

MS&E 444
Investment Practice
A finance project class.

Team 5 presents

*The Implication of
Merger & Acquisition
Activity
On
Credit Default Swap
Spreads*

7 June, 2011.

Table of Contents

<i>Table of Contents.....</i>	<i>2</i>
<i>1. Introduction and Overview.....</i>	<i>4</i>
<i>2. Hypothesis.....</i>	<i>4</i>
<i>3. Methodology.....</i>	<i>5</i>
<i>3.1 Data Collection.....</i>	<i>5</i>
<i>4 The Autoregression Model</i>	<i>6</i>
<i>4.1 Relationship between CDS and Equity.....</i>	<i>6</i>
<i>4.2 Does CDS move more than that predicted by equity?.....</i>	<i>9</i>
<i>5 Jump Behavior</i>	<i>9</i>
<i>5.1. Characterizing the Distribution of Jump Sizes in Equity Prices and CDS Spreads around M&A Activity.....</i>	<i>10</i>
<i>5.2 Searching for Evidence of Pre-Announcement Rumors in CDS Spreads.....</i>	<i>19</i>
<i>5.3. Characterizing Changes in the Jump Behavior of CDS Spreads Between Pre- and Post-Announcement Periods.....</i>	<i>23</i>
<i>6 CDS Mean Reversion</i>	<i>24</i>
<i>6.1. The Cox-Ingersoll-Ross (CIR) Process for Time Series Modeling.....</i>	<i>24</i>
<i>6.1.1 CIR process densities.....</i>	<i>25</i>
<i>6.2. Maximum Likelihood Implementation in MATLAB.....</i>	<i>25</i>
<i>6.2.1 Likelihood function.....</i>	<i>25</i>
<i>6.2.2 Initial estimates.....</i>	<i>26</i>
<i>6.2.3 Implementing the log-likelihood function using the command besseli.....</i>	<i>26</i>
<i>6.2.4 Optimization.....</i>	<i>27</i>
<i>6.3. CIR Model Results.....</i>	<i>27</i>
<i>7 Trading Strategies.....</i>	<i>28</i>
<i>7.1 Volatility strategies</i>	<i>28</i>
<i>7.2 Option Replication</i>	<i>29</i>
<i>8 Conclusion & Future Research.....</i>	<i>29</i>

Appendices:.....29

List of companies used in this study30

Matlab Code™.....31

Mean Reversion Analysis.....31

Initpar.m.....31

Loglike.m.....32

Clean_Data1.m.....32

Jump Statistic.....33

Bivariate Sorting of jumps into Bins.....37

Calculations of jump sizes by alternative definition.....37

Calculation of Jump Sizes.....38

Calculating L Statistics.....39

Sort Jumps into Bins.....40

Counting L Statistics.....42

List of references42

1. Introduction and Overview

In this paper, we examine and analyse the implications of merger & acquisition (M&A) activity on the credit spreads of firms that are potentially being acquired. Because credit and equity markets are highly interconnected in modern finance, we also investigate equity data for the same firms and compare their movements against the CDS' movements.

We study the change of dynamics in CDS spreads and equity prices in a neighbourhood of ± 60 days around each M&A announcement date. (The announcement date, not the transaction completion date, is the date when most of the movement takes place, since markets move on information.)

To accomplish our analysis, we first construct an autoregression model on the CDS movements to characterize their dynamics. Next, we examine the jump behaviour of CDS and equity prices, in order to quantify the distribution of jump sizes in both markets and the interrelationships between them. We use a Cox-Ingersoll-Ross (CIR) process and log-likelihood estimators to investigate mean reversion in the credit spreads.

Lastly, we attempt to create a trading strategy based on our collective findings. Because we used M&A data collected up to the present day, we do not have an unbiased data sample to test our strategies on. Therefore, instead of providing backtest results, we only point future researchers in a direction for further research.

2. Hypothesis

As we knew from the project brief, our primary aim concerned the implications of different M&A situations, especially LBOs, upon the credit market. As a result, we decided that prior to data collection and analysis, it would be prudent to formulate a number of hypotheses that we would test over the course of our project.

Our hypothesis was thus threefold:

- To test the possibility that announcements of M&A activity would lead to a statistically significant “jump” in credit markets for the acquisition target firm. This approach was determined to be testable by the use of “jump statistics” that would allow us to monitor the magnitude of jumps around the announcement date. We also aimed to test the “jump behavior” of credit markets both before and after the announcement date. This hypothesis was tested upon both LBO and non-LBO data.*
- We believe that the existence of such jumps is not purely a result of the well-established implications of merger activity upon equity markets, which in turn has been proven to lead to significant changes in target firm's credit. The use of a literature review as well as mean reversion and jump statistic calculation would be used to validate this hypothesis. In order to ensure that jumps in CDS and equity were statistically significant, we controlled their percentage changes on the VIX volatility index's percentage changes over the same time period. (The Chicago*

Board Options Exchange Market Volatility Index, ticker symbol “VIX,” is a popular measure of the implied volatility of S&P 500 index options.)

- We believe that our findings would enable us to formulate a basic trading strategy, most likely involving arbitrage on the price differentials between the changes in the equity and credit markets of the target firms.

3. Methodology

3.1 Data Collection

In approaching this project we realised that there was a need for an amply-sized and accurate database of M&A transactions upon which we could run a number of statistical analyses. As it is evident that our project’s success would be contingent upon the sourcing and creation of such a database, we came up with a multi-part strategy to collect data. In order to have sufficient data to establish all three hypotheses, it would be necessary for us to collect CDS, equity, and VIX data for each acquired firm within ± 60 days around the M&A’s announcement date. Additional data was collected for each M&A event, including the number of shares outstanding, announced deal value, and market capitalization. Unfortunately, we were not able to find complete, error-free information on the type of transaction (all-cash, all-stock) or market sector (technology, energy, healthcare, etc.) for each M&A, so we split our analyses by LBO and non-LBO.

Our data collection strategy was as follows:

1. Find potential sources of data
2. Collect data sample from each source
3. Analyse collected sample data upon three main criteria: accuracy, accessibility and diversity.
4. Choose data source based upon the ranking of main criteria

We found that the Bloomberg terminals contained the most extensive database of M&A transactions that we could easily access. However, through our manual inspection of downloaded Bloomberg data, we discovered numerous errors, including the miscategorisation of non-LBO transactions as LBOs, incorrect or outdated information on the current statuses of the transactions, as well as numerical inconsistencies (e.g. the number of outstanding shares multiplied by the equity price conflicts with the given market capitalisation on the same date.). There was also a significant hurdle to data collection as a result of Bloomberg’s inconsistent “Ticker Retirement” policy, whereby the completion of an M&A transaction would invalidate the ticker symbols used by the acquired firms and lead to a potential deletion of all associated data:¹

¹ We continually attempted to liaise with the Bloomberg help desk to create a help “ticket” that could be elevated to a department that would be able to recover the data or provide us with the identifiers. Although this was not possible a special thanks must go to all of the Bloomberg help desk who assisted us with all queries, especially Wilson Chau.

“ BLOOMBERG™ HELP DESK : Some securities were acquired and we do not store data, some others do. There's no general rule of thumb, it just depends on the specific security itself”

We chose our data collection parameters to ensure that the data could be verified manually and to increase the likelihood of obtaining liquid CDS and equity data. Because LBOs started gaining prominence during the 2005-2007 period, this was the ideal period to collect LBO data from. In contrast, we collected non-LBO data from a much larger date range: 2005-2011 (present). We only considered firms with market capitalizations of at least US \$1 billion prior to the M&A announcement, to ensure that they were of sufficient size and notability to have published verifiable data, as well as significant debt to yield liquid CDS data. To limit the number of external factors that could be affecting our data, as well as ensuring compatibility with VIX data, we only gathered information on public companies listed on at least one US equity index.

Because information on historical LBOs was scant, we were only able to collect complete datasets (CDS, equity, VIX) for 19 transactions.

Once the data collection of M&A transactions was complete, we laid out three coherent statistical approaches that would allow us to best address the hypotheses established. Each of the approaches is explained theoretically in their respective sections below.

Reflecting back on our progress, our most significant difficulties with this project included

1. The lack of background information and existing research pertaining to our topic – we had librarians from the GSB’s Jackson Library look for academic literature (journals, conference papers, etc.) on our topic, and they were unable to find any;
2. The difficulty in finding accurate and complete data, especially for leveraged buyouts, leading to a small sample size;
3. The broad scope and open-ended nature of the project. In the end, we had to make some cuts and define some boundaries to ensure that we could feasibly meet our objectives within the academic quarter.

4 The Autoregression Model

4.1 Relationship between CDS and Equity

Our preliminary analysis began by exploring the relationship between CDS and Equity. Existing papers by Berndt et al. and Bystrom (2005) suggest that empirically, CDS movements, unlike stock movements, show autocorrelation as indicated by the Ljung-Box test. Thus, one can find a model for CDS values at time t by regressing CDS movements on CDS values of prior days, and equity values of prior days and on day t .

To empirically verify the number of lag days needed to best model the sample, we ran a test to calculate the optimal coefficients for an equation of the form

$$r_{CDS,t} = a_0 + a_1 r_{CDS,t-1} + a_2 r_{EQ,t-1} + a_3 r_{EQ,t-2} + a_4 r_{CDS,t-2} + a_5 r_{CDS,t-3} + a_6 r_{EQ,t-3} + \dots + a_{m-2} r_{EQ,t} + a_{m-1} r_{CDS,t} + a_m r_{EQ,t} + e_t$$

The Implications of M&A Activity on CDS Spreads

7 June 2011

where

$r_{CDS,t}$ is the change in CDS on day t given by $\frac{CDS_t - CDS_{t-1}}{CDS_{t-1}}$

a_m is the best fit coefficient

$r_{EQ,t}$ is the change in CDS on day t given by $\frac{EQ_t - EQ_{t-1}}{EQ_{t-1}}$

e_t is the error term/residual

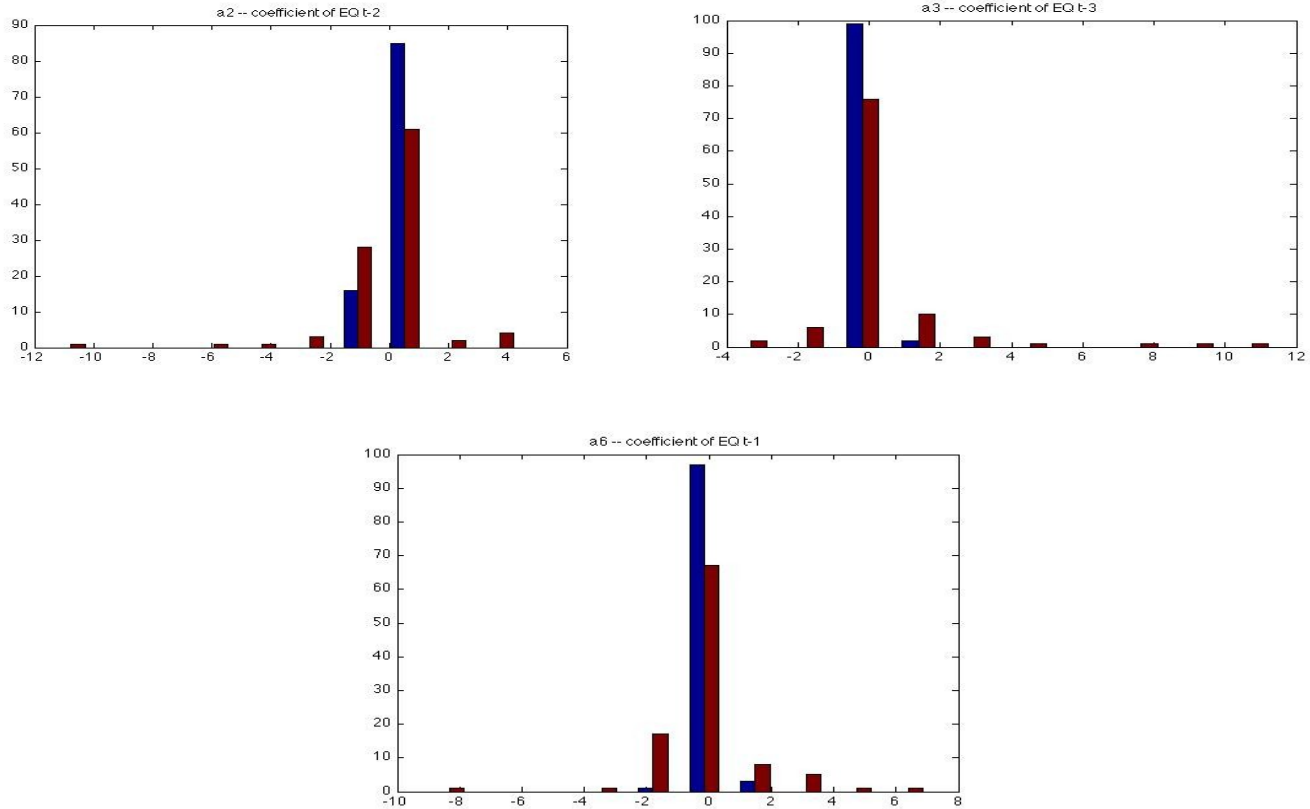
We vary the model to compute R^2 values for different number of lagged trading days considered. We start with a lag of 1 trading day and move back to 7 trading days. We find the highest average R^2 values for 3 lagged days. Our computation leads to the following autoregression formula for predicting CDS changes:

$$r_{CDS,t} = a_0 + a_1 r_{CDS,t-3} + a_2 r_{EQ,t-2} + a_3 r_{EQ,t-3} + a_4 r_{CDS,t-2} + a_5 r_{CDS,t-1} + a_6 r_{EQ,t-1} + a_7 r_{EQ,t} + e_t$$

Once we have established the three-day lagged window, we divide our data into 60 samples before the announcement date and 60 samples after that announcement date. We then compute the values of the coefficients a_0 through a_7 for each company in our data set.

Analysing the values of the coefficients for both pre-announcement and post-announcement, we assess the biggest determinants of $r_{CDS,t}$.

Figure 4.1.1: Plots of a_2 , a_6 , and a_3



In the histograms, blue bars represent values of the coefficient pre-announcement, while red bars represent the values post-announcement.

Analysing these values, we find that for pre-announcement, a_6 has the largest values (on average twice as large as the next largest coefficient). Thus pre-announcement, CDS lags equity by a day.

For post-announcement data, we find that the most significant factors are a_2 and a_3 . Thus, post-announcement, CDS begins lagging equity by more than 2 days.

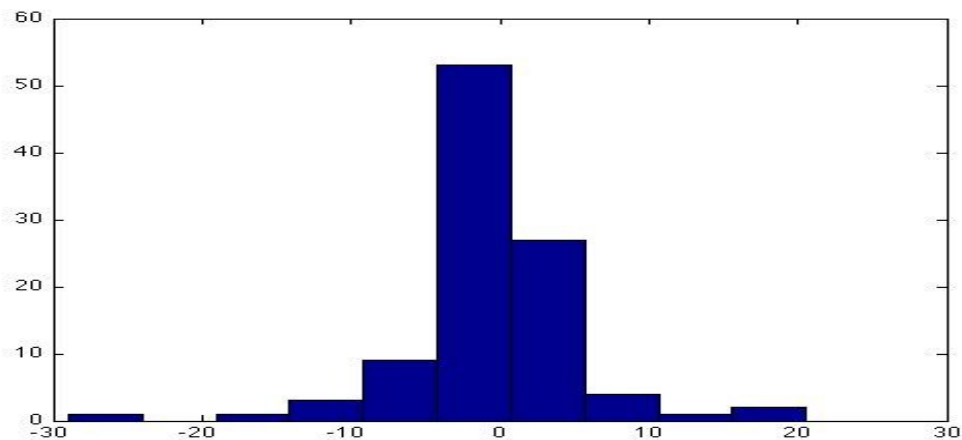
Table 4.1.1: Average values of the coefficients

a0	0.23015189	0.165770828	constant
a1	-0.0074978	0.040591245	CDS t-3
a2	-0.0366759	-0.205444947	EQ t-2
a3	0.00491337	0.26958496	EQ t-3
a4	0.01026909	-0.004764836	CDS t-2
a5	0.05155658	0.030636641	CDS t-1
a6	-0.1155763	-0.091876433	EQ t-1
a7	-0.045698	-0.324184015	EQ t
r2	0.27612052	0.251020755	

4.2 Does CDS move more than that predicted by equity?

Based on our above analysis, we see that for both pre- and post-announcement, CDS movements lag equity moves. We now attempt to extrapolate our pre-announcement values for a_0 through a_7 , and attempt to see that if we did not recalculate these values for best fit, how accurately could our initial model predict the CDS values post-announcement. Through this analysis we attempt to answer the question whether CDS movements could solely be explained by equity movements in an M&A scenario, or is there an additional movement we have to model.

We extrapolated our initial model, and for each company in our data set, we calculated the percentage difference between the actual CDS value 60 days after the announcement and the value as predicted by our initial pre-announcement model

Table 4.1.2: Histogram of percentage difference between realized CDS value and that predicted by pre-announcement CDS model

We see that the model does not change dramatically after the announcement, and for approximately 96% of the sample, the realized CDS values are within 10% of those predicted by the model.

However, for ~75% of the sample, the percentage changes are negative, reflecting that the realized CDS values are generally lower than those predicted by the model.

5 Jump Behavior

For the purposes of this part of our analysis, we handle missing data as follows. We define a run of missing values as a series of consecutive dates for which the relevant time series does not have valid data values. If such a run begins on the first date in the time series, we set all missing values in the run to the value of the first non-missing value in the series. For runs occurring between valid data values, we perform a linear interpolation between the valid data values that are on either side of the run. If the run goes through the end of the time series, then all missing values are set to the last valid data value.

5.1. Characterizing the Distribution of Jump Sizes in Equity Prices and CDS Spreads around M&A Activity

For the purposes of characterizing the probability distribution of CDS spread moves triggered by the announcement of an M&A transaction, we first calculate the empirical distribution of such jump sizes for both target firms involved in LBO M&A activity and those involved in non-LBO M&A activity separately; then, we calculate empirical jump-size distributions for groups of deals (both LBO and non-LBO) with values of the probability of deal success as implied by the equity market (to be defined below) within the same range. We perform the same analysis for the equity of the firms in our sample, splitting the analysis along the same lines. We conduct this analysis for a simple definition of the jump size triggered by announcement, i.e. the jump experienced by the firm on the announcement day only. Then, we conduct the analysis for a more sophisticated measure of the jump size triggered by announcement, which attempts to capture the moves in spreads that are attributable to the announcement over a longer period. Specifically, the procedure is as follows (for a sample of N firms):

1. Calculate the set of jump sizes, i.e. calculate the jump size $J^{(i)}$ for firm $i, i = 1, \dots, N$. The first approach used, corresponding to calculating the jump size on the announcement day only, is calculated from

$$J_{AD,CDS}^{(i)} = \frac{C_{AD}^{(i)}}{\sigma_{C^{(i)}}} + \frac{VIX_{AD}}{\sigma_{VIX}}$$

where $C_{AD}^{(i)} = \frac{S_{AD}^{(i)} - S_{AD-1}^{(i)}}{S_{AD-1}^{(i)}}$ is the simple percentage change in the variable of interest $S^{(i)}$ (e.g. CDS spread or equity price) from the day before announcement day to announcement day, and $\sigma_{C^{(i)}}$ is the empirical standard deviation of these one-day percentage changes in the variable $S^{(i)}$ over the date range from sixty days prior to announcement day to announcement day. Analogous definitions apply to VIX_{AD} and σ_{VIX} . This definition of the jump sizes attempts to control for the level of volatility in the market on the date in question; that is, it attempts to separate the effect of the announcement from the effect of market volatility on the jump size being calculated. Note that we use C to denote the changes in CDS spreads, and E to denote changes in equity; that is, we also define

$$J_{AD,Eq}^{(i)} = \frac{E_{AD}^{(i)}}{\sigma_{E^{(i)}}} + \frac{VIX_{AD}}{\sigma_{VIX}}$$

The other method considered for calculating the size of the jump caused by the announcement of M&A activity relies on the test statistic $L(i)$, which is used to identify days on which a statistically significant jump in the underlying time series (e.g. CDS spreads or equity prices) occurs (this statistic and the test based on it are described in detail below). Specifically, for each firm in the sample, we begin on announcement day, and find the closest single days t_{pre} and t_{post} to announcement day in both the pre- and post-

announcement periods on which a statistically significant jump is observed. If no such jumps are observed within some specified maximum number of days (denoted MAX_t , and taken to equal 5 in our analysis) before and/or after announcement day, then we set the missing value(s) t_{pre} and/or t_{post} equal to MAX_t . The window over which we define the underlying time series to be experiencing a jump due to the announcement of M&A activity is given by $[t_{pre}, t_{post}]$; note that the announcement day is always within this range, and the length of this window is never more than $2 * MAX_t + 1$ days.

2. With the jump sizes thus calculated (using either method), we next choose the value of the parameter $nBins$ (taken to be 10 for the univariate distributions of jump sizes of both CDS and equity), which gives an even partition of the values calculated for the jump sizes of the N firms. The size of the bins used is given by

$$bin\ size = \frac{\max_{i \leq N} J^{(i)} - \min_{i \leq N} J^{(i)}}{nBins}$$

and the partition generated is given by

$$B_k = \left\{ \min_{i \leq N} J^{(i)} + k * (bin\ size) \right\}_{k=0}^{nBins}$$

Thus, each of the calculated jump sizes $J^{(i)}$ are sorted into the appropriate bin $[B_k, B_{k+1})$ (with $\max_{i \leq N} J^{(i)}$ assigned to bin $[B_{nBins-1}, B_{nBins})$).

3. Last, we count the total number of firms which experienced a jump of size represented by each bin. From this, we can plot a histogram which gives the empirical distribution of jump sizes resulting from the announcement of M&A activity (controlled for the volatility of the overall market during the relevant time period), based on our two definitions of this jump size.

Figure 5.1.1: Firms categorized by size of equity and CDS Jumps

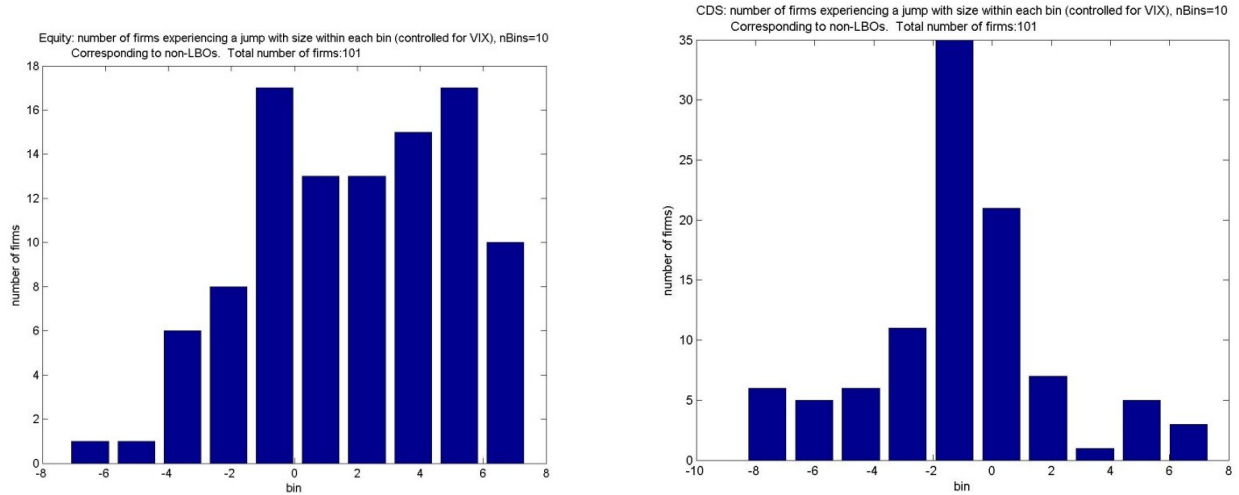


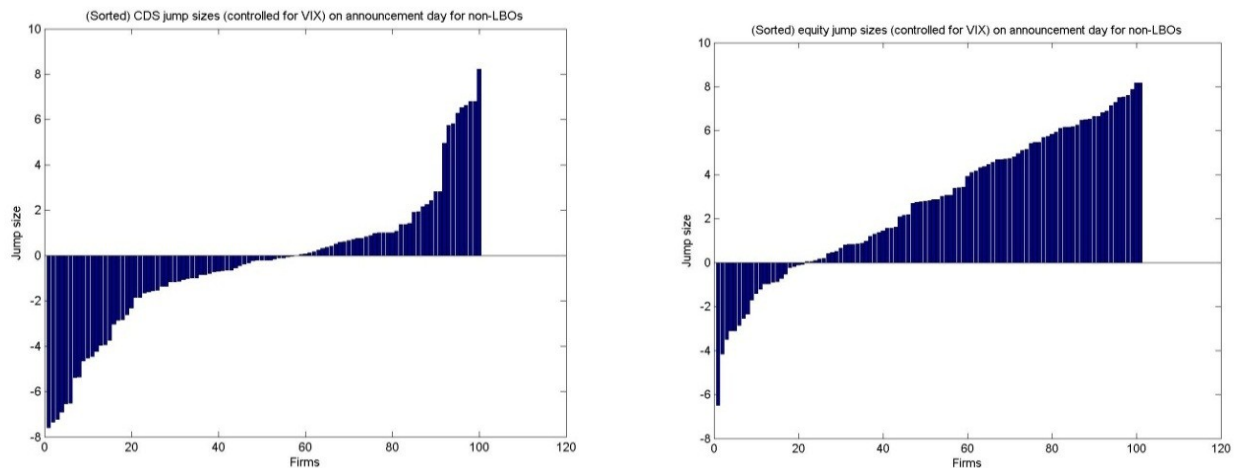
Table 5.1.1: results of carrying out this program

CDS Jumps Bins		Equity Jump Bins	
Bin	Values	Bin	Values
1	[-7.6003, -6.0178)	1	[-6.4870, -5.0218)
2	[-6.0178, -4.4353)	2	[-5.0218, -3.5565)
3	[-4.4353, -2.8527)	3	[-3.5565, -2.0912)
4	[-2.8527, -1.2702)	4	[-2.0912, -0.6260)
5	[-1.2702, 0.3123)	5	[-0.6260, 0.8393)
6	[0.3123, 1.8948)	6	[0.8393, 2.3046)
7	[1.8948, 3.4773)	7	[2.3046, 3.7699)
8	[3.4773, 5.0599)	8	[3.7699, 5.2351)
9	[5.0599, 6.6424)	9	[5.2351, 6.7004)
10	[6.6424, 8.2249)	10	[6.7004, 8.1657)

As we can see from the preceding analysis, the distribution of jump sizes in CDS spreads triggered by the announcement of potential (non-LBO) M&A activity (using the first definition of the jump size described above) is somewhat symmetric about zero, but places

more density on negative jumps in spreads. This is in contrast to the corresponding empirical distribution of the firms' equity, which is clearly (and unsurprisingly) skewed towards sizable positive jumps. We note as well that the empirical distribution of CDS spread moves is tighter than the corresponding distribution of equity moves, for firms involved in non-LBO events. These observations are further illustrated in the figures below, which show the sizes of the jumps on announcement day (controlled for market volatility) for each firm in the non-LBO sample:

Figure 5.1.2: CDS and Equity jump sizes on announcement day for non-LBOs



The fact that we do not observe a significant tendency of CDS spreads to jump upwards upon announcement of a non-LBO event is perhaps not too counterintuitive, as it seems reasonable that the announcement of a non-LBO event (as opposed to an LBO event, which often foreshadows a significantly larger amount of debt within the capital structure of the target firm and thus a potentially higher probability of default) should not necessarily always imply “bad news” for holders to the firm’s debt instruments. This is because the positive aspects of a merger (e.g. increased efficiency of the combined entity, better profit margins or competitive posture, synergistic gains, etc.) in a non-LBO situation may work to effectively make the target firm’s debt less risky, while in an LBO situation these positive effects may be overshadowed by the increased debt load.

Of course, in our analysis of jump sizes around the announcement of an LBO event (calculated using the first definition of the jump size), we do expect to see mostly positive jump in CDS spreads of the target company for these very reasons. The corresponding empirical distributions for the CDS spreads and equity prices for the sample of firms targeted in LBO events appear below:

Table 5.1.2 & Figure 5.1.3: LBOs categorized by size of CDS Jumps

Bin	Values
1	[-3.3811, -1.1226)
2	[-1.1226, 1.1359)
3	[1.1359, 3.3944)
4	[3.3944, 5.6529)
5	[5.6529, 7.9114)

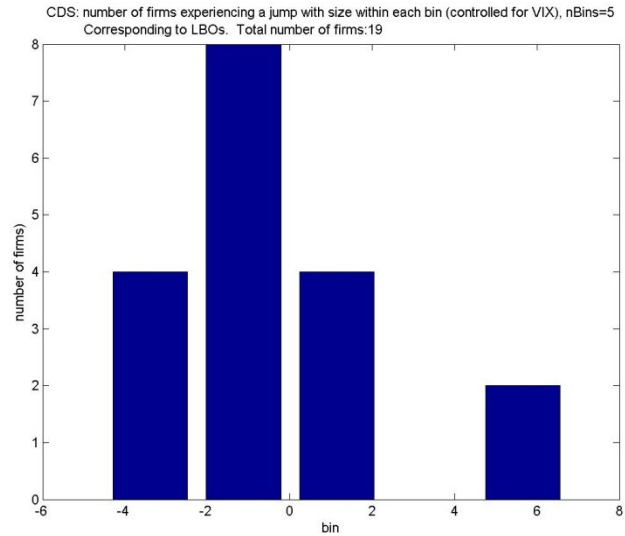
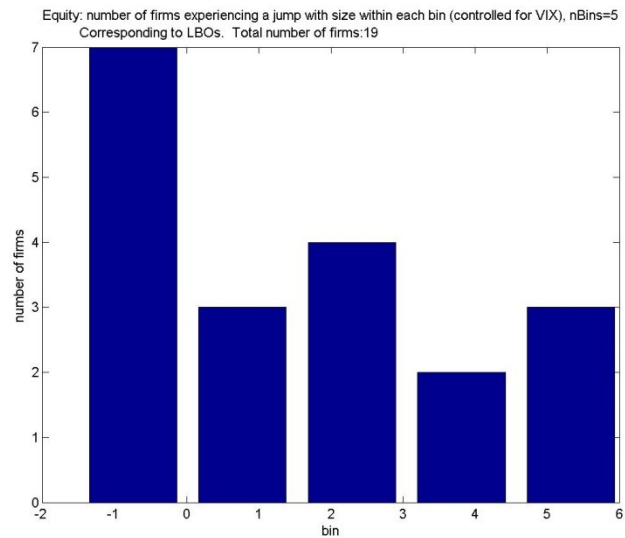


Table 5.1.3 & Figure 5.1.4: LBOs categorized by size of equity Jumps

Bin	Values
1	[-0.7466, 0.7724)
2	[0.7724, 2.2914)
3	[2.2914, 3.8103)
4	[3.8103, 5.3293)
5	[5.3293, 6.8483)



For firms that are targets of LBO activity, our expectations mentioned above are confirmed, at least partially; that is, we see the majority of the density of the empirical distribution of CDS spread jumps on small-absolute-magnitude jumps or positive jumps. This is perhaps better seen by looking at the actual jump sizes themselves:

Figure 5.1.5: Univariate jump-size distributions for CDS and equity

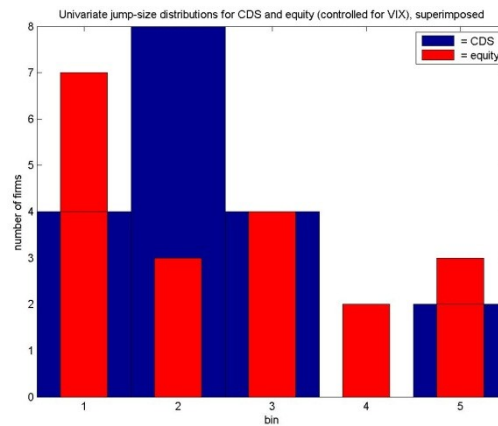
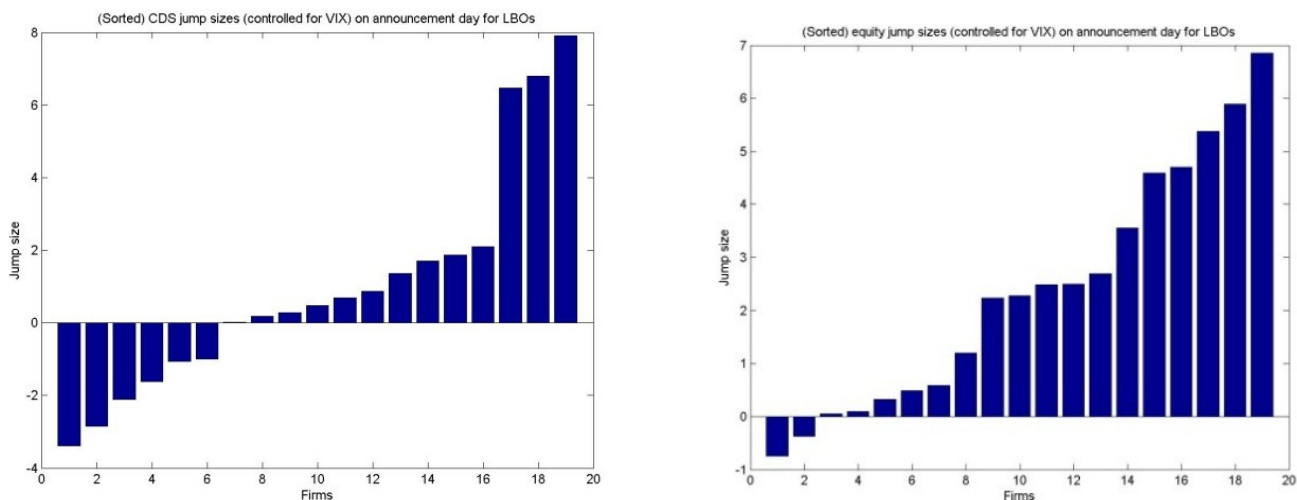


Figure 5.1.6: Sorted CDS and Equity jump sizes on announcement day for non-LBOs

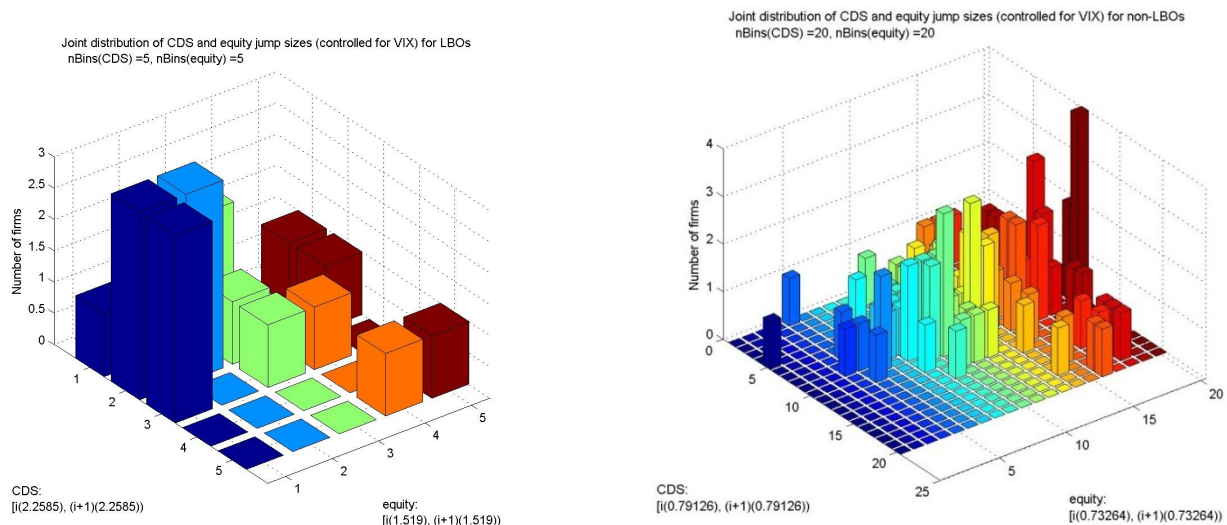


We see approximately two-thirds of the firms in the LBO sample experiencing positive jumps in their CDS spreads as a result of the announcement of LBO activity (using the first definition of jump size), as opposed to less than half of the firms in the non-LBO sample which experienced positive jumps in CDS spreads. These results are in line with our intuitions that deal type (e.g. LBO or non-LBO) makes a large difference in the behavior of CDS spreads around the announcement of M&A activity. It should be noted that the rather small sample of LBOs studied here (which consists of nineteen deals) makes it difficult to make definitive statements about the empirical jump-size distributions of CDS and equity. We therefore consider the “take-away point” of this aspect of the analysis to be the fact that firms involved in LBOs are more likely to experience positive jumps than those involved in non-LBO’s, even if our results do not give a definitive measurement as to how much more likely this is.

Figure 5.1.5: Joint distribution of CDS and equity jump sizes for both LBOs and non LBOs

The Implications of M&A Activity on CDS Spreads

7 June 2011



During the course of our analysis, we also computed the joint distribution of CDS and equity jump sizes (using the first definition of jump size) surrounding the announcement of both LBO and non-LBO activity. These results appear above in Figure 5.1.5.

Figure 5.1.5 indicates the number of firms in the non-LBO sample experiencing a jump in CDS spread of size within bin i and in equity of size within bin j . In the figure, we can clearly see the skew present in the distribution of equity jumps towards larger values, along with the propensity of jumps in CDS spreads to be near zero.

For the sample of firms involved in LBO situations, the joint distribution calculated using 5 bins for both CDs and equity does not show much; with a larger sample we would expect to see more density on the lower-right corner of the distribution, corresponding to large observed jump sizes for both CDS spreads and equity. We do not observe this here, which is an artifact of the way the bins are calculated.

As mentioned above, we also look at an alternative definition of the jump size surrounding the announcement of M&A activity, which attempts to be more sophisticated than the simple announcement-day holding period return used in the analysis above by defining a time window – over which the firm is assumed to be experiencing irregular changes in CDS spreads or equity as a result of the announcement. Unfortunately, our results using this alternative definition of the jump size are not very illuminating; we attempted to characterize the jump-size distributions using this alternative jump-size definition similarly to how we did above, but found the disparity in jump size estimates to be wide, with a large number of outliers. Therefore, we do not include the empirical distributions found with this method here.

This represents an avenue for future research in this area; specifically, looking at how to characterize what constitutes a jump resulting from the announcement of M&A activity. The alternative definition of the jump proposed above has the benefit of being able to change the parameter MAX_t depending on whether one is studying CDS or equity, or even of setting different parameters

MAX_t^{pre} and MAX_t^{post} for the pre- and post-announcement periods, respectively, (which one might do according to the observation that CDS spreads are “jumpier” post-announcement while equity is “jumpier” pre-announcement). Its chief drawback is that it is still a very rudimentary measure of the actual jump size experienced by the underlying time series as a result of the event in question.

We perform a similar analysis for samples of firms characterized by a high probability of deal success implied by the equity market and a low probability of success.

We characterize the empirical distribution of the jump size in CDS and equity according the probability of deal success implied by the equity market, which is defined as follows. Define S to be the net deal spread, T the current target price, B the expected deal-break price (calculated as described below), then the probability of deal success p is given by:

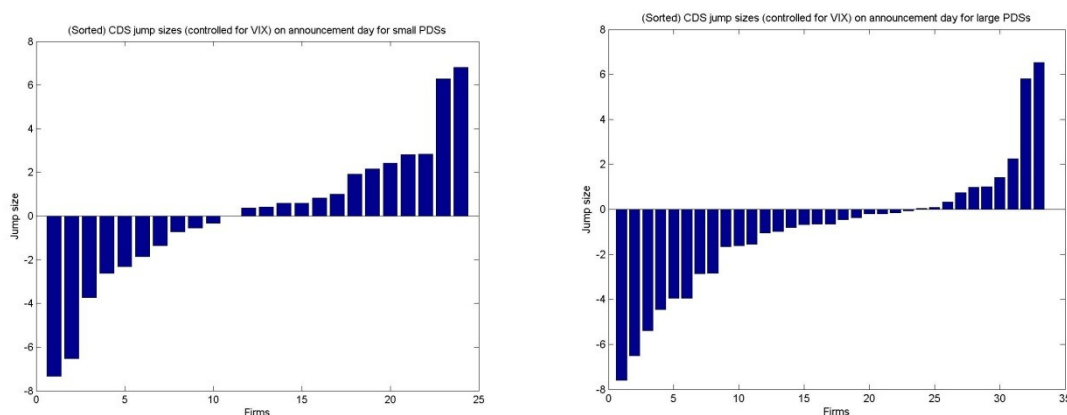
$$P = (T - B) / (S + (T - B))$$

To calculate the expected deal-break price B , we first fit a CIR model to the equity data from the beginning of the sample to five days before announcement. When then use the fitted models to predict where the equity of each firm would have been five days hence (i.e. on announcement day) had the announcement never occurred. In this way, the deal break price is assumed to be the value of the equity in the absence of the announcement of M&A activity.

Using these calculated values for the deal break price, we proceed to calculate the probability of deal success implied by the equity market. This is a valid probability (i.e. is in $[0,1]$) if the net deal spread and the loss in the event of break are both positive, as we expect them to be. From our overall sample of 101 LBOs, we find about sixty firms (from the non-LBO sample only) with a valid probability of deal success (since for some firms, these condition on the net deal spread and/or the loss in the event of break are not met).

We then divide this sample of firms with valid probabilities into three groups: high probability deals, middle probability deals, and low probability deals. The results of characterizing separately the empirical distributions of the jump sizes in CDS and equity appear below:

Figure 5.1.6: Sorted jump sizes on announcement date for different probability of deal successes

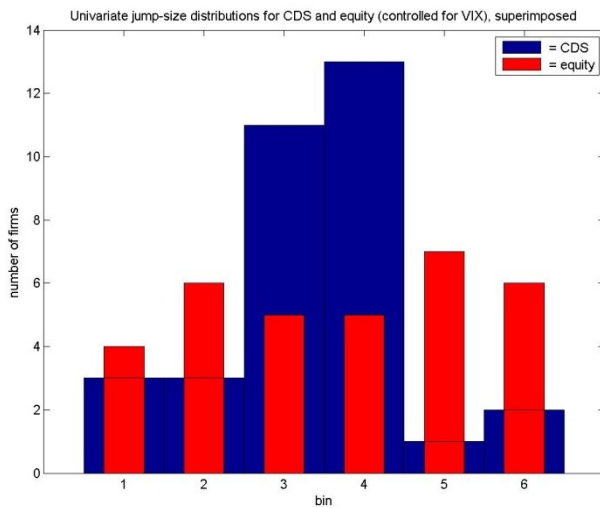


An interesting thing to note in regards to the above results is that a larger proportion of deals with a large probability of success (roughly 75% of our sample) experience negative jumps in CDS spreads on announcement day, compared with deals with small probability of success (less than 50% of which experience such negative jumps). We interpret this as providing evidence that the CDS

market views the announcement of (non-LBO) M&A activity as good news; that is, deals that are viewed as having a higher probability of completion cause negative jumps in CDS spreads more often.

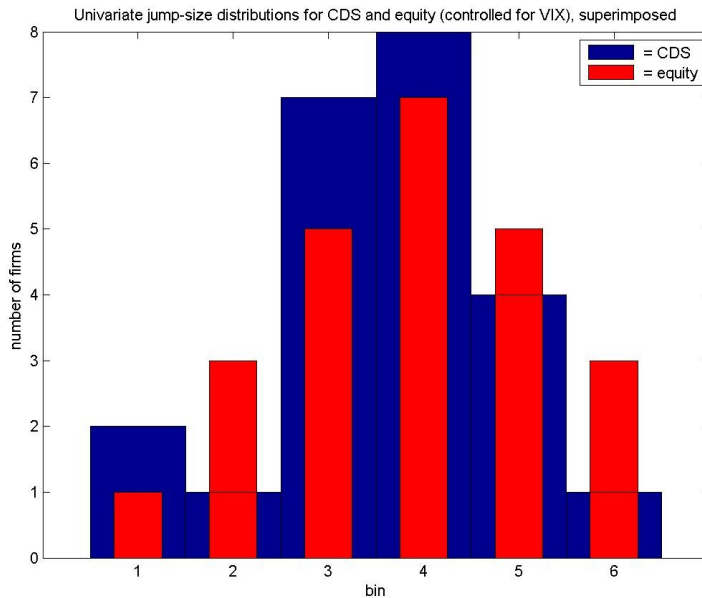
Large Probability of Deal Success ($P > 0.5$)

Figure 5.1.7: Univariate jump-size distributions of CDS and equity



Bin	CDS	Equity
1	[-7.6003, -5.2462)	[-3.1043, -1.2260)
2	[-5.2462, -2.8921)	[-1.2260, 0.6524)
3	[-2.8921, -0.5379)	[0.6524, 2.5307)
4	[-0.5379, 1.8162)	[2.5307, 4.4090)
5	[1.8162, 4.1703)	[4.4090, 6.2874)
6	[4.1703, 6.5244)	[6.2874, 8.1657)

Small Probability of Deal Success ($P < .5$)



Bin	CDS	Equity
1	[-7.3402, -4.9829)	[-3.0911, -1.2644)
2	[-4.9829, -2.6255)	[-1.2644, 0.5623)
3	[-2.6255, -0.2682]	[0.5623, 2.3890)
4	[-0.2682, 2.0892)	[2.3890, 4.2157)
5	[2.0892, 4.4466)	[4.2157, 6.0424)
6	[4.4466, 6.8039)	[6.0424, 7.8691)

5.2 Searching for Evidence of Pre-Announcement Rumors in CDS Spreads

A further part of our analysis was to look for evidence of rumors or speculation regarding the possibility of M&A activity in CDS spreads. In order to do this we employ a non-parametric statistical test designed to ascertain whether a significant jump has occurred in a financial time series on a specific date, as described in [2]. Specifically, this test is based on the intuition that if the realized return observed in the time series of interest (which we assume evolves continuously in time) on date t is large compared to its instantaneous volatility on date t (i.e. their ratio is large), then we take this to imply that a significant jump in the time series has occurred on this date t .

In order to use this intuition to develop a test statistic that can be used to test the null hypothesis that a significant jump does NOT occur on a given date t (as done in [2]), it is necessary to first estimate this instantaneous volatility. One estimate given in [8], which is consistent even in the presence of jumps in the underlying time series $S(t)$, is the realized bipower variation, defined by

$$plim_{n \rightarrow \infty} \sum_{i=3}^n |\log(S(t_i)) - \log(S(t_{i-1}))| |\log(S(t_{i-1})) - \log(S(t_{i-2}))|$$

As described in [8], the test we perform of the null hypothesis that no significant jump has occurred in the time series on date t_i , i.e. which tests on date t_i the null hypothesis that no jump has occurred from dates t_{i-1} to t_i , is based on the test statistic $L(i)$, given by

$$L(i) = \frac{\log(S(t_i)) / \log(S(t_{i-1}))}{\widehat{\sigma}(t_i)}$$

where

$$\widehat{\sigma}(t_i) = \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} |\log(S(t_j)/S(t_{j-1}))| |\log(S(t_{j-1})/S(t_{j-2}))|$$

and K is a parameter specifying the window size over which the instantaneous volatility of the time series $S(t)$ is estimated (which we set to be 20 in our analysis).

From [8], we have that (under the null hypothesis that no significant jump occurs between dates t_{i-1} and t_i), the test statistic $L(i)$ is distributed as $\frac{Z}{c}$ where $Z \sim \text{Gaussian}(0,1)$ and $c = \sqrt{2/\pi}$. Thus, the null hypothesis is rejected for large (absolute) values of $L(i)$, i.e. those falling in the tails of a $\text{Gaussian}(0,1/c^2)$ distribution.

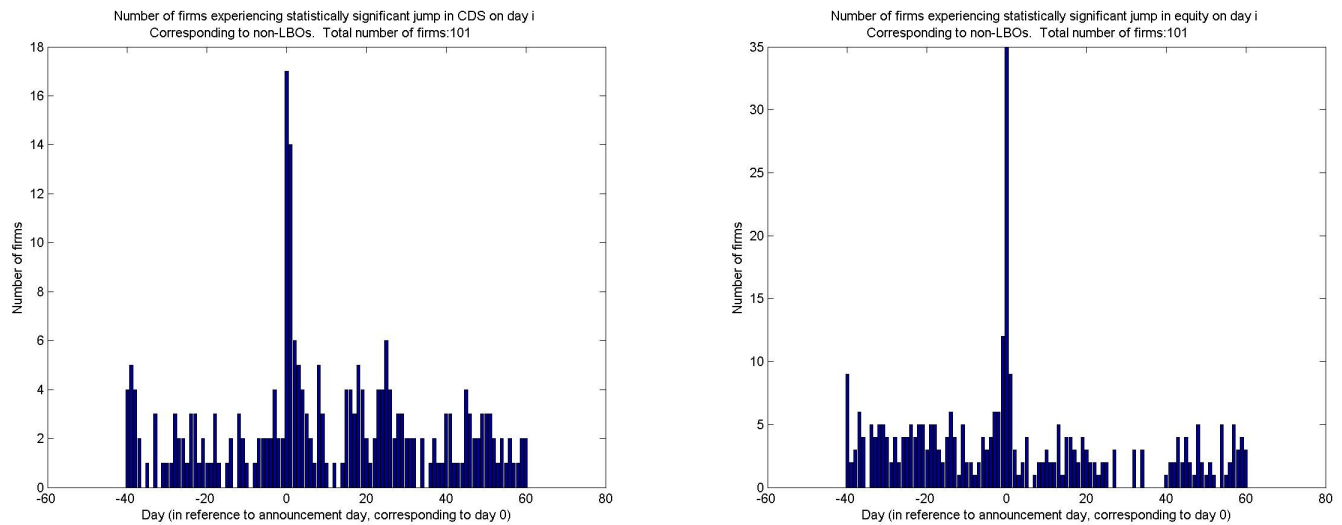
We should note that the statistical test based on these results is discussed in [8] in reference to high-frequency data, that is for values of $\Delta t = t_{i+1} - t_i$ on the order of minutes. The CDS and equity time series that we consider here consist of daily data. This discrepancy is important to understand when we use the asymptotic results regarding the test statistic $L(i)$ described in [2] to specifically accept or reject the null hypothesis under consideration. While this is clearly an important consideration, we feel that our analysis, which relies on calculating $L(i)$ for each date over the period before and after the announcement of M&A activity and using large (absolute) values of $L(i)$ as indicators of significant jumps, makes up for its lack of mathematical rigor by providing a practical way of defining and studying significant jumps in the underlying time series.

The findings we present regarding evidence of pre-announcement rumors on CDS spreads appear below:

Figure 5.2.1: Non-LBO firms experiencing significant jump in equity and CDS on day after announcement date

The Implications of M&A Activity on CDS Spreads

7 June 2011



In the plots above (which indicates the number of firms in the non-LBO sample that experience a statistically significant jump in equity on date t , with t going from forty days prior to announcement day to sixty days after), it is apparent that the equity of firms which are the target of (non-LBO) M&A activity experiences more significant jumps before announcement day than after. Indeed, the equity of the firms in the non-LBO sample experience more significant jumps than do the corresponding over the entire period studied (which is clear from looking at the vertical axes of the two plots). This provides evidence of rumors and speculation regarding impending merger announcements being a large source of irregular price movements in the equity of target firms in the period prior to the actual announcement. As mentioned above, the presence of such rumors and their effects within the equity market are well documented.

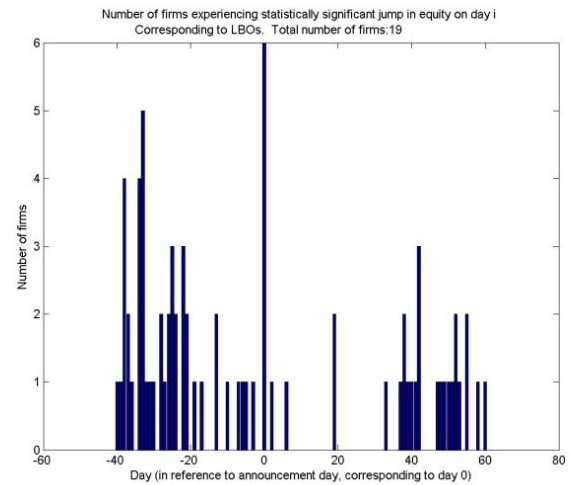
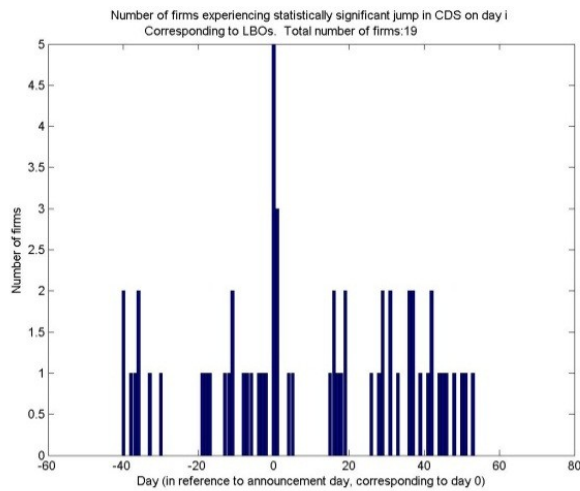
Our results suggest that the opposite is true for CDS spreads (of firms that are the target of non-LBO M&A activity); that is, we observe that CDS spreads experience fewer statistically significant jumps in the period prior to announcement as compared with the period after announcement. We interpret this as evidence that the CDS market is not as susceptible to rumors as is the equity market. Below, we will observe the differences in findings between target firms involved in LBO and non-LBO announcements, as it is intuitive that firms involved in LBO activity may experience more “jumpiness” before announcement day than those involved in non-LBO activity, inasmuch as CDS investors are more wary of the increased debt burden and associated higher probability of default that comes hand-in-hand with LBO activity. We will have more to say regarding the use of the test statistic $L(i)$ in looking for evidence of pre-announcement rumors below, when we use it to characterize the changes in jump behavior of the underlying CDS and equity time series between the pre-announcement and post-announcement periods.

For the LBO sample, the corresponding plots appear below:

Figure 5.2.1: LBO firms experiencing significant jump in equity and CDS on day after announcement date

The Implications of M&A Activity on CDS Spreads

7 June 2011



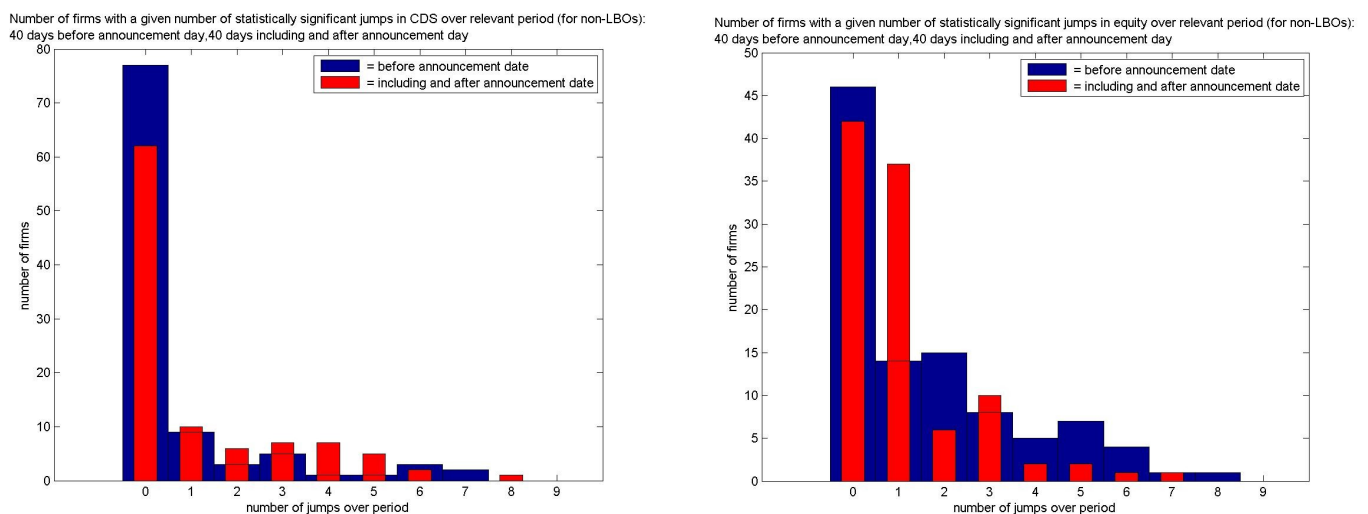
Looking at the plots above, the most apparent observation is that the equity of the firms in the LBO sample experience much fewer statistically significant jumps post-announcement than they did pre-announcement. As discussed above, we interpret this as evidence of rumors or speculation within the equity market regarding the M&A announcement, and the results here are similar to those for the non-LBO sample reported above.

The CDS spreads of the firms in the LBO sample, while appearing to experience perhaps a few more jumps post-announcement compared with pre-announcement (which is similar to the results reported above for the non-LBO sample), do not appear to experience more jumps during the pre-announcement period than their non-LBO counterparts as conjectured. Perhaps this is due to our small sample size of LBOs, or perhaps it is due to a genuine inefficiency in the CDS market (by which the rumors of M&A activity (specifically LBO activity) observed in the equity market are not accurately reflected in the CDS market). Indeed, we find it more surprising to observe this discrepancy between equity “jumpiness” and CDS “jumpiness” for LBOs than for non-LBOs, as the increased debt load often associated with an LBO would be expected to have a significant effect on the target’s CDS.

5.3. Characterizing Changes in the Jump Behavior of CDS Spreads Between Pre- and Post-Announcement Periods

We also use the test statistic $L(i)$ (and the test for a significant jump on date t_i based on it) as part of our study of how the jump behavior of CDS spreads changes from the pre-announcement to post-announcement periods (with the other part based on fitting parametric models to the pre-announcement and post-announcement time series). Specifically, we look at the number of firms experiencing j significant jumps during the pre-announcement period and k significant jumps in the post-announcement period (with $j, k = 0, 1, 2, \dots$), for both CDS and equity. Below are the results we obtained:

Figure 5.3.1: Number of Non-LBOs with a given number of significant jumps in CDS and Equity over the period 40 days before and after announcement date



The plot showing the number of firms experiencing j jumps before announcement and after announcement, for the non-LBO sample confirms the observation above that the CDS time series generally have more significant jumps post announcement, as compared with pre-announcement. Specifically, while the number of firms experiencing zero significant jumps does not decrease substantially between the pre- and post-announcement periods, we do see a mild increase in the number of firms experiencing one or more jumps between the pre- and post-announcement periods.

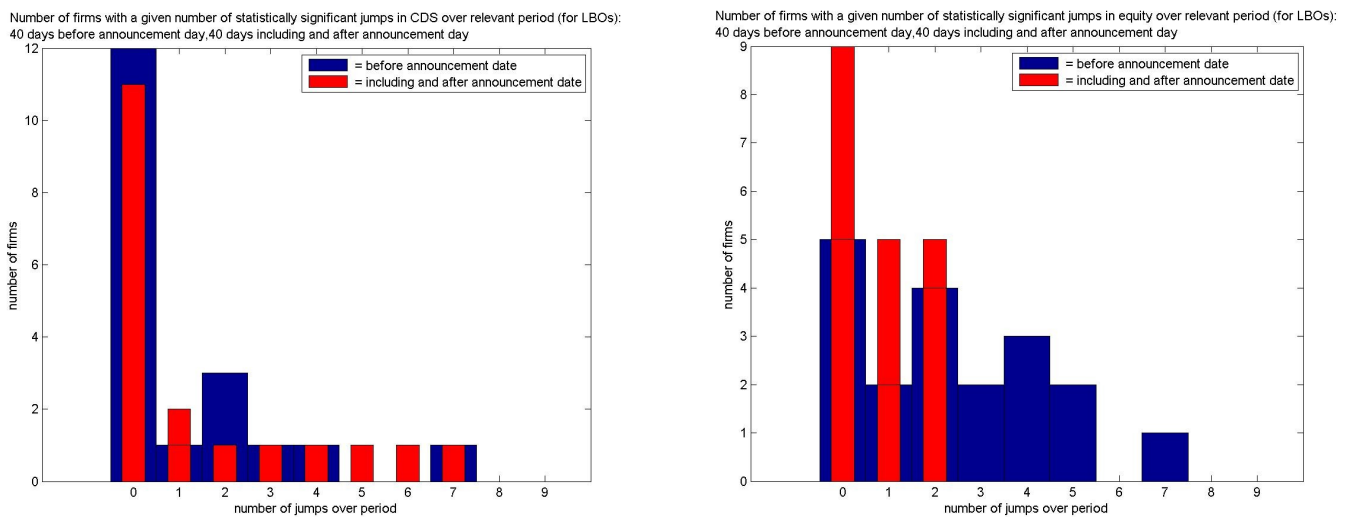
The results for equity are more mixed, although there is still evidence that the equity of target firms involved in (non-LBO) M&A activity tend to see more significant jumps before announcement day as opposed to after. From the figure at right, we actually see a large increase in the number of firms experiencing a single significant jump from pre- to post-announcement, but we see correspondingly significant declines in the number of firms experiencing two or more significant jumps.

Our interpretation of this is that the announcement of (non-LBO) M&A activity tends to make CDS slightly "jumper" in general, i.e. the CDS time series studied here generally become "jumper" after the actual announcement day. The opposite is true of the equity of the firms, which is observed to have a relatively "jumpy" pre-announcement period as compared with the post-announcement period. Our interpretation of these results, based on intuition but which we have not tested, is that the CDS market is slower to react

to M&A announcements than is the equity market. Indeed, the equity market seems to be reacting to the announcement of (non-LBO) M&A activity before even the announcement day (which is well documented: see for example [8], to the point that by the time of the actual announcement and afterwards, the equity is relatively stable. Our results suggest that the CDS market does not share similar tendencies; specifically, it lacks a well-developed rumor mechanism, and undergoes a price adjustment process resulting from M&A announcements generally after the announcements themselves. We will have something to say below regarding ways to exploit these observations via trading strategies.

Looking at the corresponding plots for the LBO sample, it is clear that analogous remarks apply.

Figure 5.3.2: Number of LBOs with a given number of significant jumps in CDS and Equity over the period 40 days before and after announcement date



6 CDS Mean Reversion

6.1. The Cox-Ingersoll-Ross (CIR) Process for Time Series Modeling

A continuous-time model in finance typically rests on one or more stationary diffusion processes $\{X_t, t \geq 0\}$, with dynamics represented by stochastic differential equations:

$$dX_t = \mu(X_t)dt + \sigma(X_t)dW_t \tag{1}$$

where $\{W_t, t \geq 0\}$ is a standard Brownian motion. The functions $\mu(\cdot)$ and $\sigma^2(\cdot)$ are, respectively, the drift and the diffusion functions of the process.

The fundamental process in modelling is the square root process governed by the following stochastic differential equation:

$$dr_t = \alpha(\mu - r_t)dt + \sqrt{r_t}\sigma dW_t \tag{2}$$

where r_t is the interest rate and $\theta \equiv (\alpha, \mu, \sigma)$ are model parameters. The drift function $\mu(r_t, \theta) = \alpha(\mu - r_t)$ is linear and possesses a mean reverting property, i.e. interest rate r_t moves in the direction of its mean μ at speed α . The diffusion function $\sigma^2(r_t, \theta) = r_t \sigma^2$ is proportional to the interest rate r_t and ensures that the process stays on a positive domain. The square root process in equation (2) is the basis for the Cox, Ingersoll, and Ross model and therefore often denoted as the CIR process in the financial literature.

6.1.1 CIR process densities

If α, μ, σ are all positive and $2\alpha\mu \geq \sigma^2$ holds, the CIR process is well-defined and has a steady state (marginal) distribution. The marginal density is gamma distributed.

For maximum likelihood estimation of the parameter vector $\vartheta \equiv (\alpha, \mu, \sigma)$, transition densities are required. The CIR process is one of a few cases, among the diffusion processes, where the transition density has a closed-form expression. Given r_t at time t the density of $r_{t+\Delta t}$ at time $t + \Delta t$ is

$$p(r_{t+\Delta t} | r_t; \theta, \Delta t) = c e^{-u-v} \left(\frac{v}{u}\right)^{q/2} I_q(2\sqrt{uv}) \quad (3)$$

$$c = 2\alpha/\sigma^2(1 - e^{-\alpha\Delta t})$$

$$u = c r_t e^{-\alpha\Delta t}$$

$$v = c r_{t+\Delta t}$$

$$q = \left(\frac{2\alpha\mu}{\sigma^2}\right) - 1$$

and $I_q(2\sqrt{uv})$ is a modified Bessel function of the first kind and of order q . Sometimes, it is particularly useful to work with the transformation $s_{t+\Delta t} = 2c r_{t+\Delta t}$. We can easily derive that the transition density of $s_{t+\Delta t}$ is

$$g(s_{t+\Delta t} | s_t; \theta, \Delta t) = g(2c r_{t+\Delta t} | 2c r_t; \theta, \Delta t) = \frac{1}{2c} p(r_{t+\Delta t} | r_t; \theta, \Delta t) \quad (4)$$

which is the non-central χ^2 distribution with $2q + 2$ degrees of freedom and non-centrality parameter $2u$.

6.2. Maximum Likelihood Implementation in MATLAB

Parameter estimation is carried out on a time series with N observations $\{r_{t_i}, i = 1 \dots N\}$. We consider equally spaced observations with Δt time step.

6.2.1 Likelihood function

The likelihood function for interest rate time series with N observations is

$$L(\theta) = \prod_{i=1}^{N-1} p(r_{t+\Delta t} | r_t; \theta, \Delta t). \quad (5)$$

It is computationally convenient to work with the log-likelihood function

$$\ln L(\theta) = \sum_{i=1}^{N-1} \ln p(r_{t+\Delta t} | r_t; \theta, \Delta t) \quad (6)$$

from which we easily derive the log-likelihood function of the CIR process

$$\ln L(\theta) = (N - 1) \ln c + \sum_{i=1}^{N-1} \{-u_{t_i} - v_{t_{i+1}} + 0.5q \ln \left(\frac{v_{t_{i+1}}}{u_{t_i}} \right) + \ln \{I_q(2\sqrt{u_{t_i} v_{t_{i+1}}})\}\} \quad (7)$$

Where $u_{t_i} = c r_{t_i} e^{-\alpha \Delta t}$ and $v_{t_{i+1}} = c r_{t_{i+1}}$. We find maximum likelihood estimates $\hat{\theta}$ of parameter vector ϑ by maximizing the log-likelihood function (7) over its parameter space:

$$\hat{\theta} \equiv (\hat{\alpha}, \hat{\mu}, \hat{\sigma}) = \arg \max_{\theta} \ln L(\theta). \quad (8)$$

Since the logarithmic function is monotonically increasing, maximizing the log-likelihood function also maximizes the likelihood function.

For solving optimization problem (8) we have to rely on a numerical solution. The function `fminsearch`, which is a standard part of MATLAB, does the job. The function `fminsearch` is an implementation of the Nelder-Mead simplex method, see MATLAB help for details.

6.2.2 Initial estimates

For convergence to the global optimum initial (starting) points of optimization, We have used Ordinary Least Squares (OLS) on discretized version of equation (2):

$$r_{t+\Delta t} - r_t = \alpha(\mu - r_t)\Delta t + \sigma\sqrt{r_t}\varepsilon_t, \quad (9)$$

where ε_t is normally distributed with zero mean and variance Δt , more precisely ε_t is a white noise process. For performing OLS we transform equation (9) into:

$$\frac{r_{t+\Delta t} - r_t}{\sqrt{r_t}} = \frac{\alpha\mu\Delta t}{\sqrt{r_t}} - \alpha\sqrt{r_t}\Delta t + \sigma\varepsilon_t, \quad (10)$$

The drift initial estimates are found by minimizing the OLS objective function

$$(\hat{\alpha}, \hat{\mu}) = \arg \min_{\alpha, \mu} \sum_{i=1}^{N-1} \left(\left(\frac{r_{t_{i+1}} - r_{t_i}}{\sqrt{r_{t_i}}} \right) - \left(\frac{\alpha\mu\Delta t}{\sqrt{r_{t_i}}} \right) + \alpha\sqrt{r_{t_i}}\Delta t \right)^2 \quad (11)$$

The diffusion parameter initial estimate $\hat{\sigma}$ is found as a standard deviation of residuals. The initial estimates $(\hat{\alpha}, \hat{\mu}, \hat{\sigma})$ are starting points for the log-likelihood function (7).

6.2.3 Implementing the log-likelihood function using the command `besseli`

For implementing the objective function (7) we need to evaluate the modified Bessel function of the first kind $I_q(2\sqrt{uv})$. The Bessel function $I_q(2\sqrt{uv})$ is available under the command `besseli(q, 2*sqrt(u.*v))` in MATLAB but direct usage of this

function results in an estimation failure. The reason is that the Bessel function $I_q(2\sqrt{uv})$ rapidly grows to positive infinity and optimization routines (e.g. `fminsearch`, `fmincon`) are not able to handle this problem.

Fortunately, there is a scaled version of the Bessel function in MATLAB, which we denote as $I_q^{-1}(2\sqrt{uv})$ and is available under the command `besseli(q, 2*sqrt(u.*v), 1)`. The $I_q^{-1}(2\sqrt{uv})$ equals $I_q(2\sqrt{uv}) \exp(-2\sqrt{uv})$ and therefore solves the problem of rapid divergence. We accordingly adjust the objective function (7) into

$$\ln L(\theta) = (N - 1) \ln c + \sum_{i=1}^{N-1} \{-u_{t_i} - v_{t_{i+1}} + 0.5q \ln\left(\frac{v_{t_{i+1}}}{u_{t_i}}\right) + \ln\{I_q^{-1}(2\sqrt{u_{t_i}v_{t_{i+1}}})\} + 2\sqrt{u_{t_i}v_{t_{i+1}}}\} \quad (14)$$

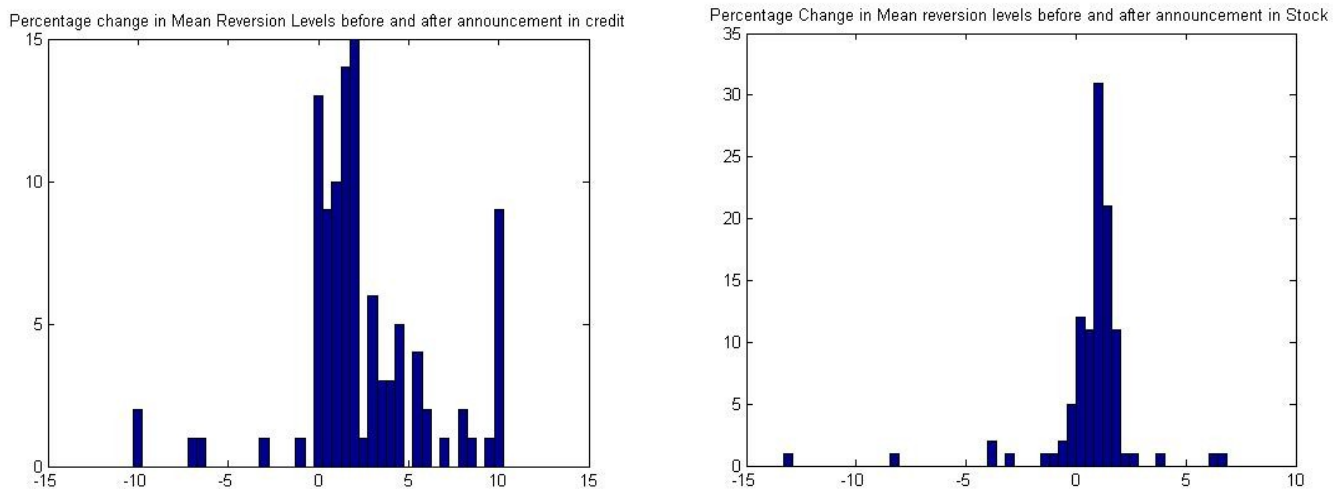
6.2.4 Optimization

The minimization of the negative of the log-likelihood function can be achieved by the `fminsearch` function. The initial estimates of the parameters and the `fminsearch` function are in `initpar.m` and the log likelihood function is returned by the `loglike.m` function.

6.3. CIR Model Results

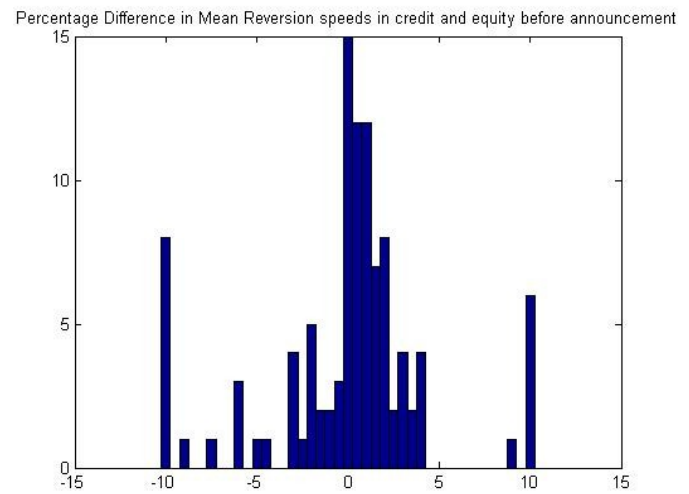
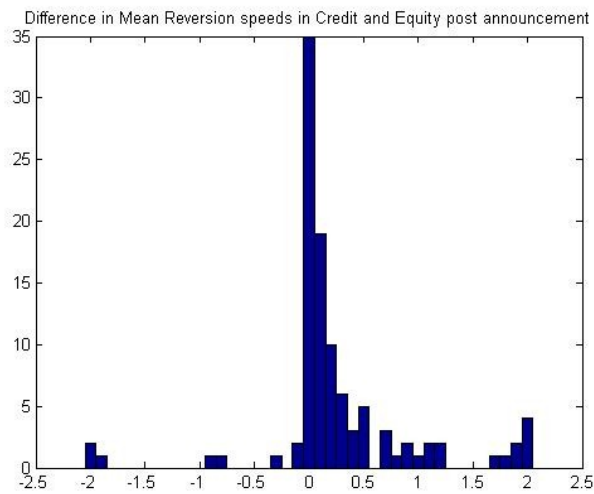
We fitted the CIR model to two time series of equity and credit values, one being pre-announcement values and the other being post announcement. The values of mean reversion speed, mean reversion level and volatility of the time series were estimated using the methods described above and a comparison of these values are plotted below:

Figure 6.3.1: Percentage changes in the mean reversion levels for both credit and equity before and after announcement



Comparing these two graphs, you can see that credit spreads mean reversion levels increase significantly, after an announcement whereas the change in mean reversion level for equity is more equally distributed.

Figure 6.3.2: Difference in mean reversion speeds in Credit and Equity before and post announcement



Before announcement, the ratios of mean reversion speeds seem to be evenly distributed for credit and equity. However, after an announcement, the proportion of companies having higher mean reversion speeds for credit than for equity increases. This essentially implies that **credit reverts faster than equity after an M&A announcement has been made**. This key result could be used in capital structure arbitrage strategies following M&A announcements. Further regression trees can be used to classify the size of the change in speeds to get a better strategy.

7 Trading Strategies

7.1 Volatility strategies

From our research, we observed that CDS spreads tend to become more volatile post-announcement, and equity less volatile. This leads us to consider volatility strategies, i.e. trading programs that are profitable when the price dynamics of an asset become more volatile. We mention the idea of using options on CDS (which we mention below as well) to form a “collar” trade, i.e. long positions in both a put option and a call option (both “at-the-money,” with the same strike and expiration time, which is chosen to be shortly after the suspected deal announcement) on the CDS of a firm suspected to be entering into an M&A transaction. Such a position will be profitable in the event that (at option expiration) the CDS spreads are experiencing high volatility, implying they are likely to be far from the strike.

Our observation that the equity market seems to anticipate the announcement of M&A activity better than the CDS market may provide a good way to source such trades; that is, when the equity market is reacting to rumors of a potential announcement, one could enter the CDS collar trade. Of course, the risk here is that the M&A is not announced and/or the CDS spreads do not become more volatile around the chosen option expiration. However, the loss to this strategy (because it entails only long option positions) is limited to the premiums paid for the two options.

One issue with CDS options is that they are thinly traded compared to equities and options on equities. We cannot predict how low levels of liquidity will impact the effectiveness of our hypothetical trading strategies. However, in the last 24 months, the CDS options

market has gradually become more liquid, as evidenced by narrower bid-ask spreads. If the trend continues, large-scale CDS option trading strategies should eventually be economically feasible.

We also noticed that mean reversion levels (i.e. long-run equilibrium levels) for CDS spreads are higher post-announcement than pre-announcement. The mean reversion speed ratio between credit and equity is higher post-announcement than pre-announcement. We can take advantage of these differentials using a hedging strategy, e.g. long CDS/short equity and short CDS/long equity, depending on current market sentiment.

7.2 Option Replication

Another potential trading strategy stemming from our analysis relates to the fact that a CDS contract can be replicated using deep-out-of-the-money European put options (described in detail in [reference]). This fact, combined with our observation that the CDS market is slower to react to the announcement (or anticipated announcement) of M&A activity than is the equity market, may suggest a relative mispricing between the CDS and the put options which can be used to replicate it.

This will be true inasmuch as the relevant put options (which are clearly tied to the equity markets) are more efficiently priced than are the CDS (which we suspect they will be, even though these options, particularly because they are deep out of the money, may be mispriced as well). Where there is such a relative mispricing, there is the potential for arbitrage. We feel that this is an interesting and potentially lucrative area of research, and leave further work to the experts.

8 Conclusion & Future Research

Based on our modelling of CDS movements, we find that equity markets in general react faster to information. There is a lag of one day, under normal circumstances, between CDS movements and equity movements. In the event of a merger announcement, this lag increases to more than two days. Additionally, CDS modelling based on previous equity and CDS movements are usually higher valued than realized CDS values suggesting that equity moves post announcement are stronger than CDS moves.

As indicated above, more needs to be done to precisely define the size of jump that results from the announcement of an M&A event. This is a crucial piece of the analysis, and we considered several alternatives. However, we recognize that a more sophisticated and statistically rigorous definition should be developed in order to better understand the relationship between CDS spreads and M&A activity studied here.

Also, we would have liked to separate our analysis by deal type (e.g. all cash, all stock, etc). Our difficulties obtaining quality data made this impossible for the current study. However, we think that there may be interesting differences in the results of these different deal types for professionals who have access to industry-standard databases. We would recommend that professional researchers approach the problem in this direction.

Appendices:

- a. **List of companies used in this study**

b. **Relevant MATLAB™ code**

c. **References**

List of companies used in this study

Firms with small prob of deal success

' CEG US'	' PSYS US'	' EOP US'
' EQ US'	' WFT US'	' HET US'
' GLB US'	' SGP US'	' 2968900Q US'
' ABS US'	' PBG US'	' LEARQ US'
' KFT US'	' 737929Q US'	' 3605818Q US'
' ME US'	' EOP US'	' DDUP US'
' 2297161Q US'	' CIN US'	' XTO US'
' TRB US'		' HLT US'

Non-LBO Acq

' 2266132Q US'	' 929530Q US'	' DNA US'	' KRB US'	' PER US'
' 2297161Q US'	' ABGX US'	' EOP US'	' KYPH US'	' PGN US'
' 2641504Q US'	' ABS US'	' EOP US'	' LAF US'	' PLD US'
' 2968900Q US'	' ACL US'	' EQ US'	' LDG US'	' PSYS US'
' 2987536Q US'	' ACL US'	' EYE US'	' LDG US'	' Q US'
' 3080867Q US'	' AIG US'	' FILE US'	' LEARQ US'	' ROH US'
' 3080867Q US'	' ANT US'	' GBBK US'	' LU US'	' SGP US'
' 3080867Q US'	' BLS US'	' GDW US'	' ME US'	' SLM US'
' 3393199Q US'	' BNI US'	' GENZ US'	' MEDX US'	' TEK US'
' 3406956Q US'	' BSG US'	' GLB US'	' MER US'	' TRB US'
' 3423152Q US'	' BSX US'	' GP US'	' MER US'	' TSO US'
' 3517233Q US'	' CEG US'	' HET US'	' MER US'	' TSY US'
' 3549162Q US'	' CEG US'	' HLT US'	' MER US'	' TXU US'
' 3605818Q US'	' CIN US'	' HRH US'	' MGG US'	' UCL US'
' 3692470Q US'	' CMX US'	' ICOS US'	' MS US'	' VAS US'
' 4134807Q US'	' CMX US'	' IKN US'	' NRG US'	' WB US'
' 737929Q US'	' CTX US'	' IMCL US'	' OPSW US'	' WFT US'
' 7585377Q US'	' CYCL US'	' IMCL US'	' ORH US'	' WYE US'
' 8206908Q US'	' DDUP US'	' ISSX US'	' PBG US'	' XTO US'
' 8249434Q US'	' DDUP US'	' KFT US'	' PD US'	
	' DLP US'	' KMG US'		

Firms with large prob of deal success

' 3423152Q US'	' KMG US'	' GBBK US'
' KRB US'	' 3517233Q US'	' VAS US'
' CEG US'	' 3692470Q US'	' MEDX US'
' TXU US'	' 929530Q US'	' IMCL US'
' 3393199Q US'	' ANT US'	' 2266132Q US'
' ICOS US'	' LDG US'	' CMX US'
' 3406956Q US'	' LDG US'	' 2987536Q US'
' 7585377Q US'	' UCL US'	' BSG US'
' ROH US'	' 4134807Q US'	' CMX US'
' KYPH US'	' BNI US'	' 2641504Q US'
' WYE US'	' 8206908Q US'	' 3549162Q US'

Matlab Code™

Mean Reversion Analysis

Initpar.m

```

%=====
% Read data from input matlab files
% CIR initial parameters estimation using OLS least squares regression
% fminsearch implementation for maximum likelihood
%=====
clear
format long
for i=2:106
str = [int2str(i) ':' int2str(i)];
creditpredata = xlsread('credit_pre-announce.xlsx',1,str);
creditpredata = creditpredata(8:end);
noofcols = size(creditpredata,2);
creditpredata=Clean_Data1(creditpredata,noofcols);
cdsdata = creditpredata(1,1:end);
cdsdata = cdsdata';
x = cdsdata(1:end-1);
dx = diff(cdsdata);
dx = dx./x.^0.5;
dt = 1/250;
regressors = [dt./x.^0.5, dt*x.^0.5];
[b,bint,r] = regress(dx,regressors);
alpha = -b(2);
mu = -b(1)/b(2);
sigma = std(r)/sqrt(dt);
InitialParams = [alpha mu sigma]; % Vector of initial parameters
val(i-1) = loglike(InitialParams,cdsdata);

```

The Implications of M&A Activity on CDS Spreads

7 June 2011

```
[Params, fval] = fminsearch(@(Params) loglike(Params, cdsdata), InitialParams);
cprespeed(i-1) = Params(1);
cpremeans(i-1) = Params(2);
cprevol(i-1) = Params(3);
end
```

Loglike.m

```
function lnL = loglike(Params, data)
%=====
% PURPOSE : Log-likelihood objective function (multiplied by -1) for the
% CIR process using the MATLAB besseli function
%=====
% RETURNS : lnL = Objective function value
%=====
dataf = data(2:end);
data1 = data(1:end-1);
nobs = length(data);
dt = 1/250;
alpha = Params(1);
mu = Params(2);
sigma = Params(3);
c = 2*alpha/(sigma^2*(1-exp(-alpha*dt)));
q = 2*alpha*mu/sigma^2-1;
u = c*exp(-alpha*dt)*data1;
v = c*dataf;
z = 2*sqrt(u.*v);
bf = besseli(q, z, 1);
lnL = -(nobs-1)*log(c) + sum(u + v - 0.5*q*log(v./u) - log(bf) - z);
end
```

Clean_Data1.m

```
function [ data ] = Clean_Data1(data, nCols)
%=====
% Purpose: Clean Data by handling missing values
% linear interpolation: assumes no rows of only NaN values
% Deletes all the NaNs before and after the timeseries
%=====
init = 1;
j=1;
fin = nCols;
while j<=nCols
    if isnan(data(j))
        if j == 1
            k = j+1;
            while isnan(data(k))
                k = k + 1;
                if k == nCols + 1 break; end
            end
            init = k;
        else
            k = j+1;
            while isnan(data(k))
                k = k+1;
                if k ==nCols;

```

The Implications of M&A Activity on CDS Spreads

7 June 2011

```

                fin = j-1;
                break;
            end
        end
        step = (data(k)-data(j-1))/(k-j+1);
        for h=j:(k-1)
            data(h) = data(j-1) + (h-j+1)*step;
        end
        j = k;
    end
end
j = j+1;
end
data = data(init:fin);
end

```

Jump Statistic

```

% FOR CDS TIME SERIES; CDS data stored in variable 'CDS_data'
% FOR EQUITY TIME SERIES; equity data stored in variable 'EQ_data'
% firm names stored in variable 'firms'

CDS_data = CDS_nLBO;
EQ_data = EQ_nLBO;
VIX_data = VIX_nLBO;
firms = firms_nLBO;
data_type = ' non-LBO';

f_path = 'C:\Users\Eric\Desktop\Spring 2011\MS&E 444\Figures\nonLBO';

% Get size of data frames:
% numFirms = numRows, numObs = numCols

numFirms = size(firms);
numFirms = numFirms(1);
numObs = size(CDS_data);
numObs = numObs(2);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Clean Data
CDS_clean = Clean_Data(CDS_data,numFirms, numObs);
EQ_clean = Clean_Data(EQ_data,numFirms, numObs);
VIX_clean = Clean_Data(VIX_data,numFirms, numObs);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Calculate L-stats, check significance of L-stats

K = 20; %size of rolling window used
announce_date_ls = floor(numObs/2) + 1 - K; %announcement day in list of lstats
first_lstat = 1-announce_date_ls;%in reference to time from announce_date
last_lstat = numObs-announce_date_ls-K;%in reference to time from announce_date

[ L_stat_cds, L_stat_sig_cds ] = Calc_L_stats( CDS_clean, numFirms, numObs, K );
[ L_stat_eq, L_stat_sig_eq ] = Calc_L_stats( EQ_clean, numFirms, numObs, K );

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Analyze L-stats

```

The Implications of M&A Activity on CDS Spreads

7 June 2011

```

% univariate distributions
num_jumps_cds = Count_L_stats( L_stat_sig_cds, numFirms, numObs, K );
num_jumps_eq = Count_L_stats( L_stat_sig_eq, numFirms, numObs, K );

% joint distribution: count number of firms with jumps on both days
num_jumps_both = Count_joint_L_stats( L_stat_sig_cds, L_stat_sig_eq, numFirms, numObs, K );

[ num_firms_i_jumps_beforeAD_cds, ~ ] = Count_L_stats_by_firm( L_stat_sig_cds, numFirms, 1,
announce_date_ls-1 );
[ num_firms_i_jumps_beforeAD_eq, ~ ] = Count_L_stats_by_firm( L_stat_sig_eq, numFirms, 1,
announce_date_ls-1 );
end_date = 2 * announce_date_ls - 2;%to insure that period looked at are the same length, e.g. 40
days here
[ num_firms_i_jumps_afterAD_cds, ~ ] = Count_L_stats_by_firm( L_stat_sig_cds, numFirms,
announce_date_ls, end_date );
[ num_firms_i_jumps_afterAD_eq, ~ ] = Count_L_stats_by_firm( L_stat_sig_eq, numFirms,
announce_date_ls, end_date );

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Characterize marginal prob. dist. of CDS, equity spread moves around announcement day

num_days_around_AD = 0; % 0 gives moves on announcement day
announce_date_abs = 61;

% calculate jumpsizes: simple one-period return
jump_sizes_cds = Calc_jump_sizes( CDS_clean, VIX_clean, numFirms, num_days_around_AD,
announce_date_abs );
jump_sizes_eq = Calc_jump_sizes( EQ_clean, VIX_clean, numFirms, num_days_around_AD,
announce_date_abs );

nBins = 10; %number of bins to categorize jump sizes for prob. dist.
[ jump_bin_counts_cds, ranges_cds ] = Sort_jumps_into_bins( jump_sizes_cds, numFirms, nBins );
[ jump_bin_counts_eq, ranges_eq ] = Sort_jumps_into_bins( jump_sizes_eq, numFirms, nBins );

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% NEW %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[ j_test ] = Calc_jum_sizes_alt( CDS_clean, VIX_clean, L_stat_sig_cds, ...
numFirms, announce_date_abs, announce_date_ls, 10, 10 );

[ j_test_bins, r_test ] = Sort_jumps_into_bins( [ j_test(1:25);j_test(27:end) ], numFirms, 25 );

bar(j_test_bins )

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Characterize joint dist of CDS, equity spread moves around announcement
% day

nBins1 = 20;
nBins2 = 20;
[ jump_bin_counts_both, binsize1, binsize2 ] = Bivariate_sort_jumps_into_bins( jump_sizes_cds,
jump_sizes_eq, numFirms, nBins1, nBins2, 1 );

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Plots
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% number of jumps on each day
fnam=strcat('num_jumps_per_day_cds-',data_type,'.jpg');
bar((first_lstat:last_lstat),num_jumps_cds)

```

The Implications of M&A Activity on CDS Spreads

7 June 2011

```

title(strcat('Number of firms experiencing statistically significant jump in CDS on day i \newline
Corresponding to ',data_type,'s. Total number of firms: ',num2str(numFirms)));
xlabel('Day (in reference to announcement day, corresponding to day 0)')
ylabel('Number of firms')
saveas(gcf,[f_path,filesep,fnam],'jpg');

fnam=strcat('num_jumps_per_day_eq-',data_type,'.jpg');
bar((first_lstat:last_lstat),num_jumps_eq)
title(strcat('Number of firms experiencing statistically significant jump in equity on day i
\newline
Corresponding to ',data_type,'s. Total number of firms: ',num2str(numFirms)));
xlabel('Day (in reference to announcement day, corresponding to day 0)')
ylabel('Number of firms')
saveas(gcf,[f_path,filesep,fnam],'jpg');

% joint distribution: count number of firms with jumps in both CDS and eq on
% a day

fnam=strcat('num_jumps_per_day_both-',data_type,'.jpg');
bar3(num_jumps_both)
title(strcat('Number of firms experiencing statistically significant jump in CDS on day i AND in
equity on day j \newline
Corresponding to ',data_type,'s. Total number of firms:
',num2str(numFirms)));
xlabel('CDS: \newline i (announcement day = 0)')
ylabel('Equity:\newline j (announcement day = 0)')
zlabel('Number of firms')
saveas(gcf,[f_path,filesep,fnam],'jpg');

fnam=strcat('num_jumps_per_day_both_diagonal-',data_type,'.jpg');
bar((first_lstat:last_lstat),diag(num_jumps_both))
title(strcat('Number of firms experiencing statistically significant jump in CDS AND equity on day
i\newline
Corresponding to ',data_type,'s. Total number of firms: ',num2str(numFirms)));
xlabel('Day (in reference to announcement day, corresponding to day 0)')
ylabel('Number of firms')
saveas(gcf,[f_path,filesep,fnam],'jpg');

% univariate distributions of size of CDS/equity jumps on announcement

day = 1;%which day from num_days_around

fnam=strcat('univar_jump_dist_cds-',data_type,'.jpg');
bar(ranges_cds(day,1:nBins),jump_bin_counts_cds(day,1:end))
title(strcat('CDS: number of firms experiencing a jump with size within each bin (controlled for
VIX), nBins=',num2str(nBins),'\newline
Corresponding to ',data_type,'s. Total number of
firms: ',num2str(numFirms)));
ylabel('number of firms')
xlabel('bin')
saveas(gcf,[f_path,filesep,fnam],'jpg');

fnam=strcat('univar_jump_dist_eq-',data_type,'.jpg');
bar(ranges_eq(day,1:nBins),jump_bin_counts_eq(day,1:end))
title(strcat('Equity: number of firms experiencing a jump with size within each bin (controlled for
VIX), nBins=',num2str(nBins),'\newline
Corresponding to ',data_type,'s. Total number of
firms: ',num2str(numFirms)));
ylabel('number of firms')
xlabel('bin')
saveas(gcf,[f_path,filesep,fnam],'jpg');

%together, on same plot
fnam=strcat('univar_jump_dists_together-',data_type,'.jpg');
bar1=bar((-0.1:0.037:0.25),jump_bin_counts_cds(day,1:end));
set(bar1,'BarWidth',1);
hold on;
bar2=bar((-0.1:0.037:0.25),jump_bin_counts_eq(day,1:end),'FaceColor','r');

```

The Implications of M&A Activity on CDS Spreads

7 June 2011

```

set(bar2, 'BarWidth', 1/2);
title('Univariate jump-size distributions for CDS and equity (controlled for VIX), superimposed');
ylabel('number of firms')
xlabel('bin')
legend(' = CDS', ' = equity');
hold off;
saveas(gcf, [f_path, filesep, fnam], 'jpg');

% Plots showing size of the jump for each firm: in sorted order
% one bar per firm, relies on 'day' above

fnam=strcat('sorted_jumps_cds-', data_type, '.jpg');
bar(sort(jump_sizes_cds(1:end, day)))
title(strcat('(Sorted) CDS jump sizes (controlled for VIX) on announcement day for ', data_type, 's'))
xlabel('Firms')
ylabel('Jump size')
saveas(gcf, [f_path, filesep, fnam], 'jpg');

fnam=strcat('sorted_jumps_eq-', data_type, '.jpg');
bar(sort(jump_sizes_eq(1:end, day)))
title(strcat('(Sorted) equity jump sizes (controlled for VIX) on announcement day for ', data_type, 's'))
xlabel('Firms')
ylabel('Jump size')
saveas(gcf, [f_path, filesep, fnam], 'jpg');

% Characterize joint dist of CDS, equity spread moves around announcement
% day

fnam=strcat('joint_dist_cds_and_eq-', data_type, '.jpg');
bar3(jump_bin_counts_both)
title(strcat('Joint distribution of CDS and equity jump sizes (controlled for VIX) for ', data_type, 's\nnewline nBins(CDS) = ', num2str(nBins1), ', nBins(equity) = ', num2str(nBins2)));
xlabel(strcat('equity:\nnewline[i(', num2str(binsize2), '), (i+1)(', num2str(binsize2), ')]'));
ylabel(strcat('CDS:\nnewline[i(', num2str(binsize1), '), (i+1)(', num2str(binsize1), ')]'));
zlabel('Number of firms')
saveas(gcf, [f_path, filesep, fnam], 'jpg');

% Number of firms with a given number of statistically significant jumps over relevant period:
before and after

fnam=strcat('num_jumps_before_after_cds-', data_type, '.jpg');
bar1=bar((0:1:9), num_firms_i_jumps_beforeAD_cds(1:10));
set(bar1, 'BarWidth', 1);
hold on;
bar2=bar((0:1:9), num_firms_i_jumps_afterAD_cds(1:10), 'FaceColor', 'r');
set(bar2, 'BarWidth', 1/2);
title(strcat('Number of firms with a given number of statistically significant jumps in CDS over
relevant period (for ', data_type, 's):\nnewline', num2str(end_date/2), ' days before announcement
day, ', ' ', num2str(end_date/2), ' days including and after announcement day'));
ylabel('number of firms')
xlabel('number of jumps over period')
legend(' = before announcement date', ' = including and after announcement date');
hold off;
saveas(gcf, [f_path, filesep, fnam], 'jpg');

fnam=strcat('num_jumps_before_after_eq-', data_type, '.jpg');
bar1=bar((0:1:9), num_firms_i_jumps_beforeAD_eq(1:10));
set(bar1, 'BarWidth', 1);
hold on;
bar2=bar((0:1:9), num_firms_i_jumps_afterAD_eq(1:10), 'FaceColor', 'r');
set(bar2, 'BarWidth', 1/2);

```

```

title(strcat('Number of firms with a given number of statistically significant jumps in equity over
relevant period (for ',data_type,'s):\newline',num2str(end_date/2),' days before announcement
day,', ' ',num2str(end_date/2),' days including and after announcement day'));
ylabel('number of firms')
xlabel('number of jumps over period')
legend(' = before announcement date',' = including and after announcement date');
hold off;
saveas(gcf,[f_path,filesep,fnam],'jpg');

```

Bivariate Sorting of jumps into Bins

```

function [ bin_counts, bin_size1, bin_size2 ] = Bivariate_sort_jumps_into_bins( data1, data2,
numFirms, nBins1, nBins2, day )
%variable 'day' gives the COLUMN in 'data1' and 'data2' to look at

bin_counts = zeros(nBins1, nBins2);

bin_size1 = ( max(data1(1:end,day)) - min(data1(1:end,day)) ) / nBins1;
bin_size2 = ( max(data2(1:end,day)) - min(data2(1:end,day)) ) / nBins2;

for k=0:nBins1
    ranges1(k+1) = min(data1(1:end,day)) + k*bin_size1;
end
for k=0:nBins2
    ranges2(k+1) = min(data2(1:end,day)) + k*bin_size2;
end

for i=1:numFirms
    if data1(i,day) == min(data1(1:end,day))
        place1 = 1;
    else
        for k=0:nBins1-1
            if data1(i,day) > ranges1(k+1) && data1(i,day) <= ranges1(k+1) + bin_size1
                place1 = k+1;
                break;
            end
        end
    end
    if data2(i,day) == min(data2(1:end,day))
        place2 = 1;
    else
        for k=0:nBins2-1
            if data2(i,day) > ranges2(k+1) && data2(i,day) <= ranges2(k+1) + bin_size2
                place2 = k+1;
                break;
            end
        end
    end
    bin_counts(place1, place2) = bin_counts(place1, place2) + 1;
end

```

Calculations of jump sizes by alternative definition

```

function [ jump_sizes ] = Calc_jum_sizes_alt( data, VIX, l_stat_sig, ...
numFirms, announce_date_abs, announce_date_l, start_default, end_default )

jump_sizes = zeros(numFirms,1);

```

The Implications of M&A Activity on CDS Spreads

7 June 2011

```

end_day = ones(numFirms,1)*end_default;
start_day = ones(numFirms,1)*start_default;

% find range over which jump is occurring
for i=1:numFirms
    for j=1:end_default
        if l_stat_sig(i,announce_date_1+j) == 1
            end_day(i) = j;
            break;
        end
    end
    for j=1:start_default
        if l_stat_sig(i,announce_date_1-j) == 1
            start_day(i) = j;
            break;
        end
    end
end

%calculate jump over the range found above
for i=1:numFirms
    j_min = announce_date_abs-start_day(i);
    j_max = announce_date_abs+end_day(i);

    std_data = std( ( data(i,2:j_min-1) - data(i,1:j_min-2) ) ./ data(i,1:j_min-2) );
    std_VIX = std( ( VIX(i,2:j_min-1) - VIX(i,1:j_min-2) ) ./ VIX(i,1:j_min-2) );

    h = 1;
    jumps = zeros(start_day(i)+end_day(i)+1,1);
    for j=j_min:j_max
        jumps(h) = ( (data(i,j) - data(i,j-1)) / data(i,j-1) ) / std_data ...
            - ( (VIX(i,j) - VIX(i,j-1)) / VIX(i,j-1) ) / std_VIX;
        if jumps(h) == 0
            jumps(h) = 0.000001;
        end
        h = h + 1;
    end

    jump_sizes(i) = prod( jumps );
end
end

```

Calculation of Jump Sizes

```

function [ jump_sizes ] = Calc_jum_sizes_alt( data, VIX, l_stat_sig, ...
    numFirms, announce_date_abs, announce_date_1, start_default, end_default )

jump_sizes = zeros(numFirms,1);
end_day = ones(numFirms,1)*end_default;
start_day = ones(numFirms,1)*start_default;

% find range over which jump is occurring
for i=1:numFirms
    for j=1:end_default
        if l_stat_sig(i,announce_date_1+j) == 1
            end_day(i) = j;
            break;
        end
    end
end

```

The Implications of M&A Activity on CDS Spreads

7 June 2011

```

end
for j=1:start_default
    if l_stat_sig(i,announce_date_l-j) == 1
        start_day(i) = j;
        break;
    end
end
end

end

%calculate jump over the range found above
for i=1:numFirms
    j_min = announce_date_abs-start_day(i);
    j_max = announce_date_abs+end_day(i);

    std_data = std( ( data(i,2:j_min-1) - data(i,1:j_min-2) ) ./ data(i,1:j_min-2) );
    std_VIX = std( ( VIX(i,2:j_min-1) - VIX(i,1:j_min-2) ) ./ VIX(i,1:j_min-2) );

    h = 1;
    jumps = zeros(start_day(i)+end_day(i)+1,1);
    for j=j_min:j_max
        jumps(h) = ( (data(i,j) - data(i,j-1)) / data(i,j-1) ) / std_data ...
            - ( (VIX(i,j) - VIX(i,j-1)) / VIX(i,j-1) ) / std_VIX;
        if jumps(h) == 0
            jumps(h) = 0.000001;
        end
        h = h + 1;
    end
    jump_sizes(i) = prod( jumps );
end

end

end

```

Calculating L Statistics

```

function [ jump_sizes ] = Calc_jum_sizes_alt( data, VIX, l_stat_sig, ...
    numFirms, announce_date_abs, announce_date_l, start_default, end_default )

jump_sizes = zeros(numFirms,1);
end_day = ones(numFirms,1)*end_default;
start_day = ones(numFirms,1)*start_default;

% find range over which jump is occurring
for i=1:numFirms
    for j=1:end_default
        if l_stat_sig(i,announce_date_l+j) == 1
            end_day(i) = j;
            break;
        end
    end
    for j=1:start_default
        if l_stat_sig(i,announce_date_l-j) == 1
            start_day(i) = j;
            break;
        end
    end
end

end

%calculate jump over the range found above

```

The Implications of M&A Activity on CDS Spreads

7 June 2011

```

for i=1:numFirms
    j_min = announce_date_abs-start_day(i);
    j_max = announce_date_abs+end_day(i);

    std_data = std( ( data(i,2:j_min-1) - data(i,1:j_min-2) ) ./ data(i,1:j_min-2) );
    std_VIX = std( ( VIX(i,2:j_min-1) - VIX(i,1:j_min-2) ) ./ VIX(i,1:j_min-2) );

    h = 1;
    jumps = zeros(start_day(i)+end_day(i)+1,1);
    for j=j_min:j_max
        jumps(h) = ( (data(i,j) - data(i,j-1)) / data(i,j-1) ) / std_data ...
            - ( (VIX(i,j) - VIX(i,j-1)) / VIX(i,j-1) ) / std_VIX;
        if jumps(h) == 0
            jumps(h) = 0.000001;
        end
        h = h + 1;
    end

    jump_sizes(i) = prod( jumps );

end

end

```

Sort Jumps into Bins

```

function [ jump_bin_counts, ranges ] = Sort_jumps_into_bins( data, numFirms, nBins )

%data coming in from variable 'data' is assumed to have the following form:
%(numFirms X numCols), where numCols is given by the number of days around
%announcement that we're looking at.
%output is in the form (numCols X
nCols = size(data); % get the number of columns: corresponds to
nCols = nCols(2); % number of days being looked at
                % = num_days_around_AD*2+1

jump_bin_counts = zeros(nCols,nBins);
ranges = zeros(nCols,nBins);

for i=1:nCols
    binsize = (max(data(1:end,i)) - min(data(1:end,i))) / nBins;
    for k=0:nBins-1
        ranges(i,k+1) = min(data(1:end,i)) + k*binsize;
    end
    for j=1:numFirms
        if data(j,i) == min(data(1:end,i))
            jump_bin_counts(i,1) = jump_bin_counts(i,1) + 1;
        else
            for k=0:nBins-1
                if data(j,i) > ranges(i,k+1) && data(j,i) <= ranges(i,k+1) + binsize
                    jump_bin_counts(i,k+1) = jump_bin_counts(i,k+1) + 1;
                end
            end
        end
    end
end

end

end

```

Handling missing data values

The Implications of M&A Activity on CDS Spreads

7 June 2011

```

% function [ clean_data ] = Clean_Data( data_mat, nRows, nCols )
%
% % Purpose: Clean Data by handling missing values
% % set missing data values to previous day's value; if missing value
% % is in column 1, take average over all (nonmissing) values in row
%
%     clean_data = data_mat; %preallocate
%     for i=1:nRows
%         if isnan(clean_data(i,1)) clean_data(i,1) = nanmean(clean_data(i,1:end)); end
%         for j=2:nCols
%             if isnan(clean_data(i,j)) clean_data(i,j) = clean_data(i,j-1); end
%         end
%     end
% end

```

```

function [ data ] = Clean_Data( data, nRows, nCols )

% Purpose: Clean Data by handling missing values
% linear interpolation: assumes no rows of only NaN values
% if a run of NaNs begins in column 1, sets all NaN values equal to first
% non-NaN. If last column has a NaN, makes it equal to the value in
% previous column

```

```

    for i=1:nRows
        j = 1;
        while j <= nCols
            if isnan(data(i,j))
                if j == nCols data(i,j) = data(i,j-1);
                else
                    k = j+1;
                    while isnan(data(i,k))
                        k = k + 1;
                        if k == nCols + 1 break; end
                    end
                    if k == nCols + 1
                        for n=j:k-1 data(i,n) = data(i,j-1); end
                        j = nCols + 1;%forces a break
                    else
                        if j == 1
                            for h=j:(k-1)
                                data(i,h) = data(i,k);
                            end
                        else
                            step = (data(i,k)-data(i,j-1))/(k-j+1);
                            for h=j:(k-1)
                                data(i,h) = data(i,j-1) + (h-j+1)*step;
                            end
                        end
                        j = k + 1;
                    end
                end
            end
            else
                j = j + 1;
            end
        end
    end
end
end

```

Calculating L Statistics by Firm

The Implications of M&A Activity on CDS Spreads

7 June 2011

```
function [ firms_with_i_jumps, range ] = Count_L_stats_by_firm( data, numFirms, start_day, end_day )
%each ROW of 'data' corresponds to a single firm
%sum along rows of 'data', from start_day to end_day
%firms_with_i_jumps(i) corresponds to i-1 jumps: cant have index 0

firms_with_i_jumps = zeros(end_day-start_day+1,1);

for i=1:numFirms
    firms_with_i_jumps( sum(data(i,start_day:end_day)) + 1 ) =
firms_with_i_jumps( sum(data(i,start_day:end_day)) + 1 ) + 1;
end

range=[0:1:end_day-start_day];

end
```

Counting L Statistics

```
function [ num_jumps ] = Count_L_stats( data_mat, numFirms, numObs, K )

num_jumps = zeros(numObs-K,1);%preallocate
for i=1:numFirms
    for j=1:(numObs-K)
        if data_mat(i,j) == 1
            num_jumps(j) = num_jumps(j) + 1; end
        end
    end
end

end
```

List of references

1. Asquith, Paul, and E. Han Kim. "The Impact of Merger Bids on the Participating Firms' Security Holders." *The Journal of Finance* 37.5 (1982): 1209-228. *Print*.
2. Asquith, Paul, and Thierry Wizman. "Event Risk, Covenants, and Bondholder Returns in Leveraged Buyouts." *International Financial Services Research Center, MIT. Print*.
3. Berndt, Oliver. "Capital Structure Arbitrage Strategies: Models, Practice and Empirical Evidence." *School of HEC at University of Lausanne Institute of Banking and Finance*.
4. Burne, Katy. "CBOE to Launch CDS Options Alternative - WSJ.com." *Business News & Financial News - The Wall Street Journal - Wsj.com. Web. 11 January 2011.*
<<http://online.wsj.com/article/SB10001424052748703791904576076222823496098.html>>.
5. Byström†, Hans. "Credit Default Swaps and Equity Prices: The iTraXX™ CDS Index Markets." *Google Scholar. (2005)*
6. Carr, Peter. "Simple Robust Linkages Between CDS and Equity Options." *Bloomberg, L.P. (January, 2008.)*
7. Imbierowicz, Bjorn, and Mark Wahrenburg. "Credit Rating Announcements – The Impact of the Agency's Reason, Public Information, and M&A." *Goethe University Frankfurt, Finance Department (2009). Print*.
8. Lee, Suzanne, and Per Mykland. "Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics." *Oxford University Press (2007). Print*.

9. Miller, Suzanne. "Despite Reform Push, CDS Options Go from Toxic to Tasty." 9 June 2011.
<<http://www.marketwatch.com/story/options-in-an-increasingly-volatile-market-2010-06-09>>. Market Watch – Wall Street Journal Network
10. Zhang, Benjamin Y. "Explaining Credit Default Swap Spreads with Equity Volatility and Jump Risks of Individual Firms." *BIS Working Papers, Volume 181*. (September, 2005.)
11. Zhang, Gaiyan. "Informational Efficiency of Credit Default Swap and Stock Markets: The Impact of Adverse Credit Events." IRABF 1.1 (2009). Print.
12. http://en.wikipedia.org/wiki/Leveraged_buyout#Age_of_the_mega-buyout_2005-2007