

Contagion in Risk Markets

Matthew Moore and James Schulhof

Faculty Advisor: Dr. Emma Rasiel

Honors thesis submitted in partial fulfillment of the requirements for Graduation

with Distinction in Economics in Trinity College of Duke University

**Duke University
Durham, North Carolina
2009**

James Schulhof is currently completing his Bachelor of Science degree in Economics with a dual major in Mechanical Engineering at Duke University. He will be employed by Deutsche Bank as an Analyst in their Sales and Trading division in New York beginning in summer 2009. James can be reached at JSchulhof@gmail.com. Matthew Moore is currently completing his Bachelor of Science degree in Economics with a dual major in Mathematics. He will be employed by JPMorgan Chase as an Analyst in their Sales and Trading division in New York beginning in summer 2009. Matthew can be reached at Moore.MatthewPaul@gmail.com.

Acknowledgements

The authors would like to thank Dr. Emma Rasiel for the tremendous amount of work and guidance she generously gave to this project. There is no doubt in our mind that this project would not have possible without her help. Additionally, we would like to thanks Dr. Tim Bollerslev for his assistance and expertise.

Table of Contents

Abstract	4
Introduction	5
Literature Review	10
<i>Regime Shift Models</i>	
<i>Asset Correlations</i>	
Data & Methodology	13
Results	19
Discussion	34
<i>Limitations of Study</i>	
<i>Areas of Further Study</i>	
References	37
Appendix	38

Abstract

During periods of market dislocation, which can be characterized by high asset volatility, correlations between assets generally tend to increase. However, there has been little research on the behavior of correlations between risk measures across securities markets. The aim of our research is to examine correlation dynamics between alternative risk measures rather than asset classes. Correlations between credit default swaps, equity volatility skew, and at-the-money volatility were found to increase during the recent period of market dislocation. To ascertain when the dislocation period began, we built a regime shift model to estimate the date at which the dislocation began. We have chosen to focus our analysis on risk measures for financial institutions in particular, as this industry has been most severely affected by the current financial crisis.

Introduction

It has long been known that during periods of high asset volatility, correlations between assets classes tend to increase (Hartmann, Straetmans, de Vries, 2004). Kyle and Xiong (2001) showed within their model that the correlation increase could be attributed to traders liquidating positions in various markets during periods of high volatility due to losses. Numerous studies have been conducted on this question with various asset classes and differing time periods (Eichengreen, 1996). There has been little research, however, on correlations between risk measures across securities markets. In addition, “with recent advances in the theoretical analysis of bank contagion, there are surprisingly few theoretical attempts to explicitly model crisis linkages between different securities markets” (Hartmann, 2003). Therefore, the aim of our research is to examine correlations between alternative risk measures rather than asset classes. We examine changes in correlation between measures of risk in the equity and credit markets from January 2005 to January 2009. We have chosen to focus our analysis on financial institutions in particular, as this industry has been most severely affected by the credit crisis which began in 2007. In addition, to more clearly identify when the volatile period began, we constructed a regime shift model which maximized the normalized difference between asset volatility and price change over the data set.

The first measure of downside risk that we use is the equity volatility smile (put skew), a phenomenon which has been observed in equity options markets since the stock market crash of 1987 (Rubenstein, 1994). This put skew

refers to the downward sloping and convex function which maps an equity option's strike price to its implied volatility. Before the 1987 crash the skew was not systematically observed across equities markets; implied volatilities at different strike prices tended to be of similar magnitude. After the crash, however, a persistent and systematic skew has been observed throughout the equity markets. Rubinstein (1994) dubs this phenomenon "crash-o-phobia," which results in higher implied volatilities for out-of-the-money (OTM) puts relative to at-the-money (ATM) puts. Bollen and Whaley (2002) argue that the skew is driven by portfolio managers hedging against downside risk. They propose that a greater demand for portfolio insurance results in a higher put skew. The implication of this hypothesis is that the put skew can be used as a proxy for the relative likelihood of downward price movements in equities markets.

We also include analysis of ATM volatility in the study as a second measure of downside risk in the equity market. One way to measure the S&P 500 implied volatility over the next month is conveniently given by the VIX Index. The VIX was at the forefront of market news during the depths of the current credit crisis, as it reached a 20 year high of 89.53% on October 24, 2008, implying a 30 day volatility of almost 26%. To give some perspective, the historical average 30 day implied volatility is around 6%.

The third measure of downside risk that we use is the credit default swap (CDS) in the credit market. A CDS is a contractual derivative created between two counterparties in which one party buys credit protection, typically on a corporate bond, by paying a premium to the other party. That party then agrees to

pay the difference between the par value of the bond and the recovery rate in the case of a default. A CDS thus functions as an insurance policy against the bond issuer defaulting on its debt. CDS is used both for hedging and speculative purposes.

Credit spreads were at historical lows from 2003-2007 and therefore banks held large amounts of long maturity CDS contracts on their balance sheets as they were perceived to be cheap credit protection. The problem with this is “derivatives contracts often go unsettled for years, or even decades, with counterparties building up huge claims against each other... Receivables and payables by the billions become concentrated in the hands of a few large dealers who are apt to be highly-leveraged in other ways as well” (Buffett, 2009). This means that when problems do arise it could be catastrophic for all of the dealers, as they all participate in a large web of intertwined contracts. This phenomenon is called counterparty risk.

The catalyst for market turmoil turned out to be subprime mortgages, which are mortgage loans made to borrowers with low credit ratings. Once investors realized these borrowers were beginning to default on a systematic basis, the value of these securities plummeted. This then led to write-downs and losses at banks that held billions of dollars worth of these loans. The losses then raised concerns regarding the capitalization of these banks.

As losses at financial institutions mounted, CDS spreads on these financial institutions soared. Some banks were purchased by other financial institutions, some filed for bankruptcy, and some were taken over through government

intervention. For example, Bear Stearns was granted an emergency loan in March 2008 from the Federal Reserve Bank of New York in an attempt to save the company. However, this loan was not sufficient and the firm ultimately sold itself to JPMorgan Chase with the United States Government guaranteeing a maximum loss level. JPMorgan Chase thus assumed Bear Stearns' debt obligations with the purchase and therefore Bear Stearns CDS contracts were not "triggered."

However, when Lehman Brothers encountered financing difficulties in September 2008, the United States Federal Reserve did not grant Lehman Brothers an emergency loan, and Lehman Brothers was forced to file for bankruptcy on September 15th, 2008. This represented a credit event for Lehman CDS contracts.

Even if governments do intervene, the style of intervention can determine if CDS contracts are exercised. Northern Rock Plc, which was nationalized in the U.K. in February 2008, did not trigger CDS contracts as the government took an equity stake in the company; Northern Rock's debt was unaffected. However, when the United States Treasury extended \$200 billion to support Fannie Mae and Freddie Mac in September 2008, CDS contracts were triggered as the companies were placed in a conservatorship. This uncertainty about the style of government action has caused unprecedented levels of volatility in CDS of financial institutions. The phenomenon can be observed in the following graph of Goldman Sachs CDS Spread vs. Time:

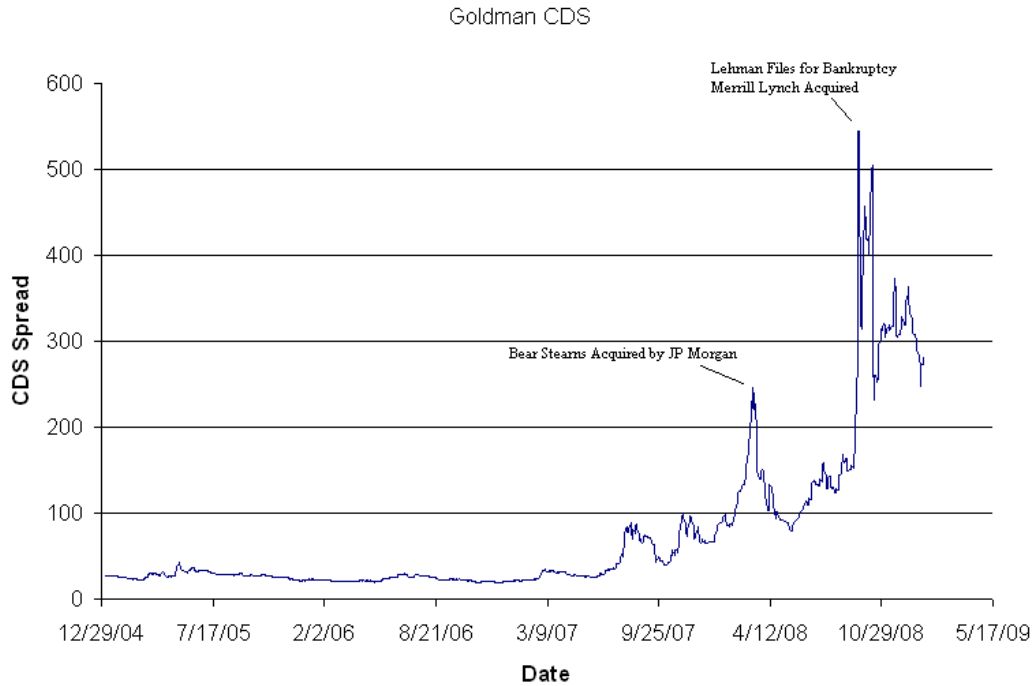


Figure 1

Figure 1 portrays how government intervention also drives up CDS spreads for other non-affected financial institutions. This increase in risk level and volatility therefore leads to increased correlations between risk measures for financial institutions, as firms such as Goldman Sachs displayed significant increases in CDS spreads even though the firm itself was not in immediate jeopardy during the specific events displayed.

In this paper, we compare and analyze these risk measures for the following financial institutions: Goldman Sachs, JPMorgan Chase, Merrill Lynch, Bank of America, Lehman Brothers, and Deutsche Bank. As a benchmark for comparison, we also evaluate risk measures for the following non-financial institutions: IBM, Dell, Apache, Proctor and Gamble, and Alcoa. In addition, we designed a regime shift model which outputs the specific date a period of market

dislocation commences based on asset volatility and price changes. Our results confirm that correlations between risk measures increase during these market dislocations, just as do correlations between asset classes.

Literature Review

Regime Shift Models

In financial markets, changing market conditions dictate the amount by which different factors influence the variables that we seek to observe and study. The variables that affect correlation, for example, change throughout time as market participants adjust to ever-changing conditions. For this reason, researchers sought a method by which they could model the effect of these different market conditions on a single data series in question. One way to do this is to model different segments of the data series according to which model makes “more sense” given the data. For example, one could allow both mean reversion and conditional heteroskedasticity in the short-term interest rate by allowing the GARCH and square root processes to be embedded in a regime-switching process (Gray, 1996). This is accomplished by modeling the regime-switch using a time-heterogeneous Markov chain. Gray’s model allowed for all of the GARCH parameters to be regime-dependent, which allows for such likely features as individual shocks during high-volatility periods showing less persistence than during low-volatility periods. Thus, regime-shift modeling allows for different theoretical constructs to be embedded in the same model to study a given set of data.

Research is very active in regime-shift modeling. Some recent examples include Medeiros and Veiga (2009), which allows for a flexible number of regimes, as it optimizes the number of regimes suited for a particular data set. The model also allows for the possibility of explosive regimes, while remaining stationary and ergodic. Another recent model, proposed by Olan T. Henry (2009), models the relationship between UK equity returns and the short-term interest rate using a two regime EGARCH model, with regime switching determined via a Markov process. The model suggests that UK equity return conditional variance responds persistently but symmetrically to equity returns in a high-return, low-variance regime. In the low-return, high-variance regime, equity return conditional volatility responds asymmetrically and without persistence to equity returns. Henry finds evidence of a regime dependent relationship between short-term interest rate differentials and equity return volatility. He also finds evidence of contagion effects when he discovers that events in the money market influence the regime-switching probabilities. Our paper extends the regime shift literature by using regime breaks to study correlation changes in the presence of market contagion.

Asset Correlations

The notion that asset correlations tend to increase in periods of market turmoil is supported by many empirical studies and has been extensively modeled. Hartmann, Straetmans, and de Vries (2004) find that simultaneous stock market crashes are more likely than simultaneous bond market crashes. Their data also suggests that cross-border market linkages are very similar to national linkages,

suggesting a possible downside to international financial market integration. They also make note of the absence of study on cross-market data between stock and bond markets: “In contrast with recent advances in the theoretical analysis of (for example) bank contagion, there are surprisingly few theoretical attempts to explicitly model crisis linkages between different securities markets. The published literature comprises King and Wadhvani (1990), Calvo and Mendoza (2000), Kodres and Pritsker (2002), and Kyle and Xiong (2001). ”

King and Wadhvani (1990) argue that the increase in correlation between stock market returns in periods of market turmoil is caused by rational agents attempting to infer information by looking at price changes in other markets. This paper models transmissions of volatilities between different stock markets, and even though it extends the analysis to a “many-markets” model, there is no modeling for the link between U.S. credit and equity markets.

Calvo and Mendoza (2000) argue that “globalization may promote contagion by weakening incentives for gathering costly information and by strengthening incentives for imitating arbitrary market portfolios.” Again, no attempt is made to model or explain contagion between stock and credit markets.

Kodres and Pritsker (2002) argue that cross-market financial contagion is caused by investors who “transmit idiosyncratic shocks from one market to others by adjusting their portfolios’ exposures to shared macroeconomic risks.” They argue that the severity of the contagion depends on the different markets’ shared sensitivities to these macroeconomic risks, and also to the relative amounts of informational asymmetry in the distinct markets. The paper argues that emerging

market economies are more at risk for contagion, but again, no attempt is made to model linkages between credit and equity markets.

Kyle and Xiong (2001) model contagion as a wealth effect, as part of a continuous-time model with only two risky assets in different markets and three traders. The key finding here is that when convergence traders lose money, they liquidate positions in both markets, which causes the correlations of the asset returns to increase.

Perhaps the most famous hedge fund collapse of all-time (that of Long-Term Capital Management) is detailed in the book: When Genius Failed by Roger Lowenstein (2000). In the account, repeated reference is made to the fact that correlations go to one in a crisis: “During a crisis, correlations always go to one. When a quake hits, all markets tremble. Why was Long-Term so surprised by this?” We attempt to extend the literature by empirically studying the contagion effect, specifically between risk measures, in both the equity and credit markets during the credit crisis beginning in mid-2007.

Data & Methodology

Daily closing levels for equity prices, CDS spreads, and implied volatilities on equity options were collected from Bloomberg for dates from January 4, 2005 through January 13, 2009 for selected companies. The exceptions to this are Lehman Brothers and Merrill Lynch, whose data ended September 12, 2008 and November 17th, 2008, respectively. Bloomberg began collecting CDS data in early 2005, and so for a relevant comparison of these asset values, only

data from that point forward was included. Not every date in Bloomberg contained data for all asset values, and so we were forced to eliminate these particular dates from our study. We utilize CDS spreads as the key measure of risk perception in the bond markets. CDS are quoted in basis points; we use 5 year contracts because these are the most liquid and actively traded maturity in this market. In the equity markets, we use both the put skew and ATM volatility as measures of perceived risk. The put skew is defined as:

$$\text{Put Skew} = \text{Implied Vol at 80\% Moneyness} - \text{Implied Vol at 100\% Moneyness}$$

Moneyness is defined as:

$$\text{Moneyness} = \frac{\text{Strike Price of Put}}{\text{Current Market Price of Equity}}$$

From this formula, it is clear that a put with 100% moneyness is ATM. A put with 80% moneyness is an out-of-the-money (OTM) put and will not be exercised unless the underlying stock falls 20% or more by the maturity date. We use implied volatilities on options with 1-month maturities, due to their high liquidity. Although the most accurate analysis would be obtained by comparing CDS spreads and equity options with the same maturity, this is not possible due to the nature of the two markets. The CDS market, which is priced based upon implied default probabilities for large institutions, necessarily trades on longer maturity contracts, due to the unlikely nature of the events that trigger the contracts. Equity options, on the other hand, rarely trade with a maturity of greater than 6 months.

With the two data series in hand, we now estimate their correlation using the Pearson coefficient, which is an unbiased estimator of the correlation between two data series X and Y, and is given by:

$$\rho = \left(\frac{1}{n-1} \right) * \sum_{i=1}^n \frac{Xi - \mu_x}{\sigma_x} * \frac{Yi - \mu_y}{\sigma_y}$$

Here σ and μ refer to the sample mean and sample standard deviation, respectively, while n is the number of observations in the sample. Here, X is the CDS time series, and Y is the put skew or ATM volatility time series. The factor we seek to measure is the change in the correlation of the data series across time, as fundamental market conditions change. We did this by breaking the data set into 2 different periods, with the break coming at some specific point in the data set. In economics literature, this method of breaking up a data set into two or more subsets, based on some significant event or change in the properties of the underlying data is referred to as a ‘regime shift’ or a ‘regime switch’. Since our analysis focuses on changes in the correlation during market dislocations, we chose to use significant “jumps” in the level and volatility of the data series across the different regimes to identify the timing of the regime change.

We first estimated the conditional volatility of the data series using the GARCH(1,1) model (Bollerslev 1986). In this model, one employs the following regression:

$$\sigma_t^2 = a * \varepsilon_{t-1}^2 + b * \sigma_{t-1}^2$$

Here, ε_{t-1}^2 refers squared log change of the data series in period t :

$$\varepsilon_t^2 = (\ln(X_t/X_{t-1}))^2$$

σ_t^2 is an estimate of the conditional volatility of the data series at time t . We ran the regression on both the CDS data series and the ATM volatility data series for regime break determination. The coefficients a and b for each series are solved via

maximum likelihood estimation. We maximize the log-likelihood function over the set $\{(a, b): 0 \leq a, b \leq 1\}$ at intervals of 0.005. We determined that a 0.005 interval gives a good balance between precision and computer running time. Using the values of a and b from the maximum likelihood function, a conditional volatility series for each day in the data set could be derived simply by assuming that: $\sigma_1 = \text{var}\left(\ln\left(\frac{X_i}{X_{i-1}}\right)\right)$, and then solving for $\sigma_i, i = 2, 3, \dots, n$. Once we have estimates for both the CDS's and the ATM volatility's conditional volatility series, we need to identify the date of the regime shift for each series. Again, we want to base the regime break on both the value of the data series and the estimated conditional volatility of the data series. We establish a new variable, ψ , defined as:

$$\psi(X, Z, \alpha_X, \alpha_Z) = \alpha_X * \left(\frac{X - \mu_X}{\sigma_X}\right) + \alpha_Z * \left(\frac{Z - \mu_Z}{\sigma_Z}\right), \quad \alpha_X + \alpha_Z = 1, \quad 0 \leq \alpha_X, \alpha_Z \leq 1$$

Here, Z is the conditional volatility series estimated via GARCH(1,1). We also “normalize” both the CDS data series and the conditional volatility data series by subtracting the mean and dividing by the standard deviation of the series. This is done so that only standard deviations from the mean count in determining the regime break. In our analysis, we always choose $\alpha_X = \alpha_Z = .5$. By construction, $\mu_\psi = 0$. There are only two possibilities for different regime combinations: a {high-volatility, high-price vs. low-volatility, low-price} ({HVHP, LVLP}) regime break; or a {low-volatility, high-price vs. high-volatility, low-price} ({LVHP, HVLP}) regime break. The regime break is then determined as follows:

1. For determination of optimal regime break point for high-volatility, high-price regime break, define a new vector, called R, where $R(i) = \sum_{j=1}^i \psi_i$.

2. The index j where the regime break occurs is defined as:

$$j = \max_{1 \leq i \leq n} |R(i)|$$

3. For determination of optimal regime break point for low-volatility, high-

price regime, define $\epsilon(X, Z, \alpha_X, \alpha_Z) = \alpha_X * \left(\frac{X - \mu_X}{\sigma_X}\right) - \alpha_Z * \left(\frac{Z - \mu_Z}{\sigma_Z}\right)$. Then,

as above, define vector $S(i) = \sum_{j=1}^i \epsilon_i$.

4. The index j where the regime break occurs is defined as: $k =$

$$\max_{1 \leq i \leq n} |S(i)|.$$

5. Choose $\max\{|R(j)|, |S(k)|\}$ to determine whether the data yields a stronger {LVLP,HVHP}, or {HVLP,LVHP} regime break. Suppose $|R(j)| > |S(k)|$. Then the regime break occurs at index j, and the regime breakup is {HVHP,LVLP} (this is what we would expect to occur for most CDS data series, as higher spreads indicate higher default probabilities which will generally result in high volatility of spreads).

It follows that j represents the index of the data series $\{\psi_i\}$ where the sums

$\sum_{i=1}^j \psi_i$ and $\sum_{i=j+1}^n \psi_i$ deviate most in magnitude from their expected values of

zero. By construction, $\sum_{i=1}^j \psi_i = -(\sum_{i=j+1}^n \psi_i)$, and so the regime break point j

represents the point in the data series where $|\sum_{i=1}^j \psi_i - \sum_{i=j+1}^n \psi_i|$ is maximized.

The sum of positive sign represents the {HVHP} subset of the original data series

and the sum of negative sign represents the {LVLP} subset.

The values $|R(j)|$ and $|S(k)|$ can be thought of as absolute measures of how “strong” the regimes are for both the $\{LVLP, HVHP\}$ and $\{LVHP, HVLP\}$ regime break points, respectively. This is because $|R(j)|$ and $|S(k)|$ describe the maximized number of standard deviations from the mean summed between the price series and volatility series in each period, for the respective regime break types. If one compares the ratio of $|R(j)|$ to $|S(k)|$, this describes the relative strength the data yields between the two regime breaks. Define strength as:

$$Strength = \max\left\{\frac{|R(j)|}{|S(k)|}, \frac{|S(k)|}{|R(j)|}\right\}$$

Intuitively, strength describes the number of times “stronger” the chosen regime break was compared to the non-used regime break. For example, if the data series in question yields a $\{LVLP, HVHP\}$ regime break, strength describes the number of times stronger this regime break was compared to the $\{LVHP, HVLP\}$ regime break, or $|R(j)|/|S(k)|$.

Correlations of CDS/put skew, CDS/ATM volatility, and ATM volatility/put skew were then estimated in each regime, using the Pearson coefficient.

Results

We first identified regime shift dates using both CDS spread and ATM volatility for each company. The regime break dates were very similar using both measures and for simplicity we used the regime dates using the CDS spread.¹ The majority of regime break points occurred during the summer of 2007, which represents one of the finest examples of market contagion in recent years, as credit markets problems began to spread throughout global financial markets. After the model was run, the specific regime break date was recorded and correlations were calculated for each regime.

Table 1A: Financial Firm Regime 1 Correlation

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Goldman Sachs	0.03	0.25	0.60
JP Morgan	-0.15	0.20	0.26
Merrill Lynch	0.44	-0.14	0.27
Bank of America	0.00	0.04	0.41
Lehman	0.09	0.11	-0.17
Deutsche Bank	-0.15	-0.27	0.27
Average	0.04	0.03	0.27

Table 1B: Financial Firm Regime 2 Correlation

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Goldman Sachs	0.83	0.67	-0.32
JP Morgan	0.84	0.32	0.38
Merrill Lynch	0.71	0.47	0.56
Bank of America	0.87	0.12	0.13
Lehman	0.87	0.49	0.38
Deutsche Bank	0.71	0.59	0.62
Average	0.80	0.44	0.29

¹ It is significant to note that the regimes for the non-financial firms studied had significant differences in dates of regime breaks running the model with ATM volatility and CDS spread. This was mainly due to how the model was designed as it equally weighted normalized volatility and price changes. However, the resulting correlations in each case were similar, therefore for consistency it was decided to use the regime using CDS spread.

Table 1C: Financial Firm Correlation Changes Between Regimes

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Goldman Sachs	0.79	0.42	0.94
JP Morgan	1.00	0.13	0.12
Merrill Lynch	0.27	0.61	0.29
Bank of America	0.87	0.08	-0.28
Lehman	0.78	0.38	0.55
Deutsche Bank	0.85	0.86	0.35
Average	0.76	0.41	0.33

Table 2A: Non-Financial Firm Regime 1 Correlation

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
IBM	0.30	0.30	0.30
Dell	0.44	0.20	0.44
Apache	0.51	0.32	0.09
Proctor and Gamble	0.31	0.27	0.32
Alcoa	-0.34	0.14	0.09
Average	0.24	0.25	0.25

Table 2B: Non-Financial Firm Regime 2 Correlation

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
IBM	0.79	0.61	0.60
Dell	0.75	0.40	0.38
Apache	0.83	0.60	0.55
Proctor and Gamble	0.77	0.72	0.75
Alcoa	0.88	0.64	0.48
Average	0.80	0.60	0.55

Table 2C: Non-Financial Firm Correlation Changes Between Regimes

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
IBM	0.49	0.31	0.30
Dell	0.31	0.20	-0.06
Apache	0.32	0.28	0.46
Proctor and Gamble	0.46	0.45	0.43
Alcoa	1.22	0.50	0.39
Average	0.56	0.35	0.30

The calculated correlation from regime 1 (shown in Table 1A and 2A) is subtracted from regime 2 (shown in Table 1B and 2B), and the difference is recorded in Table 1C and 2C. From Tables 1C and 2C, it can be seen that the average correlation between risk measures increases in every case. In addition,

there are only two cases of any correlation decreasing between regimes. The first correlation between ATM volatility and CDS spread increases by an average of 0.76 for financial firms and by 0.56 for the firms from other sectors. These increases are both significant and show that the correlations between the two risk measures increase during the regime which experiences significant security price volatility.

The correlation between CDS spread and put skew increased by an average of 0.41 for financial firms and 0.35 for non-financials. There were no correlation decreases in this category. It is also very interesting to note here that the two financial firms viewed to be in the best shape in January 2009, JP Morgan and Bank of America, had relatively small correlation increases in this category. This leads us to believe that put skew is more of a proxy for extreme downside risk such as bankruptcy, whereas ATM volatility is a proxy for mark-to-market risk. This can also be observed from the correlation between ATM volatility and put skew: in this case, Bank of America actually had a decrease in correlation and JP Morgan had an insignificant increase in correlation, which suggests that these healthier firms, while subject to equity price risk, did not appear to be at risk of systematic failure. These firms did display a large increase in correlation between CDS spread and ATM volatility, which suggests that mark-to-market price risk was high, but the likelihood of extreme downward movements was low given the low correlation of CDS spread and put skew.

The average correlation increase is higher for the financial institutions in every category. This was expected as financial institutions were experiencing

extreme volatility in security prices, and some firms filed for bankruptcy.

Correlations between risk measures apparently increase more for firms and industries more affected by market dislocations. However, every chosen company experienced equity price decreases and extreme volatility. For example, Alcoa (an aluminum producer) experienced a dramatic correction in commodity prices, which significantly reduced the equity value of the company. Additionally, Apache was affected by oil prices falling from \$147 a barrel in July 2008 to under \$44 on January 15th, 2009 (the last date used in this study).

Next, we look at each company individually to create a more in depth picture of the correlation changes.

Goldman Sachs

Table 3: Goldman Sachs Correlations

	CDS vs. ATM Vol	CDS vs. Vol Skew	ATM Vol vs. Vol Skew
Entire Period	0.90	0.66	0.60
Regime 1	0.03	0.25	-0.32
Regime 2	0.83	0.67	0.62
Difference	0.79	0.42	0.94

Applying the Goldman CDS data series to our model, we see that regime 1 occurred from 1/5/2005 to 7/19/2007 and is a {LVLP} regime. Regime 2 occurred from 7/20/2007-1/13/2009 and is a {HVHP} regime. The strength of the regime break is 59.05, the highest strength measured, and indicates that the data strongly supports a {LVLP,HVHP} regime break. The first significant correlation measure is the change between CDS and ATM volatility correlations over the two regimes. The correlation between these two measures of perceived risk increased from 0.03 in regime 1 to 0.83 in regime 2. This clearly shows that the correlation between the two downside measurements in the credit and equity market became

much higher in the second, more volatile regime. Additionally, this relationship can be observed in Figure 2 which displays CDS spread and ATM volatility. It is clear that these move more closely together in the higher-volatility regime.

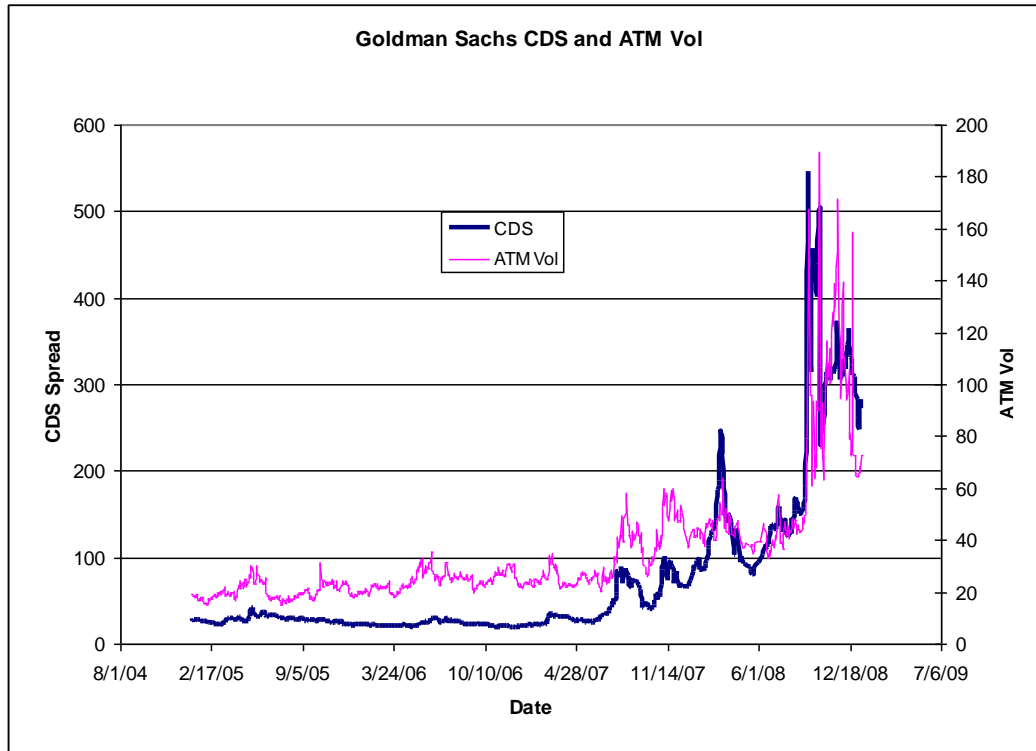


Figure 2

The second significant correlation regarding downside risk is the correlation between CDS spread and put skew. This correlation increased from 0.25 in the {LVLP} regime 1 to 0.67 in regime 2, again showing that the correlation between risk measurements increases in the {HVHP} regime. The CDS spread and the put skew are plotted on Figure 3. The put skew data is fairly volatile, and displays less of an upward trend than does the CDS data. However, during significant events such as the bankruptcy of Lehman Brothers, CDS and put skew both experience an extreme spike. This reflects the hypothesis that volatility skew is a proxy for extreme downside risk, and tends to experience

sudden, extreme changes when the market sentiment for the underlying company changes.

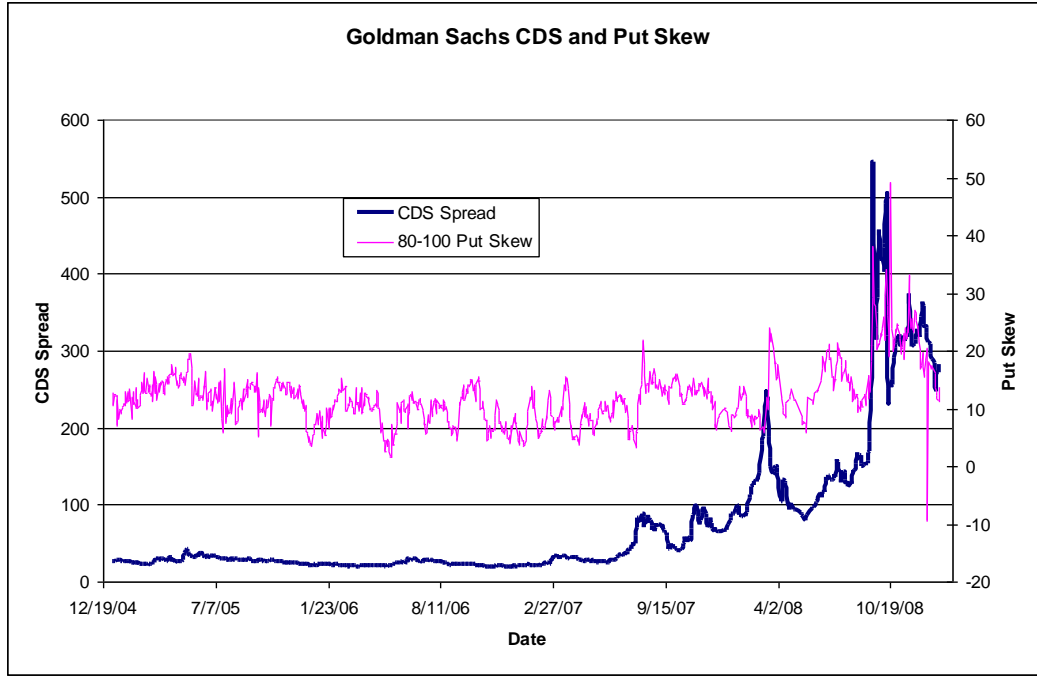


Figure 3

The final significant correlation is the correlation between ATM volatility and put skew. This correlation increased from -0.32 to 0.62 between the two regimes, a considerable increase. This again confirms the fact that during periods of high volatility, correlations between risk measures increase. All three measures increased significantly between regimes for Goldman Sachs.

JP Morgan Chase

Table 4: JPMorgan Chase Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.93	0.68	0.69
Regime 1	-0.15	0.20	0.26
Regime 2	0.84	0.32	0.38
Difference	1.00	0.13	0.12

The regime shift model output dates for regime 1 of 1/5/2005-7/10/2007 and showed that regime 1 is a {LVLP} regime. Regime 2 was from 7/11/2007-1/13/2009 and is a {HVHP} regime. The strength of the regime break is 19.72. Correlation between CDS and ATM volatility increased from -0.15 to 0.84 between the two regimes, which shows that these risk measurements in the credit and equity market became much more correlated during the market dislocation in regime two.

Correlation between CDS and put skew increased from 0.20 to 0.32, much less than the financial sector average of a 0.41 increase. This small increase is likely due to the fact that JPMorgan was viewed as one of the healthiest financial institutions, and therefore was never subject to extreme downside risk such as a possible bankruptcy, which was a feasible outcome for other firms. It is also interesting to note that there is a large spike in volatility skew in Figure 4 directly after JP Morgan acquired Washington Mutual on September 25th, 2008 and a smaller spike on March 17th 2008 when JP Morgan acquired Bear Stearns.

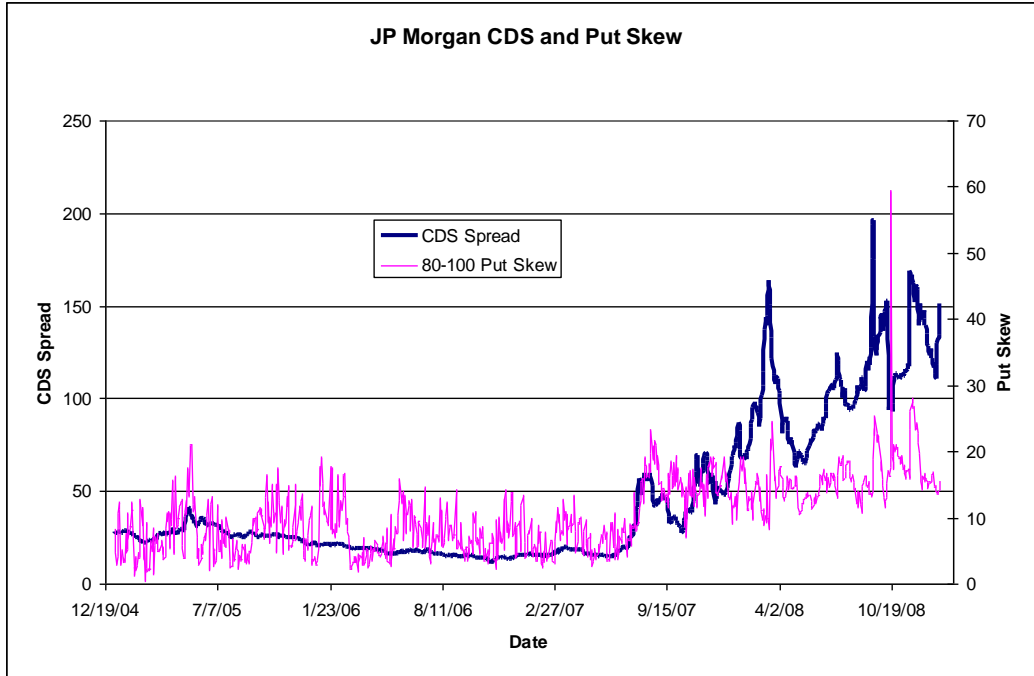


Figure 4

The correlation between ATM volatility and put skew increases from 0.26 to 0.38 between the two regimes. This was expected to be less than the sector average due to the overall health of JPMorgan during this time period. JPMorgan Chase had correlations between all risk measures increase during the {HVHP} regime.

Merrill Lynch

Table 5: Merrill Lynch Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.89	0.66	0.71
Regime 1	0.44	-0.14	0.27
Regime 2	0.71	0.47	0.56
Difference	0.27	0.61	0.29

Merrill Lynch is an interesting case study as Bank of America announced its acquisition of the company on September 14th, 2008. As with all other financial companies, our model suggests that regime 1 was {LVLV} and regime 2 {HVHP}. Regime 1 ran from 1/5/2005-7/24/2007 and regime 2 from 7/25/2007-

11/17/2008. The strength of the regime break is 9.20. The correlation between ATM volatility and CDS spread increased by 0.27, from 0.44 to .71, between the two regimes. Perhaps this number was lower than we might otherwise expect due to the Bank of America acquisition, as Merrill's equity price tended to mirror Bank of America's.

Next the correlation between CDS spread and put skew was calculated and was found to increase 0.61, from -0.14 during the {LVLP} regime to 0.47 during the {HVHP} regime. This is significant because this correlation actually increased more than did the correlation between CDS spread and ATM volatility. This supports the idea that put skew is more of a representation for extreme downside risk, as Merrill Lynch was exposed to this risk as it was forced to sell itself to Bank of America.

Finally, the correlation between ATM volatility and put skew increased by 0.29, from 0.27 in the {LVLP} regime to 0.56 in the {HVHP} regime, which shows that all three correlations between risk measures increase during the latter {HVHP} regime.

Bank of America

Table 6: Bank of America Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.93	0.60	0.55
Regime 1	0.00	0.04	0.41
Regime 2	0.87	0.12	0.13
Difference	0.87	0.08	-0.28

The regime shift model returned regime 1 dates of 1/5/2005-7/24/2007 and regime 2 dates of 7/25/2007-1/13/2009, with a relatively low strength of 2.75.

The correlation between ATM volatility and CDS spread increased by 0.87, from

a virtually uncorrelated 0.00 in the {LVLV} regime 1 to a strongly correlated 0.87 in the {HVHP} regime 2, a significant increase.

The correlation between CDS spread and put skew increased 0.08 between the two regimes, an insignificant increase. This makes sense as, like JP Morgan, Bank of America was viewed as one of the healthier firms during the dates studied.

Finally, the correlation between ATM volatility and put skew actually *decreased* by 0.28 between the two regimes. This was the only significant correlation to decrease between regimes for financial firms. This is significant because it shows that the larger, healthier firms during the studied period did not have extreme downside risk measures become as correlated in the latter regime, which supports the hypothesis that put skew is more of a proxy for extreme downside risk whereas ATM volatility is a proxy for mark-to-market risk.

Lehman Brothers

Table 7: Lehman Brothers Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.92	0.66	0.56
Regime 1	0.09	0.11	-0.17
Regime 2	0.87	0.49	0.38
Difference	0.78	0.38	0.55

The regime shift model gave regime 1 as 1/5/2005 to 7/20/2007 and regime 2 as 7/21/2007 to 9/12/2008, as well as a strength of 41.25. Lehman is the only financial firm in our study which filed for bankruptcy, which was filed on September 15th, 2008. The correlation between CDS spread and ATM volatility increased by 0.78 between the regimes, and the correlation in the second regime was 0.87, which is significant.

The correlation between CDS spread and put skew increased by 0.38, which is not as much as we would have thought given the fact that Lehman filed for bankruptcy and therefore experienced an event of systematic failure. However, we believe that in the few days before the Lehman bankruptcy, equity volumes were very high but over the counter (OTC) derivative spreads were so large given the uncertainty that it was virtually impossible to price securities retroactively as is done on Bloomberg. This can be seen in Figure 5 as the skew is seen to decrease substantially on the date of Lehman's bankruptcy, which is more likely due to large broker spreads tainting the data rather than a decrease in correlation.

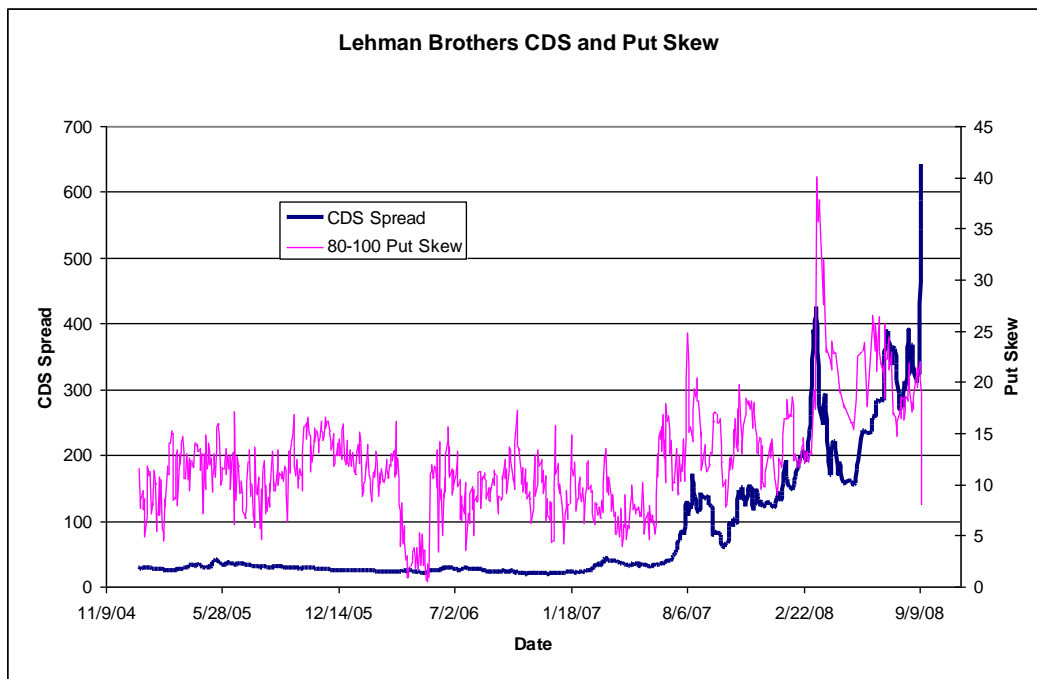


Figure 5

Deutsche Bank

Table 8: Deutsche Bank Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.80	0.77	0.74
Regime 1	-0.15	-0.27	0.27
Regime 2	0.71	0.59	0.62
Difference	0.85	0.86	0.35

The regime shift model estimated 1/15/2005-7/23/2007 for regime 1 and 7/24/2007-1/13/2009 for regime 2. The strength of the regime break was 34.64, indicating that the data very strongly favored a {LVLP,HVHP} regime break. It can be seen from Table 8 that Deutsche Bank shows increased correlations during the {HVHP} regime which is inline with other financial firms. Overall, all except one correlation change for financial firms increased during the latter {HVHP} regime, which confirms that in our study, correlations between risk measures for financials increase during periods of market dislocation.

IBM

Table 9: IBM Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.85	0.66	0.66
Regime 1	0.30	0.30	0.30
Regime 2	0.79	0.61	0.60
Difference	0.49	0.31	0.30

The regime shift model estimated 1/5/2005-6/1/2007 for a {LVLP} regime 1 and 6/2/2007-1/13/2009 for a {HVHP} regime 2, as well as a strength of 7.06. It can be seen from Table 9 that all correlations increase between the two regimes, except that the average increase is slightly lower than for that of financial firms.

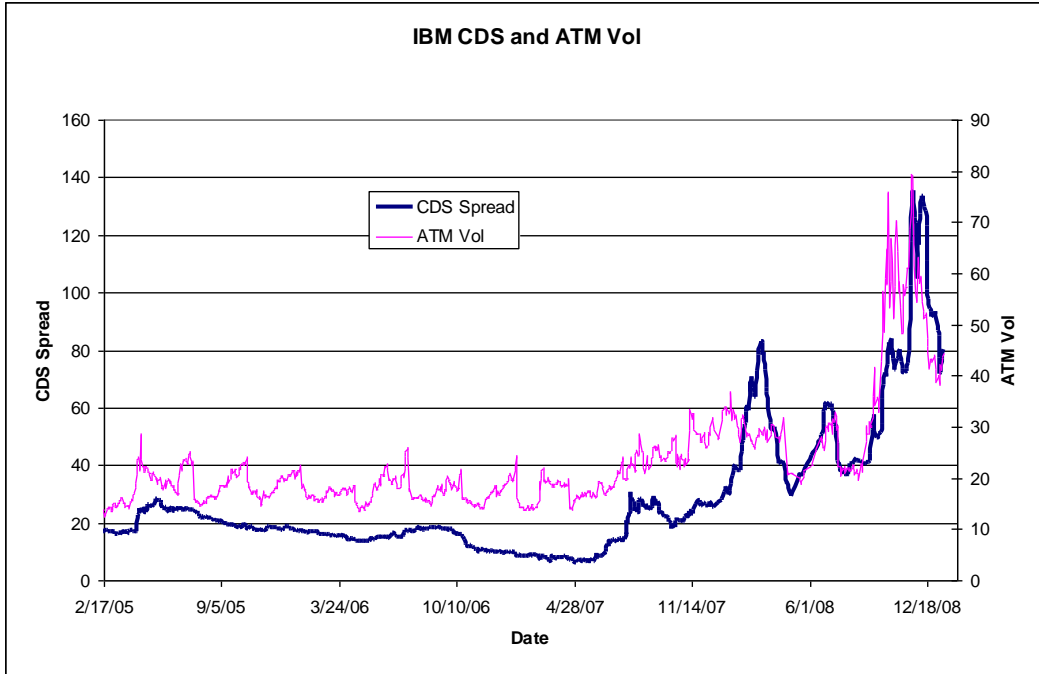


Figure 6

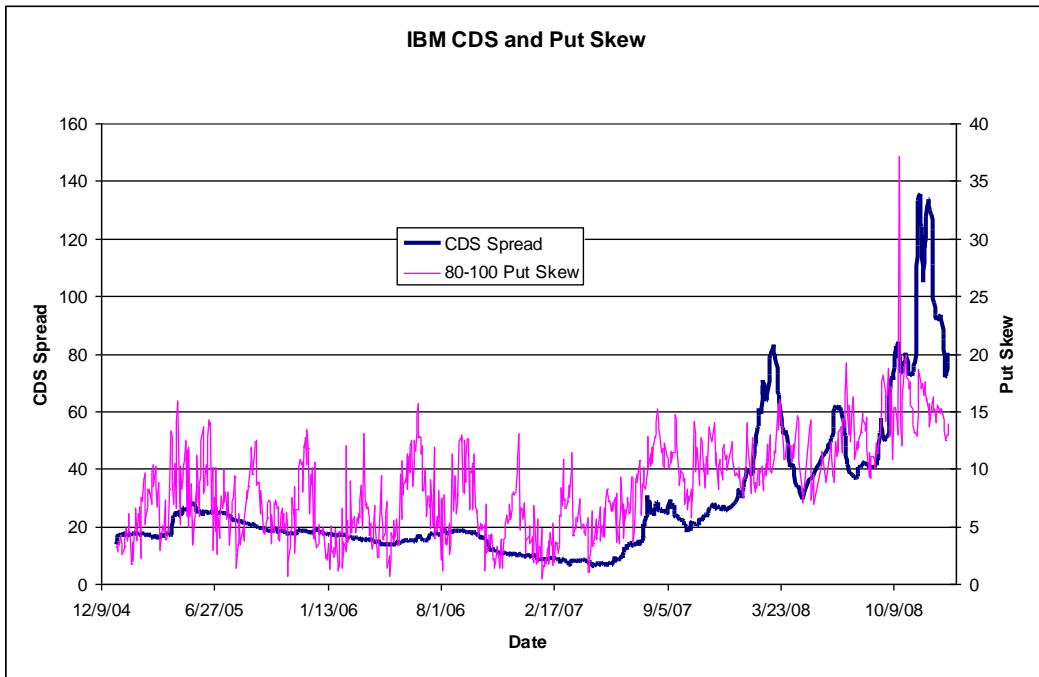


Figure 7

Dell

Table 10: Dell Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.81	0.43	0.50
Regime 1	0.44	0.20	0.44
Regime 2	0.75	0.40	0.38
Difference	0.31	0.20	-0.06

The regime shift model returned a {HVLP} regime 1 from 1/5/2005-9/4/2007 and a {LVHP} regime 2 from 9/5/2007-1/13/2009. The latter regime in this case actually exhibits less volatility and higher price changes, which never happened for financial firms. This occurs in three non-financial firms (Dell, Apache, and Proctor & Gamble). A reason for this could be that these firms were viewed to be very healthy and did not exhibit much volatility on their CDS spreads in the second period. However, the strength measure for the {HVLP,LVHP} break was very low, indicating that this regime break was not much better of an estimator than the {LVLP, HVHP} regime break. For example, the strength measure for Dell was given to be 1.41, whereas the strength measure for Goldman Sachs was 59.05. This indicates that the regimes were much more pronounced for the financial firms than for the non-financials.

Dell also experiences a decrease in correlation between ATM volatility and put skew, again showing that non-financial firms had smaller increases in correlations than did financial firms.

The last three non-financial firms behave very similarly and are listed below for reference.

Apache

Table 11: Apache Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.91	0.58	0.54
Regime 1	0.51	0.32	0.09
Regime 2	0.84	0.60	0.55
Difference	0.32	0.28	0.46

The regime shift model returned a {HVLP} regime 1 from 1/5/2005-11/27/2007 and a {LVHP} regime 2 from 11/28/2007-1/13/2009. The strength of the {HVLP,LVHP} regime break was 1.11, indicating that this regime break was hardly a better estimator than a {LVLP,HVHP} regime break.

Proctor and Gamble

Table 12: Proctor & Gamble Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.89	0.78	0.78
Regime 1	0.31	0.27	0.32
Regime 2	0.77	0.72	0.74
Difference	0.46	0.45	0.43

The regime shift model returned a {HVLP} regime 1 from 1/5/2005-12/4/2007 and a {LVHP} regime 2 from 12/5/2007-1/13/2009. The strength of the {HVLP,LVHP} regime break was 1.52, indicating again that this regime break was hardly a better estimator than a {LVLP,HVHP} regime break.

Alcoa

Table 13: Alcoa Correlations

	CDS vs. ATM Vol	CDS vs. Put Skew	ATM Vol vs. Put Skew
Entire Period	0.88	0.53	0.44
Regime 1	-0.34	0.14	0.09
Regime 2	0.88	0.64	0.47
Difference	1.22	0.50	0.39

The regime shift model returned a {LVLP} regime 1 from 1/5/2005-5/7/2007 and a {HVHP} regime 2 from 5/8/2007-1/13/2009. The strength of this regime break was 9.45, which, while higher than for the above non-financials, remains below the majority of financial regime break strengths.

Discussion

The fact that financial firms' risk measures exhibit higher change in correlation than non-financial companies may be explained by a number of theories. One possible explanation for this higher correlation change would be the fact that securities for financial firms became much more liquid during the credit crisis. This increase in volume for virtually all financial institution securities could have increased the demand for hedging instruments, thus driving up correlations between risk measures as the market began paying closer attention to these firms' CDS and options prices. An alternative theory could be the effect of the SEC short selling ban implemented on September 19th, 2008 which temporarily prohibited the short selling of 799 financial institution equities. This could have driven the demand for hedging instruments such as options and credit default swaps, which would have greatly increased correlations. However, the complete ramifications for the short selling ban are still widely debated and beyond the scope of this paper. Finally, non-financial firms exhibited higher correlations on average during regime 1 and therefore correlations had less room to increase in regime 2. However, it should be noted that for three out of the five non-financials studied, regime 1 is a {HVLP} regime, and a regime change from

{HVLV} to {LVHP} represents “less” of a dislocation than observed in the financial firms. Regardless, correlations between risk measures in both financials and non-financials increased significantly between regimes.

1. Limitations of Study

A major limitation of this study was the lack of access to data. Five year CDS contracts were used along with one month equity put options. Ideally, the maturities on these two securities should be the same, but this was not feasible due to the different maturity structures of these securities. One month equity put options are generally the most liquid. If a less liquid option was used, it could lead to artificially increased asset volatility as the security would be more difficult to mark-to-market for Bloomberg. The same holds true with five year CDS contracts.

Another limitation was data congruency, as correlations between many securities were calculated and it was necessary that every security have a value at every data point. Some securities were missing data values on certain dates and therefore the entire date had to be removed from the data set. This could lead to inaccuracies in calculated volatilities and correlations. However, given the limited access to data, this was a necessary step in order to create the best correlation matrices possible.

All of the models created for this paper made assumptions such as the use of the normal distribution in the maximum likelihood function in the GARCH(1,1) model. Additionally, the regime shift model we created gives equal weight to

volatility and price changes. However, the regimes would be different if the model were weighted to favor volatility or price deviations more heavily.

Finally, the crisis that we study is still ongoing and the securities markets have continued to show an extreme amount of volatility as this paper is being written. No one knows what new developments will come in the near or distant future, and these changes could affect the overall correlations of risk measures during the period.

2. Areas of Further Study

Yield curves could be constructed for CDS and the relationship between the yield curve and the volatility skew could be studied over the whole curve, which could provide interesting results that are beyond the scope of this study. Additionally, options are beginning to trade on CDS and CDS indices, exploring these volatility skews could be informative as well.

Another possible application would be to weight equity beta by normalizing credit spreads or weighting beta in relation to how correlated risk measures have become. There are many methods to weight equity beta, however few incorporate information from the credit market or information regarding the changing market risk dynamics.

Finally, the regime shift model could be extended to involve other parameters instead of security volatility and price decreases.

References

- Bollen, Nicolas P. B. and Whaley, Robert E., Does Net Buying Pressure Affect the Shape of Implied Volatility Functions? (September 2002). AFA 2003 Washington, DC Meetings. Available at SSRN: <http://ssrn.com/abstract=319261> or DOI: 10.2139/ssrn.319261
- Bollerslev, Tim. "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics* 31(1986): 307-327.
- Buffet, Warren. "Berkshire Hathaway Inc. 2008 Annual Report." *BerkshireHathaway.com*. 2009. Berkshire Hathaway. 1 Apr 2009 <<http://www.berkshirehathaway.com/2008ar/2008ar.pdf>>.
- Calvo, Guillermo, Mendoza, Enrique G.. "Rational Contagion and the globalization of securities markets." *Journal of International Economics* (51) 2000 79-113.
- Eichengreen, Barry, Rose, Andrew K., and Wyplosz, Charles. "Contagious Currency Crises." *National Bureau of Economic Research* (1996).
- Gray, Stephen F.. "Modeling the Conditional Distribution of Interest Rates as a Regime-Switching Process." *Journal of Financial Economics* 42(1996): 27-62.
- Hartmann, P., Straetmans, S., C.G. de Vries. "Asset Market Linkages in Crisis Periods." *The Review of Economics and Statistics* 86(1)(2004): 313-326.
- Henry, Olan T.. "Regime Switching in the Relationship Between Equity Returns and Short-term Interest Rates in the UK." *Journal of Banking & Finance* 33(2009): 405-414.
- Kodres, Laura, Pritsker, Matthew. "A Rational Expectations Model of Financial Contagion." *The Journal of Finance* 57(2)2002 769-799.
- Kyle, Albert, Xiong, Wei. "Contagion as a Wealth Effect." *The Journal of Finance* 56(4)2001 1401-1440.
- Lowenstein, Roger. *When Genius Failed: The Rise and Fall of Long-Term Capital Management*. 1st. New York, NY: Random House Publishing Company, 2000.
- Medeiros, Marcelo C., Veiga, Alvaro. "Modeling Multiple Regimes in Financial Volatility with a flexible coefficient GARCH(1,1) model." *Econometric Theory* 25(2009): 117-161.
- Rubinstein, M. "Implied Binomial Trees." *Journal of Finance* 69(3), (1994) 771-817.
- Wadhwani, Sushil, King, Mervyn A.. "Transmission of Volatility Between Stock Markets." *The Review of Financial Studies* 3(1)(1990): 5-33.

Appendix

Matlab Code for Regime Shift Model

```
function [regime regime1sign hvhplevel lvhplevel index1] =  
regimeshift7(companyvector1,meancoeff)  
[amax bmax volvector]=returncondvol(companyvector1);  
volcoeff=1-meancoeff;  
[Rows Columns] = size(companyvector1);  
% Throw out first day since volvector does too  
companyvector=zeros(Rows-1,Columns);  
for i=1:Rows-1  
    companyvector(i)=companyvector1(i+1);  
end  
% now, convert both these vectors into N(0,1)  
stdcompanyvector=std(companyvector);  
stdvolvector=std(volvector);  
meanprice=mean(companyvector);  
meanvol=mean(volvector);  
normalizedcompanyvector=zeros(Rows-1,1);  
normalizedvolvector=zeros(Rows-1,1);  
  
for i=1:Rows-1  
    normalizedcompanyvector(i)=(companyvector(i)-meanprice)/stdcompanyvector;  
    normalizedvolvector(i)=(volvector(i)-meanvol)/stdvolvector;  
end  
  
% high vol, high price regime determination  
flowvectorhvhp=zeros(Rows-1,1);  
flowvectorhvhp(1)=meancoeff*normalizedcompanyvector(1)+volcoeff*normalizedvolvector(1);  
for i=2:Rows-1  
    flowvectorhvhp(i)=flowvectorhvhp(i-1)+  
(meancoeff*normalizedcompanyvector(i)+volcoeff*normalizedvolvector(i));  
end  
flowvectorhvhpabs=abs(flowvectorhvhp);  
indexhvhp=1;  
maxhvhp=flowvectorhvhpabs(1);  
for j=2:Rows-1  
    if flowvectorhvhpabs(j)>maxhvhp  
        maxhvhp=flowvectorhvhpabs(j);  
        indexhvhp=j;  
    end  
end  
hvhplevel=flowvectorhvhp(indexhvhp);  
  
% low vol, high price regime determination  
flowvectorlvhp=zeros(Rows-1,Columns);  
flowvectorlvhp(1)=meancoeff*normalizedcompanyvector(1)-volcoeff*normalizedvolvector(1);  
for i=2:Rows-1  
    flowvectorlvhp(i)=flowvectorlvhp(i-1)+meancoeff*normalizedcompanyvector(i)-  
volcoeff*normalizedvolvector(i);  
end  
flowvectorlvhpabs=abs(flowvectorlvhp);  
indexlvhp=1;
```

```

maxlvhp=flowvectorlvhpabs(1);
for j=2:Rows-1
    if flowvectorlvhpabs(j)>maxlvhp
        maxlvhp=flowvectorlvhpabs(j);
        indexlvhp=j;
    end
end
lvhplevel=flowvectorlvhp(indexlvhp);

if maxhvhp>=maxlvhp
    regime='high vol/high price and low vol/low price';
    index1=indexhvhp+1;
else
    regime='low vol/high price and high vol/low price';
    index1=indexlvhp+1;
end

if maxhvhp>=maxlvhp
    % High vol high price
    if flowvectorrhvp(index1)>0
        regime1sign='regime 1 is high vol, high price';
    else
        regime1sign='regime 1 is low vol, low price';
    end
else
    %low vol high price
    if flowvectorlvhp(index1)>0
        regime1sign='regime 1 is low vol high price';
    else
        regime1sign='regime 1 is high vol low price';
    end
end

% Adds 1 since the first data point is necessarily thrown out. So if you
% import 500 sized vector and it returns 300, the 300 refers to the index of
% the original vector imported.

```