa3	63.40	26.23	46	30	16	5411
Toys R Us Inc	Baa2	466.46	214.28	40	28	12	5945
Tyson Foods Inc	Baa3	100.01	40.20	54	36	18	2015
Verizon Comms Inc	WR	63.17	67.01	44	30	14	4813
Wal Mart Stores Inc	Aa2	16.75	7.72	65	32	33	5311
Walt Disney Co	Baa2	48.69	34.67	31	23	8	7812
Wells Fargo & Co	Aa2	23.97	15.76	44	21	23	6021
Weyerhaeuser Co	Ba2	69.48	33.04	24	11	13	2400
Whirlpool Corp	Baa1	52.01	19.04	44	27	17	3639
Wyeth	A3	43.45	34.58	48	21	27	2834
XL Cap Ltd	A1	71.53	58.38	36	20	16	6351
Average	-	85.35	67.85	47	26	22	-

Table 1: **Firm-by-Firm Descriptive Statistics:** For each firm, we list its Moody's credit rating at the start of our sample on January 29^{th}, 2002, the number of negative and positive jumps, and the total number of jumps as detected by the non-parametric method. We also list the average CDS spread during the sample and the standard deviation of the spread, as well as the Standard Industry Classification.

Panel A: Full Sample Statistics (Number of Observations = 132559)

	Total Number of Jumps	Unconditional Jump Probability
All jumps	4132	3.12%
Positive jumps	2225	1.68%
Negative jumps	1907	1.44%

Panel B: Cumulated CDS Spread Return Around Jumps

	All Jumps		Isolated Jumps	
Days Relative to Jump	Positive Jumps	Negative Jumps	Positive Jumps	Negative Jumps
-2	0.65%	−0.17%	0.61%	−0.37%
-1	2.13%	−0.47%	1.55%	−0.79%
0	14.80%	−7.50%	15.11%	−8.35%
1	17.24%	−7.71%	16.29%	−8.73%
2	18.68%	−8.01%	17.10%	−9.08%

Table 2: **Full Sample Jump Statistics:** We present descriptive jump statistics for the full sample of 87 firms for the sample period January 29, 2002 to March 7, 2008. Panel A reports the full sample jump statistics. The total number of observations (i.e. daily CDS spread changes) in our sample is 132,559. The unconditional jump probability is the proportion of total observations when jumps are detected. This can be thought of as the long-run jump probability that is not conditional on any event. We report the unconditional jump probability for all jumps, positive jumps, and negative jumps. Panel B contains the averaged cumulative arithmetic return in the CDS spread around positive and negative jumps: from two days before to two days after the jump. We show the cumulative CDS returns conditional on a jump, as well as conditional on an isolated jump. We define isolated jumps as those that are not preceded by another jump within the previous two days nor followed by another jump in the next two days.

Panel A: Firm-Specific Events

Event	Average Number of Events per Firm-Year	Jump Frequency Conditional on the Event	Average Jump Size Conditional on the Event
Earnings announcement	3.73	6.43%	4.26%
Positive earnings surprise	1.24	6.12%	−0.04%
Negative earnings surprise	0.30	13.55%	11.14%
Management guidance	3.63	7.78%	4.33%
Positive guidance surprise	0.72	8.81%	3.54%
Negative guidance surprise	0.68	12.71%	11.54%
Analyst recommendation change	7.04	5.33%	8.01%
Analyst upgrade	3.46	5.14%	5.29%
Analyst downgrade	3.74	5.63%	10.50%
Credit rating change	0.32	12.42%	10.70%
Credit upgrade	0.07	7.50%	1.05%
Credit downgrade	0.24	14.05%	12.41%
Credit watch	0.25	26.36%	20.65%
Positive watch	0.05	17.86%	−15.01%
Negative watch	0.20	28.71%	26.79%
Bond issuance	0.94	6.94%	1.30%
Jumps in implied volatility	3.58	7.72%	13.99%

Panel B: Macroeconomic Events

Event	Number of Events	Jump Frequency Conditional on the Event	Average Jump Size Conditional on the Event
Jump in S&P 500	1	30.49%	12.70%
FOMC	54	3.58%	3.47%

Table 3: **Jump Statistics for Various Events:** We present descriptive jump statistics for various events. The sample consists of the 87 firms in Table 1 for the sample period January 29^{th}, 2002 to March 7^{th}, 2008. Panel A reports the frequency of firm-specific events, the jump frequency conditional on the event, and the average jump size conditional on the event. We report the average number of events across all firms, expressed on an annual basis to show the relative frequency of each event per firm-year. Jump frequency conditional on the event is the number of jumps detected on the event date divided by the total number of occurrences of that event. It represents a simple univariate jump probability which does not take into account the confounding arrival of other news releases. Average jump size conditional on the event is the mean of the arithmetic return in the daily CDS spread when jumps are detected on the day of the event. Panel B presents the same information as Panel A for macroeconomic events. Jump in S&P 500 refers to jumps that are detected in the daily S&P 500 index return during our sample period. FOMC refers to the dates of the Federal Open Market Committee meetings.

	Equity Accounting News			Credit News			Equity Accounting and Credit		
	Coefficient	p-value	Change in Jump Prob.	Coefficient	p-value	Change in Jump Prob.	Coefficient	p-value	Change in Jump Prob.
Earnings announcement	0.36	0.002	1.28%				0.36	0.002	1.30%
Management guidance	0.72	0.000	3.10%				0.69	0.000	2.93%
Analyst recommendation change	0.55	0.000	2.16%				0.53	0.000	2.08%
Bond issuance				0.88	0.000	4.10%	0.89	0.000	4.16%
Credit re-rating				1.34	0.000	7.84%	1.35	0.000	7.95%
Credit watch				2.40	0.000	23.02%	2.25	0.000	20.28%
FOMC				0.16	0.056	0.51%	0.15	0.062	0.50%
Log-Likelihood		-18044.02			-18050.17			-17978.93	

Table 4: **Determinants of Jumps in CDS Spreads:** We present logistic regression results using jumps detected on CDS spreads of the 87 firms in Table 1. The sample is from January 29^{th}, 2002 to March 7^{th}, 2008. The dependent variable is equal to one if a jump occurred, zero otherwise. The explanatory variables include equity accounting events for the first regression, credit events for the second, and both categories for the last regression. For each regression, we report the estimated coefficient, its p-value, as well as the change in jump implied by the estimates when the event occurs. Note that the change in jump probability is computed relative to the long-run (unconditional) probability of observing a jump in CDS spread, which is 3.10% in our sample. Firm fixed effects are included in each specification. Earnings announcement and management guidance are indicator variables equal to one on days respectively when earnings are announced and guidance is provided by management. Analyst recommendation is equal to one on days when at least one analyst either upgrades or downgrades her recommendation. Similarly, credit re-rating and credit watch are indicator variables respectively for credit rating upgrades or downgrades, and for when the firm is put on negative or positive watch by Moody's. Bond issuance is equal to one on dates when debt is issued by the firm, and FOMC is equal to one on days when the Federal Open Market Committee announces a rate decision.

	Conditional Jump Prob	Average Number of Events per Firm-Year	Expected Number of Jumps due to the Event per Firm-Year	Expected Jump Size due to the Event per Firm-Year
Earnings announcement	4.42%	3.73	0.16	0.70%
Management guidance	6.05%	3.63	0.22	0.95%
Analyst recomm change	5.19%	7.04	0.37	2.93%
Bond issuance	7.28%	0.94	0.07	0.09%
Credit re-rating	11.07%	0.32	0.04	0.38%
Credit watch	23.40%	0.26	0.06	1.27%
FOMC	3.62%	6.68	0.24	0.84%

Table 5: **Economic Impact of Jump Determinants:** We present the economic impact of information events on CDS spread changes by accounting for the frequency of each information event. The sample period is from January 29^{th}, 2002 to March 7^{th}, 2008 and the sample contains the 87 firms in Table 1. The first column reports the conditional jump probability implied by the logistic regression coefficient in Table 4, using the regression specification in the third column. This represents the probability of observing a jump when an event type happens. The second column reports the frequency of each event type that we observe per year; it is taken from Table 3. The third column reports the expected number of jumps due to each event per firm-year. It is computed as the product of the conditional jump probability and the average number of observations of each event-type per firm-year. The last column reports the expected jump size due to each event type per firm-year. It is computed by multiplying the expected number of jumps per firm-year due to each event with the average jump size conditional on the event reported in Table 3. The average jump size conditional on the event is the mean of the daily CDS spread return when jumps are detected on the day of the event.

	Equity Accounting News			Credit News			Equity Accounting and Credit		
	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.
Earnings with no surprise	0.19	0.251	0.62%				0.21	0.199	0.69%
Positive earnings surprise	0.20	0.289	0.65%				0.21	0.261	0.70%
Negative earnings surprise	1.13	0.000	5.97%				1.12	0.000	5.85%
Guidance with no surprise	0.48	0.001	1.83%				0.46	0.001	1.73%
Positive guidance surprise	0.97	0.000	4.71%				0.94	0.000	4.47%
Negative guidance surprise	1.20	0.000	6.57%				1.15	0.000	6.11%
Analyst upgrade	0.48	0.000	1.80%				0.46	0.000	1.74%
Analyst downgrade	0.53	0.000	2.05%				0.51	0.000	1.97%
Credit upgrade				0.88	0.145	4.08%	0.84	0.167	3.79%
Credit downgrade				1.46	0.000	9.01%	1.49	0.000	9.38%
Positive watch				1.89	0.000	14.37%	1.80	0.000	13.20%
Negative watch				2.52	0.000	25.43%	2.32	0.000	21.64%
Bond issuance				0.88	0.000	4.11%	0.90	0.000	4.19%
FOMC				0.16	0.057	0.51%	0.15	0.064	0.50%
Log-Likelihood		-18032.29			-18049.00			-17967.13	

Table 6: **Good News, Bad News, and Jumps in CDS Spreads:** We present logistic regression results using jumps detected on CDS spreads of the 87 firms in Table 1. The sample period is from January 29^{th}, 2002 to March 7^{th}, 2008. The dependent variable is equal to one if a jump occurred, zero otherwise. The explanatory variables include equity accounting events for the first regression, credit events for the second, and both categories for the last regression. For each regression, we report the estimated coefficient, its p-value, as well as the change in jump probability when that event happens. Note that the change in jump probability is computed relative to the long-run (unconditional) probability of observing a jump in CDS spread, which is 3.10% in our sample. Firm fixed effects are included in each specification. We generate positive and negative earnings surprise indicator variables following the classification of earnings surprises in **?**. The indicator variables positive and negative management guidance surprises are generated using the classification provided by First Call. Analyst upgrade and downgrade are indicator variables for days on which at least one analyst respectively upgrades and downgrades his recommendation. Credit upgrade and downgrade are equal to one on days when the firm‘s credit rating is respectively upgraded and downgraded by Moody‘s. Positive and negative watch are indicator variables for days on which the firm is put on positive and negative watch respectively by Moody‘s. Bond issuance is equal to one on dates when debt is issued by the firm, and FOMC is equal to one on days when the Federal Open Market Committee announces a rate decision.

	Positive CDS Jumps			Negative CDS Jumps		
	Coefficient	p-value	Change in Jump Prob.	Coefficient	p-value	Change in Jump Prob.
Equity accounting news						
Earnings with no surprise	0.22	0.299	0.40%	0.18	0.466	0.32%
Positive earnings surprise	−0.40	0.190	−0.55%	0.70	0.003	1.42%
Negative earnings surprise	1.32	0.000	4.32%	0.45	0.382	0.81%
Guidance with no surprise	0.31	0.133	0.59%	0.57	0.004	1.26%
Positive guidance surprise	0.84	0.003	2.12%	0.95	0.000	2.20%
Negative guidance surprise	1.58	0.000	5.98%	0.12	0.756	0.17%
Analyst upgrade	0.44	0.003	0.89%	0.47	0.003	0.85%
Analyst downgrade	0.65	0.000	1.50%	0.25	0.136	0.41%
Credit news						
Credit upgrade	0.42	0.681	0.85%	1.07	0.147	2.63%
Credit downgrade	1.81	0.000	7.76%	0.63	0.282	1.24%
Positive watch	–			2.57	0.000	14.56%
Negative watch	2.84	0.000	20.92%	−0.50	0.621	−0.56%
Bond issuance	0.61	0.020	1.38%	1.12	0.000	2.84%
FOMC	0.32	0.002	0.61%	−0.08	0.551	−0.11%
Log-Likelihood		-11018.85			-9726.77	

Table 7: **Explaining Positive and Negative Jumps in CDS Spreads:** We present logistic regression results using jumps detected on the CDS spreads of the 87 firms in Table 1. The sample is from January 29^{th}, 2002 to March 7^{th}, 2008. For the first regression, the dependent variable is equal to one if a jump is detected and is positive, zero otherwise. The second regression uses an indicator variable for negative jumps as dependent variable. For each regression, we report the estimated coefficient, its p-value, as well as the change in jump (positive and negative) when that event happens. The change in positive (negative) jump probability is computed with respect to the unconditional probability of observing a positive jump (negative jump) in CDS spread, which is 1.67% (1.44%) in our sample. Firm fixed effects are included in each specification. We generate positive and negative earnings surprise indicator variables following the classification of earnings surprises in Dellavigna and Pollet (2009). The indicator variables positive and negative management guidance surprises are generated using the classification provided by First Call. Analyst upgrade and downgrade are indicator variables for days on which at least one analyst respectively upgrades or downgrades his recommendation. Credit upgrade and downgrade are equal to one on days when the firm‘s credit rating is respectively upgraded and downgraded by Moody‘s. Positive and negative watch are indicator variables for days on which the firm is put on positive and negative watch respectively by Moody‘s. Bond issuance is equal to one on dates when debt is issued by the firm, and FOMC is equal to one on days when the Federal Open Market Committee announces a rate decision. We do not observe any positive CDS jumps on the day of positive watch news and hence we exclude positive watch from this particular regression in order to avoid reporting non-meaningful estimate. Consequently, we report a "-" in the cell for the regression coefficient of positive CDS jumps on positive watch.

	Panel A						Panel B					
	Positive CDS Jumps			Negative CDS Jumps			Positive CDS Jumps			Negative CDS Jumps		
	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.
Equity accounting news												
Earnings no surprise	0.22	0.305	0.40%	0.19	0.436	0.30%	0.09	0.682	0.15%	0.15	0.543	0.23%
Earnings no surprise lag	0.08	0.734	0.14%	0.39	0.127	0.67%	0.11	0.656	0.19%	0.42	0.098	0.74%
Positive earnings surprise	−0.41	0.177	−0.56%	0.71	0.003	1.45%	−0.51	0.103	−0.67%	0.75	0.002	1.55%
Positive earnings surprise lag	−0.57	0.116	−0.72%	0.01	0.971	0.02%	−0.53	0.147	−0.68%	0.07	0.847	0.10%
Negative earnings surprise	1.30	0.000	4.24%	0.47	0.366	0.84%	1.40	0.000	4.78%	0.55	0.294	1.02%
Negative earnings surprise lag	0.08	0.868	0.14%	0.03	0.967	0.04%	−0.16	0.757	−0.24%	−0.09	0.906	−0.12%
Guidance no surprise	0.32	0.124	0.61%	0.58	0.003	1.11%	0.20	0.334	0.36%	0.48	0.016	0.88%
Guidance no surprise lag	0.12	0.599	0.22%	0.16	0.504	0.24%	0.01	0.974	0.01%	0.05	0.818	0.08%
Positive guidance surprise	0.86	0.002	2.18%	0.96	0.000	2.25%	0.77	0.007	1.87%	0.93	0.001	2.14%
Positive guidance surprise lag	0.25	0.506	0.46%	0.36	0.314	0.62%	0.13	0.731	0.23%	0.22	0.550	0.34%
Negative guidance surprise	1.62	0.000	6.24%	0.13	0.735	0.19%	1.47	0.000	5.20%	−0.06	0.875	−0.08%
Negative guidance surprise lag	1.19	0.000	3.65%	−1.17	0.103	−0.99%	0.99	0.000	2.72%	−1.42	0.049	−1.09%
Analyst upgrade	0.40	0.008	0.80%	0.44	0.006	0.78%	0.31	0.046	0.59%	0.36	0.028	0.60%
Analyst upgrade lag	−0.06	0.761	−0.09%	0.16	0.393	0.25%	−0.15	0.431	−0.24%	0.08	0.671	0.12%
Analyst downgrade	0.58	0.000	1.29%	0.24	0.152	0.39%	0.47	0.000	0.98%	0.16	0.366	0.24%
Analyst downgrade lag	0.04	0.818	0.07%	0.02	0.912	0.03%	−0.04	0.829	−0.06%	−0.07	0.740	−0.09%
Credit news												
Credit upgrade	0.42	0.682	0.84%	1.07	0.145	2.66%	0.58	0.567	1.28%	1.23	0.095	3.32%
Credit upgrade lag	0.47	0.645	0.97%	0.49	0.631	0.89%	0.05	0.961	0.09%	0.35	0.734	0.59%
Credit downgrade	1.79	0.000	7.58%	0.63	0.284	1.23%	1.69	0.000	6.82%	0.51	0.387	0.94%
Credit downgrade lag	1.18	0.003	3.56%	−0.52	0.606	−0.58%	0.89	0.031	2.31%	−0.88	0.383	−0.84%

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	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.
Credit news												
Positive watch	–			2.57	0.000	14.58%	–			2.60	0.000	14.99%
Positive watch lag	–			1.59	0.031	5.25%	–			1.24	0.105	3.34%
Negative watch	2.86	0.000	21.31%	−0.49	0.631	−0.55%	2.68	0.000	18.27%	−0.86	0.397	−0.83%
Negative watch lag	1.72	0.000	7.04%	−0.36	0.725	−0.43%	1.17	0.001	3.54%	−1.02	0.313	−0.92%
Bond issuance	0.60	0.024	1.33%	1.09	0.000	2.73%	0.66	0.013	1.52%	1.13	0.000	2.90%
Bond issuance lag	0.08	0.819	0.13%	0.99	0.000	2.36%	−0.07	0.846	−0.11%	0.88	0.000	1.96%
FOMC	0.32	0.002	0.61%	−0.09	0.514	−0.12%	0.36	0.001	0.71%	−0.08	0.573	−0.10%
FOMC lag	0.26	0.016	0.48%	−0.13	0.327	−0.18%	0.26	0.016	0.49%	−0.15	0.275	−0.20%
Other Controls												
CDS jump lag							1.65	0.000	6.52%	1.56	0.000	5.08%
Implied Volatility Jump							1.01	0.000	2.80%	0.34	0.034	0.57%
Implied Volatility Jump lag							−0.08	0.644	−0.12%	−0.07	0.707	−0.10%
S&P 500 jump							3.26	0.000	29.09%	–		
S&P 500 jump lag							−0.86	0.397	−0.96%	−0.73	0.471	−0.74%
Log-Likelihood		-10978.78			-9709.25			-10589.48			-9450.80	

Table 8: **Price Discovery in the CDS Market:** We present logistic regression results using jumps detected on the CDS spreads of the 87 firms in Table 1. The sample period is from January 29^{th}, 2002 to March 7^{th}, 2008. For the first regression in each panel, the dependent variable is equal to one if a jump is detected and is positive, zero otherwise. The second set of regressions in panels A and B uses an indicator variable for negative jumps as dependent variable. For each regression, we report the estimated coefficient, its p-value, as well as the change in jump probability (positive and negative) when that event happens. The change in positive (negative) jump probability is computed with respect to the unconditional probability of observing a positive jump (negative jump) in CDS spread, which is 1.67% (1.44%) in our sample. Firm fixed effects are included in each specification, and we include a lag for each explanatory variable. We generate positive and negative earnings surprise indicator variables following the classification of earnings surprises in **?**. The indicator variables positive and negative management guidance surprises are generated using the classification provided by First Call. Analyst upgrade and downgrade are indicator variables for days on which at least one analyst respectively upgrades or downgrades his recommendation. Credit upgrade and downgrade are equal to one on days when the firm‘s credit rating is respectively upgraded and downgraded by Moody‘s. Positive and negative watch are indicator variables for days on which the firm is put on positive and negative watch respectively by Moody‘s. Bond issuance is equal to one on dates when debt is issued by the firm, and FOMC is equal to one on days when the Federal Open Market Committee announces a rate decision. Panel B adds several other controls. We include the first lag for the jump indicators in CDS spreads, as well as for the jump indicator variables in the firm‘s implied volatility and in the S&P 500 index return. One month implied volatility is measured as the average of the closest pairs of out-of-the-money calls and puts that have at least 20 days to maturity. Jumps in implied volatility and S&P 500 are detected with the same non-parametric method as for jumps in CDS. We report a "-" for certain regression coefficients. This situation arises when we do not observe any jumps in CDS spreads on the day of the event and hence its indicator variable is excluded from the logistic regression to avoid reporting non-meaningful estimates.

	Positive CDS Jumps			Negative CDS Jumps		
	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.
Equity accounting news						
Earnings no surprise	0.19	0.389	0.32%	0.32	0.203	0.45%
Earnings no surprise lag	0.01	0.958	0.02%	0.36	0.217	0.51%
	−0.51	0.160	−0.60%	0.47	0.100	0.70%
Positive earnings surprise	−0.31	0.317	−0.40%	0.74	0.003	1.28%
Positive earnings surprise lag	−0.47	0.198	−0.56%	0.09	0.815	0.11%
	−0.44	0.290	−0.53%	−0.22	0.620	−0.23%
Negative earnings surprise	1.33	0.000	3.99%	0.30	0.612	0.42%
Negative earnings surprise lag	0.13	0.787	0.21%	0.15	0.837	0.19%
	–			0.16	0.829	0.20%
Guidance no surprise	0.31	0.155	0.55%	0.66	0.002	1.09%
Guidance no surprise lag	0.01	0.963	0.02%	0.21	0.419	0.28%
	0.26	0.327	0.44%	0.17	0.524	0.22%
Positive guidance surprise	0.87	0.003	2.03%	1.12	0.000	2.38%
Positive guidance surprise lag	0.35	0.352	0.62%	0.13	0.774	0.16%
	−0.19	0.716	−0.26%	−0.21	0.686	−0.23%
Negative guidance surprise	1.65	0.000	5.96%	0.02	0.954	0.03%
Negative guidance surprise lag	1.31	0.000	3.90%	−0.97	0.180	−0.74%
	0.18	0.677	0.30%	−0.16	0.758	−0.18%
Analyst upgrade	0.42	0.007	0.78%	0.44	0.012	0.65%
Analyst upgrade lag	−0.09	0.645	−0.14%	0.13	0.525	0.17%
	0.11	0.576	0.17%	0.09	0.681	0.11%
Analyst downgrade	0.69	0.000	1.46%	0.36	0.042	0.52%
Analyst downgrade lag	0.07	0.685	0.11%	−0.07	0.741	−0.08%
	0.08	0.669	0.12%	−0.16	0.496	−0.18%
Credit News						
Credit upgrade	0.49	0.628	0.94%	1.24	0.091	2.85%
Credit upgrade lag	0.54	0.596	1.06%	0.66	0.518	1.09%
	–			0.69	0.496	1.17%
Credit downgrade	1.79	0.000	6.95%	0.38	0.601	0.54%
Credit downgrade lag	1.26	0.002	3.66%	−0.37	0.716	−0.37%
	0.70	0.175	1.50%	0.33	0.650	0.45%

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	Positive CDS Jumps			**Negative CDS Jumps**		
	Coeff.	p-value	Change in Jump Prob.	Coeff.	p-value	Change in Jump Prob.
Credit News						
Positive watch	–			2.72	0.000	14.45%
Positive watch lag-1	–			1.74	0.019	5.27%
	–			0.98	0.340	1.93%
Negative watch	2.82	0.000	19.11%	−0.32	0.752	−0.33%
Negative watch lag-1	1.76	0.000	6.72%	−0.23	0.820	−0.24%
	1.20	0.010	3.35%	−0.22	0.824	−0.24%
Bond issuance	0.54	0.068	1.06%	0.89	0.002	1.67%
Bond issuance lag-1	0.10	0.773	0.16%	1.12	0.000	2.39%
	0.48	0.103	0.92%	0.50	0.140	0.77%
FOMC	0.37	0.001	0.67%	−0.13	0.386	−0.15%
FOMC lag-1	0.19	0.099	0.32%	−0.05	0.719	−0.06%
	−0.23	0.109	−0.31%	−0.34	0.040	−0.35%
Log-Likelihood		-9752.95			-8108.82	

Table 9: **Robustness to Stale Quotes:** We remove all observations following a gap in the data. Also, we eliminate observations that occur after the CDS quote has not changed for at least three days. We present logistic regression results using jumps detected on the CDS spreads of the 87 firms in Table 1. The sample period is from January 29^{th}, 2002 to March 7^{th}, 2008. For the first regression, the dependent variable is equal to one if a jump is detected and is positive, zero otherwise. The second regression uses an indicator variable for negative jumps as dependent variable. For each regression, we report the estimated coefficient, its p-value, as well as the probability of a jump when that event happens. The change in positive (negative) jump probability is computed with respect to the unconditional probability of observing a positive jump (negative jump) in CDS spread, which is 1.52% (1.20%) in our sample. Firm fixed effects are included in each specification, and we include a lag for each explanatory variable. We generate positive and negative earnings surprise indicator variables following the classification of earnings surprises in Dellavigna and Pollet (2009). The indicator variables positive and negative management guidance surprises are generated using the classification provided by First Call. Analyst upgrade and downgrade are indicator variables for days on which at least one analyst respectively upgrades and downgrades his recommendation. Credit upgrade and downgrade are equal to one on days when the firm‘s credit rating is respectively upgraded and downgraded by Moody‘s. Positive and negative watch are indicator variables for days on which the firm is put on positive and negative watch respectively by Moody‘s. Bond issuance is equal to one on dates when debt is issued by the firm, and FOMC is equal to one on days when the Federal Open Market Committee announces a rate decision.

Panel A : Proportion of Jumps

	Non-Parametric	Gaussian	Exponential
All jumps	0.0264	0.0314	0.0195
Only positive jumps	0.0157	0.0223	0.0195
Only negative jumps	0.0107	0.0090	-

Panel B: Joint Detection of Jumps

	Joint Occurrence with Gaussian	Joint Occurrence with Exponential (Positive Jumps)
Non-parametric	0.9617	0.9687
Gaussian	-	0.9879

Table 10: **Parametric Jump Detection**: We present jump detection results for the non-parametric and the two parametric methods considered. To estimate the parametric models, we restrict our sample to 59 firms for which there are no gaps in the CDS data. We consider two parametric cases, where jumps in the risk-neutral instantaneous default intensity are assumed to follow the normal and exponential distributions respectively. The latter specification allows only for positive jumps. As the parametric methods also permit multiple jumps per day, we construct an indicator variable for jumps that is one when the filtered number of jumps is higher than 0.99. Panel A shows the different proportion for positive, negative, and all jumps. Panel B examines if detected jumps fall on the same day for the different methodologies. For each method in the first column, we compute the proportion of jumps detected that are also detected by the other method.