2010

CREDIT DEFAULT SWAPS - ESSAYS ON MODEL AND MARKET EFFICIENCY

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(Thesis format: Integrated-Article)

By

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A thesis submitted in partial fulfillment
of the requirements for the degree of

Doctor of Philosophy

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ABSTRACT

Essay 1 tests the ability of a commercial structural credit default swap pricing model to predict market spreads. Consistent with several previous studies testing other models, we find our model unable to price credit risk precisely and observe an illiquidity premium reflecting a credit risk component which should be incorporated into future pricing models. We also identify macroeconomic and stock market factors that help explain movements in CDS spreads beyond the levels suggested by the model.

Essay 2 looks at bid and ask spreads to find evidence of quote shading where dealers manipulate their quotes in order to attract sell orders. This is something not yet studied in CDS literature and we draw on studies on the foreign exchange markets for theoretical support. We find that dealers are more likely to indulge in quote shading when firm risk increases but not close to weekends or holidays. We also look at price discovery with and without quote shading but our results are inconclusive. Using the put-call ratio as a risk level indicator, we find that price discovery in the CDS market decreases as firm risk increases.

Essay 3 looks at the quality of the CDS market in the backdrop of the recent financial crisis. Previous studies have found that CDS markets lead price discovery only in the case of high risk firms and this paper tests if price discovery dynamics have shifted in favour of the CDS market since overall firm risk levels have increased. Using Granger-causality tests, we compare stock and CDS markets before and since the crisis and finds that despite an overall increase in risk levels, the stock market continues to lead the CDS market in all risk categories. We also test the CDS market for mis-reaction using Variance Ratios and find that while there was evidence of over-reaction before the crisis, CDS market is under-reacting since the crisis.

Key Words: Credit Default Swaps, CreditGrades, CDS Implied Volatility, Liquidity, Price Discovery, Quote Shading, Day-of-Week Effect, Post-Crisis Analysis, Over-reaction, Under-reaction.

ACKNOWLEDGEMENTS

This PhD has been an amazing journey for me. During this time, I have been helped, guided and motivated by many people.

I owe a ton of gratitude to Professors Zeigham Khokher and Walid Busaba in helping me keep things in perspective and make it to the finish line. Without their guidance, I would not be here and would like to thank them for all the advice, support and mentorship.

I would also like to thank Professor Stephen Sapp for his guidance and patience as well as the valuable insight he provided on my research. I am thankful to Professor George Athanassakos who introduced me to database management and gave me the opportunity to learn at his expense.

A huge thank you to Linda Dittmer-Pino and Mahillah Rafek at the Program Office for the help they provided. I am grateful to my colleagues in the PhD program for making the dark, depressing hours seem brighter. A special thanks to David Mackay for our long discussions on capital markets and research ideas.

I would also like to thank my parents for their encouragement and for teaching me the importance of education. To my sister, Fariha, and my in-laws, I am grateful for the support they provided through this journey.

Last but definitely not least, I would like to thank my wife, Muna and daughters, Rida and Kaamila, without whose support and love, I would not be where I am. Thank you for the sacrifices, for the belief and for asking what I want to be when I grow up.

Thank you all so much.

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Chapter 1. Introduction

"...But if the economy keeps slowing, credit default swaps, like subprime mortgages, may become a household term. Credit default swaps form a large but obscure market that will be put to its first big test as a looming economic downturn strains companies' finances."

New York Times, February 17, 2008[1]

Credit Default Swaps (CDS) are derivative instruments that allow investors protection against credit events like downgrades of or defaults by single-name or a basket of obligors. Estimated by the Bank of International Settlements (BIS) to be at \$32.6 tln in Dec 2009[2], these instruments represent one of the largest and fastest growing financial product markets globally, making the comments expressed in the New York Times a cause for concern.

The need to develop a better understanding of these instruments and their associated risks has gained significance in the backdrop of the global financial crisis that started with the subprime mortgage problems in 2007. From an academic perspective, a significant amount of research in this area has focused on the development of models to price risk and the focus has recently shifted to empirical research.

Given that our understanding of the "over-the-counter" (OTC) market for CDS is still in the nascent stages, my dissertation examines the CDS market to understand the behaviour of participants and market dynamics. As a result, all three chapters in this document

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[1] "Arcane Market Is Next to Face Big Credit Test", Morgenson, Gretchen; 2008, February 12. *New York Times*.

[2] http://www.bis.org/statistics/otcder/dt1920a.pdf

look at issues that are at the heart of the ongoing discussion on CDS, ranging from the accuracy of pricing models to market informational efficiency and quality. We examine the following:

1. Performance of a commercial structural CDS pricing model.
2. Dealer quotes and their impact on informational efficiency of the CDS market.
3. The CDS market quality in the backdrop of the financial crisis.

1.1 Beyond Structural Models

One of the issues to emerge from the financial crisis was the inability of the models to explain market spreads. Without a commonly accepted pricing model, trading institutions typically use internally developed, proprietary models that are not available to the public for review. However, most of these models build upon either structural or reduced-form theoretical models which have been the focus of academic research for some time.

Ericsson et al (2005) test some of the popular theoretical models – by Leland, Leland-Toft and Fan-Sundaresan – to find that the Leland and Fan-Sundaresan models, on average, underestimate actual CDS spreads by 50 and 33 bps respectively while the Leland-Toft model, on average, overestimates market CDS spreads by 8 bps. Eom et al (2004) also test models to find that they fail to price market CDS spreads precisely. Given these studies and other papers with similar findings, we find that pricing models only provide a benchmark price and are unable to price spreads accurately.

Our paper tests CreditGrades, a commercially available CDS pricing model, against market CDS spreads. In case of any evident mispricing, we identify factors that improve the accuracy of the spreads so that these risk factors can be integrated into future pricing models.

Consistent with findings of studies testing other models, we find CreditGrades unable to price credit risk accurately. We find evidence of an illiquidity premium in the CDS market which contradicts arguments from previous studies. We believe that this reflects credit risk and is a component missing from existing pricing models which should be incorporated into the pricing dynamics. We also identify macroeconomic and stock market factors that help explain movements in CDS spreads beyond the levels suggested by the model. Although including these factors significantly improves the fit of the pricing model, we find a large part of the spread changes remains unexplained suggesting risk factors that are still being omitted by our model and possibly, the market as well.

1.2 Dealer Quotes and Their Impact on Price Discovery

Given the CDS market's OTC structure and limited data availability, there is little research studying how dealers manage their open positions. We draw from literature on the foreign exchange market, which is also OTC, to understand how dealers manage their inventory through "quote shading". This concept was first introduced by Garman (1976) and then developed further by Amihud and Mendelson (1980) who built a multi-period model where dealers increase prices if their inventory is shrinking and reduce prices in case of an inventory build up.

Using bid and ask spreads, we look for evidence of "quote shading" in the CDS market as dealers adjust quotes to encourage counterparties to buy or sell CDS, allowing them to close out open positions.

We find evidence of quote shading in around 10% of the data. We recognize that it is also possible for dealers to cover their open short positions at prevailing market ask spreads as quote shading could reveal important information about their positions. We find that dealers are more likely to carry out quote shading when the firm is going through a high risk period.

More importantly, we test the impact this practice has on the informational efficiency in the CDS market. Using Hasbrouck's informational share measure, we find that price discovery in the CDS market is slower when the firm risk is high, implying that quote shading may come at a cost of reduced informational efficiency in the CDS market.

1.3 Market Quality and the Financial Crisis

CDS and stocks offer the chance to study two different markets for the same underlying asset but with different price discovery dynamics. While the stock market has a relatively large number of retail investors, the less liquid CDS market consists primarily of banks, hedge funds and other financial institutions which may be considered relatively well informed compared to retail investors in the stock market.

Blanco et al. (2005) examine the CDS and bond markets to conclude that there is greater price discovery in the CDS markets than in the bond markets. Forte and Pena (2009) find the stock market leading CDS and both CDS and shares leading the bond market. While it is generally accepted that the bond market lags CDS and stocks, research reflects mixed results when comparing the CDS and the stock markets.

Forte and Lovreta (2008) look at the stock and CDS markets for the period 2002-2004 to find CDS spreads leading price discovery for the higher risk (lower rated) credits supporting findings from Acharya and Johnson (2007). More importantly, they also find evidence suggesting the informational dominance of the stock market declining over the period 2002-2004.

We add to literature by extending the analysis to include the financial crisis and any impact it may have had on the price discovery process. Using Variance Ratios developed by Lo and MacKinlay (1988), we also look for any evidence of mis-reaction in the CDS market before and since the crisis.

We find that contrary to our expectations, the stock market continues to lead the CDS market across all risk categories. Interestingly, we also find that while the CDS market was characterized by over-reaction in the pre-crisis period, the market is now under-reacting in a less liquid environment contradicting Cox and Peterson (1994) findings where markets over-react in tighter liquidity conditions.

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Chapter 2. Beyond Structural Models

> "Credit swaps are very hard to price. The easiest and most common way to determine price is the market pricing approach. "If the bond market is pricing 10-year Italy at Libor+25 basis points (bp) then, regardless of any internal pricing model telling you the swap premium should be 40bp, you have to price the swap at 25bp," says Lincoln Benet, head of credit derivatives at Morgan Stanley in London."
>
> Euromoney, Mar 1996[3]

> "John Mauldin, another influential investor, thinks counterparty risk in CDS will be one of the big stories in 2008, particularly as already-fragile bond insurers are big in that market."
>
> The Economist, January 12, 2008[4]

2.1. Introduction

Credit Default Swaps (CDS) represent one of the largest and fastest growing financial product markets globally. The size and growth of this market make the Euromoney comments a cause for concern. The practitioner view of model mispricing is confirmed by academic literature testing the relationship between theoretical and market spreads. Ericsson et al (2005) test some of the popular theoretical models – by Leland, Leland-Toft and Fan-Sundaresan – to find that the Leland and Fan-Sundaresan models, on average, underestimate actual CDS spreads by 50 and 33 bps respectively while the Leland-Toft model overestimates market CDS spreads by 8 bps on average. Eom et al (2004) also tests models to find that they fail to price market CDS spreads precisely.

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[3] "But how do you price them?", Parsley, Mark. Mar 1996, *Euromoney*, Iss. 323; pg. 30

[4] "Finance And Economics: Stepping beyond subprime; Banks and the credit crunch.", 2008, January. *The Economist,* 386(8562), 66.

Given these and other studies with similar findings, we see that theoretical pricing models only provide a benchmark price and are unable to price spreads accurately.

The goal of this paper is to test a commercial CDS pricing model against market CDS spreads. In case of mispricing, we identify factors that help improve the accuracy of the model spreads so that these risk factors can be integrated into future pricing models.

Complicating our ability to price these assets using our existing models is the influence of different types of financial risk. Unlike for the bond market, Longstaff et al (2005) argue that liquidity does not need to be priced in the CDS market. They state that it does not play a part in driving CDS spreads as the swaps are synthetic and can be issued by any market participant willing to trade at the prevailing prices. However, as indicated in the earlier quote, counter-party and credit risk may influence the price in ways that are not currently incorporated in our models. According to the Economist[4], the ability of the "already-fragile bond insurers" to sell credit risk with limited disclosure requirements has resulted in uncertainty about the quality of counterparty risk. As some of the heavily leveraged hedge funds are major sellers of insurance in the CDS market, regulators are concerned about their ability to honour obligations in case of an unravelling of the credit chain. The degree to which different types of financial risk influence the observed prices is an empirical question which we consider even though these types of risk are not formally included in our model.

In the backdrop of the sub-prime crisis, it is of vital importance that the market accurately estimates default probabilities, thus pricing credit risk correctly. According to Darrell Duffie, "...this is one area of finance where our ability to structure financial products may be running ahead of our understanding of the implications"[5]. In the absence of a single dominant pricing model, the majority of literature on CDS has focused on credit risk modeling and it is only recently that focus has shifted to empirical studies of the CDS market.

In this paper, we use the Dow-30 firms to test the credit default spreads derived from the CreditGrades model (Finger, 2001) developed by the RiskMetrics Group and find that the model, on average, underprices credit by 10 bps. Given that the 10 bps may represent noise, we conduct a further test using volatility implied by the CDS model based on market prices. Using Root Mean Square Error (RMSE) as a basis for comparison, we test the Equity Options Implied Volatility (EOIV) and CDS Implied Volatility (CDSIV) against realized volatility to find higher error levels for CDSIV. This confirms that the EOIV is a better predictor of volatility especially in the shorter term and supports the need for incorporating additional risk factors into the CDS pricing model.

Confirming that our model misprices CDS spreads, we draw on Tang and Yan (2007) and Collin-Dufresne et al (2001) to use liquidity and macroeconomic variables as risk factors in a regression model to explain the mispricing. Using macroeconomic factors as a proxy for risk, we find that they improve the fit of the model suggesting that the CreditGrades model suffers from omitted economic risk factors and is therefore unable to reflect credit risk accurately. Additionally, we find that the buyers in the CDS market pay an illiquidity premium which contradicts the argument presented by Longstaff et al (2005) that unlike bonds, CDS spreads do not reflect a liquidity premium.

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[5] "Irresistible Reasons For Better Models of Credit Risk", Darrell Duffie, *Financial Times. London (UK)*, Apr 16, 2004. pg. 17

Our contribution to the literature is the testing of the CreditGrades pricing model to find that, on average, it underprices market CDS spreads by 10 bps. We also identify stock index volatility and risk premium as risk factors that should be incorporated in future pricing models to reduce the level of mispricing. More importantly, contrary to previous studies, we argue that liquidity is a measure of risk that should be included into the pricing models and show this factor to be empirically significant. However, with a low adjusted R-square and a statistically significant regression constant, we recognize that there are still factors that need to be identified and built into the theoretical pricing models.

The remainder of the paper is organized as follows. The following section introduces credit default swaps, the different pricing models, our choice of model and review of research on factors explaining credit spreads. Section 2.3 looks at the data set and the expected relationship between our variables and credit spreads. We test the performance of our model in Section 2.4. In Section 2.5 we examine some of the omitted risk factors that may help explain CDS spread movements and present our test results with our conclusion in Section 2.6.

2.2. Credit Default Swaps

Prior to the emergence of credit derivatives in the 1990s, the task of managing credit risk was limited to the use of traditional financial analysis, covenants and counterparty limits. These measures were typically undertaken by financial institutions or large investors and included the use of triggers & covenants, collateral and regular business review.

However, the high demand for structured solutions in the field of credit risk management led to the introduction of credit risk instruments like CDS, developed on the basis of complex statistical models. According to ISDA estimates[6], the outstanding notional amount of CDS in June 2006 was US$ 26 trillion as compared to only US$6.4 trillion for equity derivatives. Despite the financial crisis and the resulting slowdown, the CDS market was sized at $32.6 tln in Dec 2009[7]. With plans of taking CDS from the OTC market to an exchange based setting, these numbers are expected to show higher growth going forward and it is important to understand how these instruments are priced.

The CDS works as insurance on debt that an investor (buyer of protection) can purchase from the market (Figure 2.1). Therefore, similar to the insurance mechanism, the investor is required to make regular premium payments (quoted in bppa) to the counterparty (seller of protection) and in case of a defined credit event, either a downgrade or a default of a third party (reference entity), the insurer gets a physical or cash settlement on the exposure. In the case of physical settlement, the buyer surrenders the underlying asset (bond etc.) to the seller and receives the full and final settlement in return. If the settlement basis is cash, the buyer gets to keep the asset and only receives the difference between the face value and the recovery (or prevailing market) value as settlement.

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[6] "Summaries of Recent Survey Results", http:///www.isda.org/statistics/recent.html

[7] http://www.bis.org/statistics/otcder/dt1920a.pdf

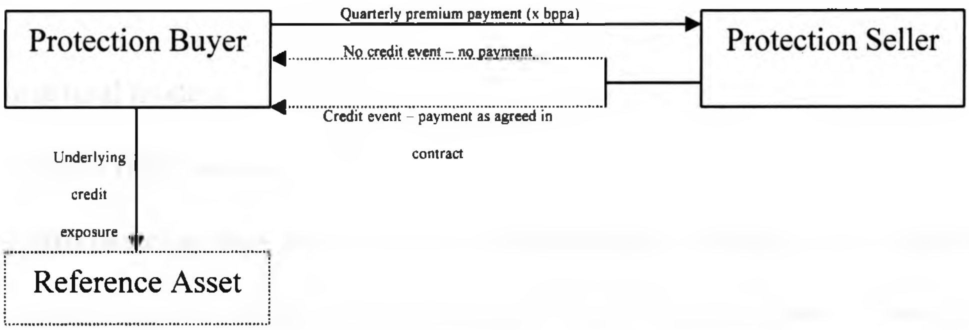

Figure 2.1 CDS Transaction Structure

2.2.1 Pricing Models

Our discussion with a major CDS trading institution confirmed that while some CDS pricing models may be more commonly used than others, there is currently no single pricing model that can be considered the primary pricing tool for the market. Given the absence of a dominant pricing tool, an investor may be quoted different prices for the same contract by two different banks, both using their proprietary models.

To understand the reasons for the lack of a uniform pricing tool, it is important to highlight two of the key inputs that are needed for pricing credit risk; the time to default and the subsequent recovery rate. A credit event is not limited to default and may include rating downgrades as well. It is therefore important to accurately forecast the evolution of the credit risk, a task that is very difficult to model. Additionally, it is important to be able to estimate the recovery rates for the loans. While there are ways to arrive at estimates for both these inputs, they are based on historical data and therefore include proprietary data unique to each firm and its experiences.

Most of the valuation models can be grouped into one of the following two categories (or a hybrid):

1) Structural models
2) Reduced form models

The main difference between the two models is that structural models base default on the firm's asset-liability evolution process and reduced form models assume that default is a stochastic event independent of the firm's financial position, dependent on the general level of interest rates.

2.2.2 Structural Models

These are characterized by modeling of a firm's total value in order to develop an estimate for the probability of default. According to these models, the source of credit risk is the uncertainty concerning the market value of the firm and they build upon Merton's model (1974) for valuing risky debt.

For our study, we use a structural model and therefore only present a general overview here with the detailed mathematical model presented in Appendix 2A and 2B.

The underlying Merton (1974) model is built on insights from the Black-Scholes (1973) options pricing model using the following premise:

1) Default events are predictable based on the value of debt and the value of the firm.
2) The value of the assets of the firm evolves randomly.

A firm with debt and equity in its capital structure will pay the bondholders, on maturity, the lower of the face value of debt or the market value of the firm, the latter case representing a default scenario. In other words, if the market value of the firm is greater than the face value of debt, the bondholders get their debt repaid and the residual value flows to the equity holders. On the other hand, if the market value of the firm is less than the face value of debt, the bondholders take over the firm thereby getting the market value of the firm with the equity holders getting nothing.

Using the following notation, we can replicate the position of the equity holders and the bond holders through options.

A – Market Value of firm

S – Market Value of equity

B – Market Value of debt

F – Face Value of debt (on maturity, *T*)

Where A = B + S

Table 2.1 shows the payoffs to the respective investor groups:

	Equity Holders receive	Bond Holders receive
If $A_T > F$	$A_T - F$	F
If $A_T < F$	0	A_T
Net Position	Max $(0, A_T - F)$	Min (F, A_T)

Table 2.1 Payoff to Bond and Equity Investors in a Firm

From the above payoffs, we can see that the position of the equity holders is similar to holding a call option with the underlying asset being the firm itself. Using this with the put-call parity where $C = P + S - Xe^{-rT}$, we can draw an analogous relationship with the call option being the market value of stock and the underlying asset being the firm. As a result, we get

$$S = P + A - Fe^{-rT}$$

Substituting for S in the above equation, we get the following result:

$$A - B = P + A - Fe^{-rT}$$

$$B = Fe^{-rT} - P$$

Therefore, the defaultable bond is equivalent to holding a risk free bond with a short put position on the assets of the firm. Merton uses this relationship to arrive at a value for the risky debt. The yield on the risky debt less the yield from a matching term risk-free instrument represents the credit spread since it is the return that an investor requires for taking on the additional risk.

While Merton's paper is groundbreaking in the area of pricing defaultable debt, it suffers from two major limitations in the model. Firstly, it only allows for a default to occur upon maturity of debt. We know that in the real world, default or credit events can happen at any time during the life of a loan. Additionally, one of the inputs in the model is the market value of the firm. This is again difficult to estimate especially if the firm has privately placed debt and may therefore lead to valuation errors in the pricing process. Another limitation in the model is that in case of multiple class debt, it requires absolute priority of settlement to be maintained in case of a default which may not necessarily be the case especially in case of debt secured through multi-tiered security structure.

Subsequent structural models developed have tried to relax some of the assumptions underlying Merton's model especially the limitation that default may occur only at maturity. Black and Cox (1976) first developed a model that allows for default to occur as soon as the firm value falls below a threshold level during the term of the loan. However, their model assumes a constant interest rate and also does not address issues regarding the seniority of debt and its subsequent impact on recovery rates. In their paper, Longstaff and Schwartz (1995) present a model that builds on Black and Cox's model and address these two key issues from that model.

Despite improvements on Merton's model, critics of structural models argue that these models require data on parameters related to the firm's value and may be difficult to estimate. Additionally, not all defaults occur from a gradual deterioration in credit quality. Often surprise events force a firm to file for bankruptcy and these are difficult to capture through the structural models.

2.2.3 Reduced-Form Models

Limitations to the structural models led to the development of another line of pricing models that do not condition credit events on the value of the firm and related parameters. However, as with other arbitrage based models, reduced form models are best suited for highly liquid assets and may not be as accurate in case of low market liquidity.

Unlike in a structural model where the evolution of credit may help identify possible default, with a reduced-form model, the default event is stochastic with the probability of default linked to variations in the level of interest rates. While a lot of research has focused on developing these models, we limit ourselves to structural models in our paper.

2.2.4 Choice of Model

Both forms of models have their strengths and weaknesses and the choice often depends on the intended use and methodological preference of the user. For example, in order to study the changes in cost of capital due to a change in the capital structure, a structural model should be used.

With regards to the methodology involved, fixed income modellers may have a preference for reduced-form models while equity focused researchers may prefer a firm value based structural model.

2.2.5 CreditGrades

For the purpose of our study, we use the CreditGrades credit default swap (CDS) pricing model designed by the RiskMetrics Group (Finger, 2001). Our choice of model is based on the following:

1) We prefer using a structural model over reduced form models given that Arora et al (2005) compare the two forms of models and find structural models to outperform reduced form models in estimating CDS levels. Additionally, these models use firm volatility which has been found to be important in determining CDS spreads (Consigli, 2004).

2) As CreditGrades is a commercially available CDS pricing model that allows investors to go online and use it as a CDS calculator, it is likely to reflect market beliefs better than the non-commercial models. Although statistics about market usage of this model are not available, Currie and Morris (2002) state that the model is commonly used by practitioners.

3) CreditGrades model has been developed by four leading institutions in the area of risk modeling, namely JP Morgan, Deutsche Bank, Goldman Sachs and RiskMetrics Group.

4) We prefer CreditGrades over other commercially used CDS pricing models as this is the only one, to our knowledge, with modeling details in the public domain. Most other commercially used models are proprietary and cannot therefore be replicated for the purpose of our study.

2.2.6 Credit Spreads and Market Risk Variables

Research finds that theoretical model spreads differ from market spreads – Ericsson et al (2005) and Eom et al (2004) . This could be explained by arguing that models ignore variables such as demand and supply interactions or liquidity related factors that affect market behaviour. Alternatively, it could be argued that the use of lagged accounting data in the models taken from quarterly or annual announcements may be causing the observed gap between theoretical and market spreads. Bystrom (2006) tests the CreditGrades model to find that while there is a correlation between theoretical CDS spreads and market CDS spreads, the two spreads often differ prompting the author to suggest running a capital arbitrage scheme between the two to generate returns.

We therefore turn to factors that have been seen to explain market spreads in an effort to improve on the spread estimates derived from the models. Collin-Dufresne et al (2001) look at macroeconomic and financial variables to explain changes in the credit spreads on industrial bonds. Using various firm and market variables to explain changes in credit spreads, they find these factors to explain only 25% of the credit spread movements. They also find the residuals from the regressions to be correlated pointing to a single common factor explaining most of the changes in the credit spreads. As a result, they introduce liquidity and macroeconomic factors but are unable to identify any variable as the common factor.

Ang and Piazzesi (2003) also introduce macroeconomic factors in a pricing kernel to explain movements in bond prices and find that these factors explain around 60% to 85% of the changes in bond yields. Amato and Luisi (WP, 2005) look at bond portfolios and regress yields against macroeconomic factors to find that changes in real activity and financial conditions are significant. They measure real activity using the index of help wanted ads, the unemployment rate, employment levels and the industrial production index.

Ericsson et al (2005) use macroeconomic and liquidity factors to explain mispricing between model and market spreads on bonds and CDS. They find that macroeconomic factors do not improve the fit of the model suggesting that the models price risk accurately. However, they also find that liquidity measures are significant in the case of bonds but not with CDS.

Tang and Yan (2007) also look at the pricing effect of liquidity in the CDS market. Since the CDS market is OTC and liquidity levels are not available, they use various proxy measures to capture the effect of liquidity. Unlike Ericsson et al, they find evidence of an illiquidity premium in the CDS market.

Looking at some of the macroeconomic risk factors consistently used in previous studies, we know that variables like index returns, index volatility, default premium and term structure have explained CDS spreads. Furthermore, a study also suggests that liquidity may be priced in CDS spreads. We therefore select these variables to explain the mispricing levels in our analysis.

2.3. Data

2.3.1 CDS Spreads

We use daily CDS mid-spreads on 5-year risk from the Thomson DataStream database for the period 1 Jan 2005 to 31 Dec 2006. Our choice of firms is limited to Dow-30 names since these represent some of the most liquid CDS contracts and also help us overcome certain data availability constraints. However, we exclude companies that (1) do not have CDS spreads reported during the period, or (2) are in the financial sector, or (3) have a subsidiary with significant lending exposure. The reason for excluding financial firms is that as the CreditGrades model involves the use of debt in computing the spreads, firms in the lending business may not have the true debt level reflected in their consolidated accounts. We are therefore left with 23 firms and we use 5-year CDS spreads for senior, unsecured bonds as these are the most liquid swaps in the CDS market.

2.3.2 Model Parameters

Share Price and Volatility: We get daily adjusted closing share prices for the 23 Dow firms for the period under review from DataStream. Stock return volatility is derived from the share returns. We use equity options implied volatility which is taken from Bloomberg as the weighted average of the volatilities of the three options closest to the at-the-money strike. The Bloomberg implied volatility function, HIVG, uses front month options with a minimum of 20 business days to expiration. In the case where the options have less than 20 days to expiration, it uses the options in the next available month.

Risk-Free Rate: This is taken as the rate on a 5-year government bond from the DataStream database.

Accounting Data: To arrive at the Debt/Share levels, we use Compustat to compute the ratio from quarterly accounting data using a 1-month lag period from the quarter end. The ratio, computed as follows, is based on the definition prescribed in the CreditGrades Technical Document:

Debt/Share = Debt / Total Number of Shares, where

Debt = Financial Debt – Minority Interest, where

> Financial Debt = Short Term Borrowings + Long Term Borrowings + 0.5 * (Other Short Term Liabilities + Other Long Term Liabilities)
>
> Where, Minority Debt < = 50% of Financial Debt

Total Number of Shares = Common Shares + Preferred Shares, where

Common Shares = Market Capitalization / Common Stock Price

Preferred Shares = Preferred Equity / Common Stock Price

In case of stock splits, we ensure that the stock price and debt per share are consistent with pre-split levels to avoid non-credit related jumps in our model CDS spreads.

2.3.3 Risk Factors

Liquidity: In the absence of daily trading volume levels, we use the bid-ask spread as a proxy for liquidity. The more liquid CDS will have a narrow bid-ask spread while the less liquid instruments will reflect a larger bid-ask spread. However, to account for varying levels of risk in our database, we standardize the bid-ask spread by dividing it by the mid-price (average of bid-ask spreads). In line with Tang and Yan (2007) findings, we expect this to be positively related to risk. Therefore, the bid-ask spreads would increase given a higher level of risk.

Stock Index Measures: We use the S&P500 index daily return as well as daily volatility over a 30-day rolling window to proxy for market based risk. We expect to see a negative relationship between index returns and CDS spread changes as an increase in index levels should reflect a reduction in risk.

An increase in index return volatility shows greater uncertainty in the markets and therefore would result in increased credit spreads.

Macroeconomic Measures: Given that our study looks at daily spread level changes while most of the other studies use monthly or quarterly macroeconomic factors, we cannot use some of the measures identified in studies covered in the previous section. Instead we use the following as these are available at a daily or weekly frequency:

1) Investor Sentiment: The Sentiment Survey by the American Assoc of Individual Investors is a weekly investor sentiment survey that asks investors whether they are bearish, neutral or bullish on the stock market for the next 6 months e.g. 27 Dec 2007 split was 50-20-30. We use the Bull Ratio, defined as %Bull / (%Bulls + %Bears), to capture the market outlook. We expect to see an inverse relationship as the greater the number of investors expecting positive market developments, the lower is the perceived risk level in the market.
2) 3-M risk free rates: Das et al (2007) find that the 3-M risk-free rates are significant in explaining CDS spread movements. We decide to include this even though our model uses the 5-year swap rates since we expect the short term interest rates to capture the immediate economic conditions while the longer term rates may reflect a smoothed out view of the future. As low interest rates are usually experienced in downturns, we would expect to see a negative relationship between interest rate movements and CDS spread changes.
3) Risk Premium: This is defined as the change in the daily difference between the ML High Yield Master II Index and the JP Morgan US Govt Bond index. We expect to see CDS spreads to increase with an increase in the risk premium and therefore a positive relationship between the two.
4) Term Structure: We also use term structure as defined by the difference in yields between 1M and 10Y government debt. Similar to the previous factor, we expect to see CDS spreads to increase with an increase in the term premium.

We base our tests on the belief that markets are efficient. As a result, we exclude firm specific financial performance indicators since we believe this information would have already been incorporated in the stock price.

2.4. Model Performance

2.4.1 Mean Error

Using the daily input data, we run the CreditGrades model on Matlab to derive the 5-year CDS spreads suggested by the model. As a test of our program code, we also compare our model derived spreads with those derived from the CreditGrades website and find them to be the same. For equity volatility, an input in our model, we use the 1250-day historical volatility as this matches the term of our CDS. We also try using equity options implied volatility but find the historical volatility to generate more accurate CDS spreads and therefore continue with the historical volatility measure. This is in line with results from the CreditGrades Technical Document (Finger, 2002) that compares equity options implied volatility and historical volatility to find the 1000 day historical volatility provides the best estimate of actual CDS spreads.

Figure 2.2 presents a graphical comparison of the model spreads against market spreads for the same credit. It is evident from the graphs that the model overestimates the market CDS spreads in some instances and underestimates them at other times. More importantly, we do not see any evidence of consistent under or over pricing except in case of the low risk firms where our model consistently generates a very low spread and thus appears to underprice the risk.

One of the arguments presented to explain the difference between the model and market spreads is the use of quarterly accounting data in our model. Markets, by comparison, are much more efficient and therefore, able to price company and market events in real time thereby being a possible reason for the model's failure. However, as share price, an input in the model, has been seen to lead the bond and CDS markets (Norden and Weber, 2004), such events should be priced into the model spreads through share price changes. We note, however, that events may have different implications for equity risk and debt risk and therefore, our model may not be able to reflect accounting information changes perfectly through stock price movements.

Table 2.2 presents a snapshot of the key statistics for the market CDS spreads as well as our model generated CDS spreads. We observe that CreditGrades spreads are mostly below market levels and the model generates near-zero spreads for the lower risk firms in our database. While standard deviation is at similar levels, as the model CDS spreads are considerably below the market ones, it translates into much higher levels of dispersion of spreads.

The Mean Error, the difference between the market CDS spreads and the model CDS spreads has typically been used as a performance measure for testing models. We use this measure to find that, on average, our model underprices CDS spreads by 10 bps. Table 2.3 presents ours findings for each firm as well as the result for the entire dataset.

In summary, our comparison between the model derived CDS spreads and the actual market CDS spreads shows no clear relationship emerging between the two as there is evidence of underpricing as well as overpricing at different points in time. However, we see that, on average, our model underprices spreads by 10 bps. This could potentially signal that some risk factors are missing from our pricing model that need to be included to arrive at more precise spread estimates.

2.4.2 CDS Model Implied Volatility

While most of the inputs into the model are observable from the market, we look at some of the implied parameter values to test the model and understand the difference between the market and theoretical spreads. These input parameters could either relate to the equity volatility, as we use the historical volatility as a proxy for future volatility, or to the recovery rates. Our objective is to extract one of the implied values from the model and match it against the realized value as a further test of our model.

In the absence of defaults and subsequent recoveries, it is not viable to extract the recovery rates as we would not have a metric to test it against. However, we note that as we can derive realized volatility from stock returns, we can extract this from the model in a manner similar to that used for equity option implied volatility.

We therefore use market CDS spreads as an input in the model and derive the equity volatility (CDSIV) implied by the market. Once we have this measure, we compare it against the realized volatility using 22 and 250 day windows (Table 2.4). Our choice of length for the windows stems from the fact that as our EOIV data is for options with approximately 20 days to expiration, the EOIV should be able to predict return volatility over this period. For similar reasons, as we use 5-year CDS, we would like to use a 1,250 day period as well. However, given that our data is from 2005-2006, we are limited to using 250 days as a longer period would take us beyond 2008 for which realized volatility is not available.

Consistent with findings of the Uhrig-Homburg paper (2002), we find the EOIV to be the best predictor for the 22-day period since it matches the duration of the options data being used. However, over the longer horizon, we find that historical volatility is the best predictor of realized volatility.

2.5. Omitted Risk Factors

The results of the two tests of the model show that our model fails to accurately estimate market CDS spreads. Looking at some of the literature reviewed in the earlier sections, we believe that the addition of certain macroeconomic risk factors may improve the performance of our model. Additionally, CDS liquidity may be an omitted factor in our model as we believe that it is a proxy for risk in the CDS market.

2.5.1 Liquidity

Longstaff et al (2005) argue that CDS contracts are much less vulnerable to liquidity pressures than bonds which have a fixed supply. Further, as CDS are cheaper to transact than bonds, liquidity concerns are much less relevant in the case of these swaps. They therefore assume that CDS levels represent the true level of credit risk. However, we believe, depending on the level of credit risk involved, there may be an element of liquidity reflected in the spreads which can be represented by an inverted-U curve.

In the absence of fixed supply quantities and with much lower transaction costs, CDS liquidity represents the demand and supply situation reflecting the market perception about the risk of the underlying bond. Our intuition is that there is likely to be low demand for the very low risk firms and therefore, this would result in low CDS liquidity. As we move towards the riskier firms, demand for credit insurance would increase, resulting in greater liquidity in the market.

However, beyond a certain level of risk, suppliers of insurance would stop providing cover to bond holders, thereby drying up liquidity in the market. As a result, the risk-liquidity curve would have an inverted-U shape. The source of low liquidity in case of the low risk firms would be demand-based while at the higher end would be supply-based. In either case, it would make hedging more difficult as one side would require more compensation to take on the position.

As the CDS market is OTC, we use the bid-ask spread standardized by the mid-price as a proxy for liquidity. In this paper, we test the relationship between liquidity and mispricing to see if traders are charging a premium for the illiquid CDS. A Hausman test shows that a Fixed-Effects model is appropriate for our panel data and we look at both, contemporaneous (equation I below) as well as 5-day lagged FE regressions (equation II) to find liquidity to explain some of the mispricing in both sets of regressions - our regression results are provided in Table 2.5.

$$\text{Mispricing}_{i,t} = \alpha_i + \beta'\Delta\text{Liquidity}_{i,t} + \varepsilon_{i,t} \qquad \text{- Equation I}$$

$$\text{Mispricing}_{i,t} = \alpha_i + \beta'\Delta\text{Liquidity}_{i,(t-1 \text{ to } t-5)} + \varepsilon_{i,t} \qquad \text{- Equation II}$$

Where,

$\text{Mispricing}_{i,t}$ = Mispricing for firm *i* at time *t* (i.e. Market $\text{CDS}_{i,t}$ – Model $\text{CDS}_{i,t}$);

α_i = Individual effect (assumed constant over time);

β = Regression coefficient;

$\Delta Liquidity_{i,t}$ = Change in liquidity for firm *i* at time *t*;

$\Delta Liquidity_{i,(t-1 \text{ to } t-5)}$ = 5-day lagged changes in liquidity for firm *i*;

$\varepsilon_{i,t}$ = Stochastic error term

The liquidity t-stat of 13.04 and 14.93 in the case of contemporaneous and lagged regressions strengthens our assertion above that it may be playing a role in market spreads. However, we recognize the t-stats of 50.22 and 45.18 for the constant as capturing other variables that may explain the remaining part of the mispricing.

As the purpose of this study is to explain the mispricing from the CreditGrades model, we use liquidity as a variable in the pricing regression and analyse the relationship between liquidity and risk in a subsequent paper.

2.5.2 Market Factors

Using the factors outlined in the data section, we extend our analysis to using market factors in a FE model to explain changes to the market CDS spreads. To avoid unit-root issues, we take the first differences for all variables in the model. Furthermore, we use 5-day lagged values of the factors as it allows us to capture the dynamic market environment better than a one-day snapshot would do. The regression equation is in form outlined below.

$$\Delta Mkt\_CDS_{i,t} = \alpha_i + \beta_1'\Delta Mkt\_CDS_{i,(t-1 \text{ to } t-5)} + \beta_2'\Delta Risk\_Factor_{i,(t-1 \text{ to } t-5)} + \varepsilon_{i,t}$$

Where,

$\Delta Mkt\_CDS_{i,t}$	= Change in Market CDS Spread for firm *i* at time *t*;
α_i	= Individual effect (assumed constant over time);
β	= Regression coefficients;
$\Delta Mkt\_CDS_{i,(t-1 \text{ to } t-5)}$	= 5-day lag values of Changes in Market CDS Spreads for firm *i*;
$\Delta Risk\_Factor_{i,t}$	= 5-day lag values of changes in omitted risk factors for firm *i*;
$\varepsilon_{i,t}$	= Stochastic error term

In addition to testing each market risk factor against the market CDS spread changes, we use, as the independent variable, the model generated spreads, the CDSIV as well as liquidity since our prior test has shown it to be significant in explaining the mispricing. Before running the regression, we test the Variance Inflation Factors (VIFs) for the explanatory variables to check for multicollinearity (Table 2.6). Other than the lagged market CDS spread changes and the CDSIV which reflect slightly elevated VIF levels, all other variables are below the threshold level of 4.

We also check the one-to-one correlations between the market CDS spread changes and CDSIV to find a high level of correlation ranging between 0.3 and 0.8. This can be explained by the fact that determining the CDSIV requires using market CDS spreads as an input and we may be capturing the interplay between the two.

Based on the results presented in Table 2.7, we find that, as expected, lagged values of changes in CDSIV are the most important factor for explaining market spread changes as they have an adjusted R-square of 16.1%. The strength of this factor can be attributed to the fact that the CDSIV incorporates data from the CDS market, the stock market and firm level accounting information. In contrast, the model CDS spreads do not use data from the CDS market and as a result, the CDSIV presents a factor with a richer representation of information.

With regards to the stock market and macroeconomic factors we find the following to be significant:

1) Stock index returns (-2.239) have a negative relationship with CDS spread changes. This relationship is as expected since a decrease in index levels are experienced with growing risk and therefore increasing CDS spreads.
2) Index return volatility (1.736) has a positive relationship since higher volatility shows increasing risk.
3) Investor Sentiment (0.495) reflects an inverse relationship since an improvement in investor sentiment should be met with a reduction in risk spreads.
4) The coefficient on the risk premium (-1.933) suggests that CDS spreads decrease with an increase in the risk premium. While this is counterintuitive and contrary to expectations, it may be a result of the type of firms included in our dataset. As we are only considering the Dow-30 names, these firms are typically larger and less risky than most other firms in the market. Therefore, it may be that with an increase in the general market risk premium, investors increase exposure on the Dow-30 names and reduce exposure on the relatively more risky firms. As a

result, the reduced demand for Dow-30 CDS would result in a decrease in their spreads while spreads for other firms may increase. However, without a formal study of the relative movement in spreads between firms with different ratings, it is difficult to confirm the reason for this result.

We find that the other variables are not significant in explaining credit risk movements.

2.5.3 Multi-factor Analysis

Having established some of the factors that are important in explaining the changes in CDS spreads, we extend our analysis to running them in a multivariate setting that includes model derived variables as well. As our intent is to identify factors that may explain risk beyond levels suggested by our model, we ensure that either CDSIV or the Model Based CDS Spreads are included in our regressions.

With regards to the evidence of strong correlation between the Market CDS spreads and the CDSIV, we avoid using both factors in the same regression as it could lead to flawed results. Using a stepwise variable selection process that includes either Market CDS Spreads or CDSIV, we drop any risk factors that lose significance in a multivariate setting to arrive at the results presented in Table 2.8.

Our key findings are as follows:

1) Based on the adjusted R-square of 16.8% versus 13.2%, we find lagged CDSIV values explain CDS spreads movements better than the lagged values of CDS spreads. As discussed earlier, a possible reason is that the CDSIV is extracted from the model that includes market CDS spreads, stock returns as well as

accounting data on debt per share and is therefore carrying more information than the market CDS spread itself.

2) Liquidity (0.077 and 0.071) remains significant in both regressions which contradicts some of the arguments in existing literature. However, we believe that, unlike bonds where supply is limited by the number of bonds available in the market, liquidity in the CDS market is a function of the demand-supply which is driven by the risk of the underlying bond. Therefore, it can be taken as a reflection of risk and should be a pricing factor in the model.
3) Stock Index Volatility and Risk Premium are both significant in explaining the CDS spread changes. However, further investigation into the relationship between risk premium and CDS spreads is required to test if the relationship varies with the risk of the underlying bond.

With a constant that is significantly different from zero and an adjusted R-squared ranging between 13.2% to 16.8%, we recognize that there are yet other factors that the CreditGrades model may not be pricing. Looking at the residuals from the two regressions, we find them to have a correlation of 0.95 confirming that there are one or more omitted risk factors that are common to the two regressions and need to be included in the pricing models.

2.6. Conclusion

Credit risk plays a key role in the current market environment and is expected to become increasingly important. Therefore, it is imperative that the market is able to price credit risk accurately. However, we have seen from previous studies as well as our own tests that these models fail to price risk in line with market spreads.

We test one of the leading commercial pricing models, CreditGrades, to find that it is unable to generate the spreads seen in the market. Using different factors, we introduce various risk proxies that are not included in the CreditGrades model to help improve the fit of our model from 12% to 16.8%. We therefore suggest incorporating these measures into the pricing model to improve its ability to price risk.

Interestingly, contrary to arguments in previous papers that CDS spreads are unaffected by liquidity, we find liquidity to be priced in CDS spreads. In light of this result, we believe the relationship between credit spreads and liquidity deserves further examination and postulate the shape of the relationship as an avenue for follow-up research. We also find that an increase in risk premiums is met by a decrease in credit spreads which is contrary to our intuition on the matter and also requires further study.

Even after including market and economic variables, we can only explain a small part of the changes in market spreads and observe a strong correlation between the residuals of the two multivariate regressions. This suggests that some common factors that could improve the fit of the model have been omitted from the model. Until these factors are identified and priced, markets remain vulnerable to the possibility that the market CDS spreads may still not be reflecting the true credit risk completely.

Appendix

2.A. CreditGrades Parameters

The CreditGrades model requires eight inputs to compute the credit spread, namely the share price (S), the equity volatility (σ_s), the debt per share (D), the interest rate (r), the time to expiration (T), the overall recovery rate ($\bar{L}$), the recovery rate standard deviation (λ) and the debt recovery rate (R).

While we may be able to come up with the values for the first five variables, the recovery rates and the related standard deviation are not directly observable. CreditGrades allows users to plug in their own estimates but as a default it uses a measure of 50% for $\bar{L}$ and 30% for λ , based on estimates derived from the Standard & Poor's (S&P) LossStats database. As our intention is to use the model as the investors, we continue to use the same recovery rates in our analysis.

Given that the CDS are traded in an OTC market, data availability is an issue. To the best of our knowledge, the Markit Group is currently the only institution that collects trading data from all the major traders on a daily basis and in turn, provides the market data to the participating trading firms and certain financial database like Thomson/DataStream etc. As a result, the CDS spreads represent an average of the closing spreads that the trading institutions report to Markit.

2.B. The CreditGrades Model

As with other structural models, CreditGrades models the firm value against a default barrier where a default occurs when the firm value crosses the barrier from above. The model used by CreditGrades assumes that the value of the assets evolves through Brownian motion with the following structure:

$$\frac{dV_t}{V_t} = \sigma dW_t + \mu_D dt$$

Where W defines standard Brownian motion, σ is the volatility of the assets, μ_D is the drift which we assume to be equal to zero.

A zero drift is assumed since the focus of the model is the drift of the asset value relative to the default barrier and if the firm, on average, maintains leverage at a steady level, debt will have the same drift as the stock price.

Structural models have been seen to reflect low short-term spreads due to their inability to reflect true ex-ante market value of debt resulting in an underestimated default barrier level. CreditGrades addresses this by introducing a jump process in the diffusion process to allow defaults to occur close to start of the model.

The default barrier is defined as L.D where L is the average recovery rate and D is the debt/share for the firm. To increase the short-term spreads, randomness is introduced to the recovery rate which is assumed to follow the following lognormal distribution with mean $\bar{L}$ and standard deviation λ.

$$\bar{L} = \mathbf{E}\mathrm{L};$$

$$\lambda^2 = \mathrm{Var}\ \ln(\mathrm{L});\ \text{and}$$

$$\mathrm{LD} = \bar{L}\,\mathrm{D}e^{\lambda Z - \lambda^2/2}$$

Z has a standard normal distribution, independent of the Brownian motion. The introduction of the randomness to Z implies that there is a true value of Z which is unknown at the start and is only known once default takes place.

Furthermore, default does not occur as long as the asset value is greater than the default barrier level giving us the following constraint:

$$V_0 e^{\sigma W_t - \sigma^2 t/2} > \bar{L}De^{\lambda Z - \lambda^2/2}$$

An event of default will not occur until the first passage of V_t to the default threshold of L.D. The survival probability, P(t), at time t is therefore given by the probability that the asset value does not cross the default barrier before time t. σ represents the asset volatility while σ_s is the equity volatility with the relationship:

$$\sigma_s = \sigma\left(1 + \frac{\bar{L}D}{S}\right)$$

The CreditGrades model arrives at a solution for the probability as the following:

$$P(t) = \Phi\left(-\frac{A_t}{2} + \frac{\log(d)}{A_t}\right) - d.\Phi\left(-\frac{A_t}{2} - \frac{\log(d)}{A_t}\right)$$

Where

$$d = \frac{V_0 e^{\lambda^2}}{\bar{L}D}$$

$$A_t^2 = \sigma^2 t + \lambda^2$$

In order to convert the probability model to a specific credit price, two more parameters need to be defined, *r*, the risk-free rate and *R*, the recovery rate on the asset. The difference between *R* and $\bar{L}$ is that former pertains to the recovery rate for a specific class of debt while $\bar{L}$ is the average recovery rate for all debt classes.

To compute the credit spread, c*, the model equates the expected premium payments to the expected loss payout to arrive at the following:

$$c^* = r(1-R)\frac{1 - P(0) + e^{r\xi}(G(t+\xi) - G(\xi))}{P(0) - P(t)e^{-rt} - e^{r\xi}(G(t+\xi) - G(\xi))}$$

Where

$$\xi = \lambda^2 / \sigma^2$$

$$G(u) = d^{z+1/2}\Phi\left(-\frac{\log(d)}{\sigma\sqrt{u}} - z\sigma\sqrt{u}\right) + d^{-z+1/2}\Phi\left(-\frac{\log(d)}{\sigma\sqrt{u}} + z\sigma\sqrt{u}\right)$$

$$z = \sqrt{1/4 + 2r/\sigma^2}$$

With the model for deriving the credit spreads completely defined, it is important that we convert the model specifications into easily measurable parameters. We must use the relationship between asset volatility and the observable equity volatility to arrive at a more meaningful parameter for volatility. With a share price of S, we use the approximation $V = S + \bar{L}D$ to get:

$$\sigma_s = \sigma\left(1 + \frac{\bar{L}D}{S}\right)$$

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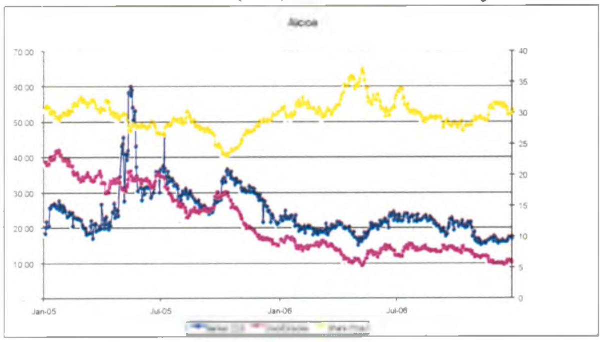
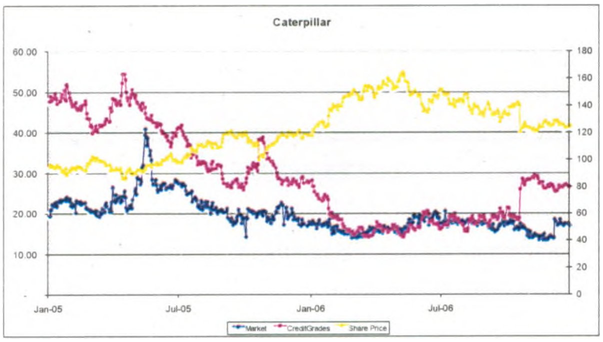
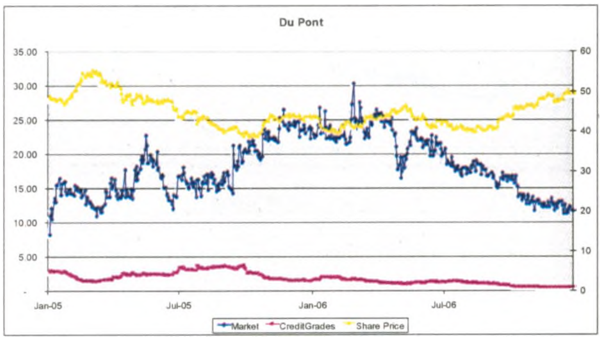
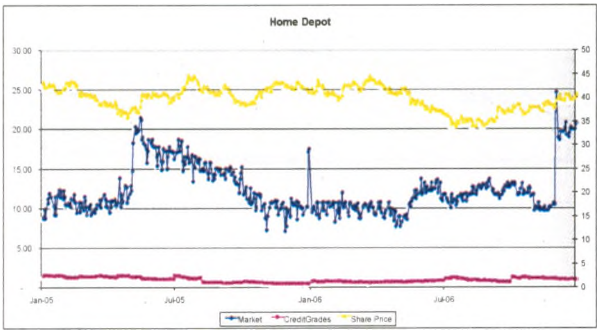
Figure 2.2 - Map of Market vs. Model Spreads

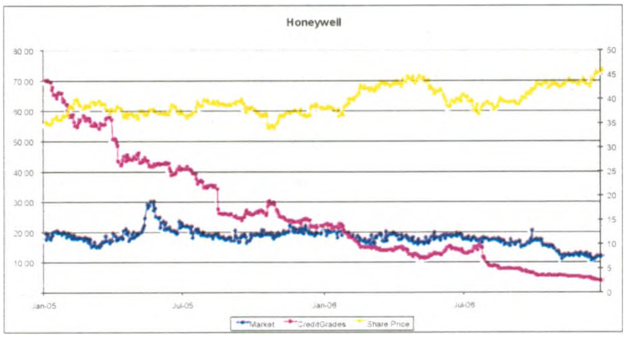
The following charts present the Market and Model CDS Spreads (bppa) on the primary y-axis and the Share Price (U$) on the secondary Y-axis.

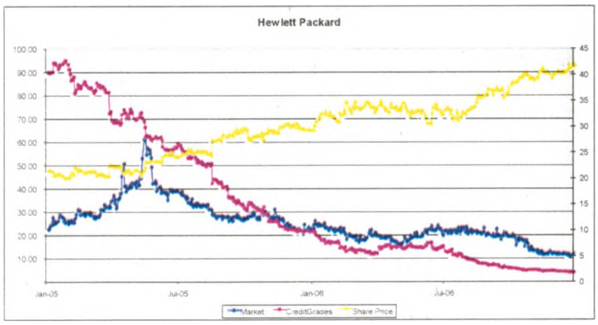


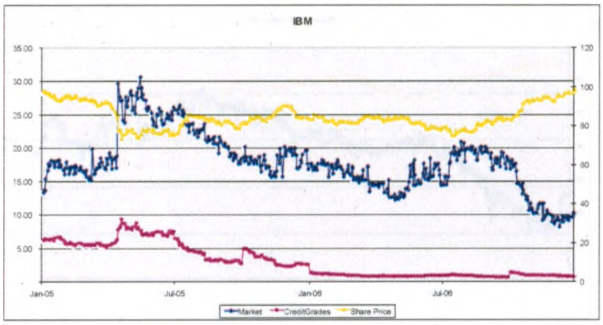


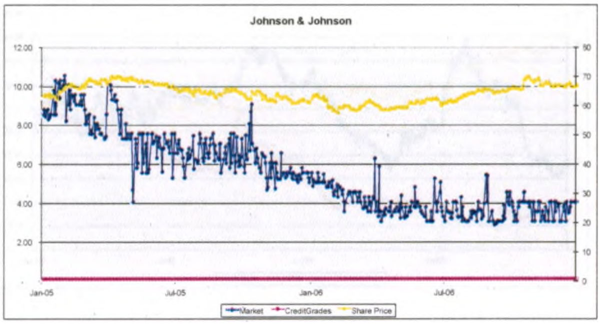


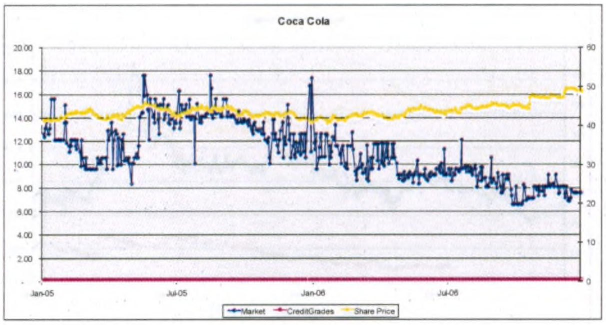


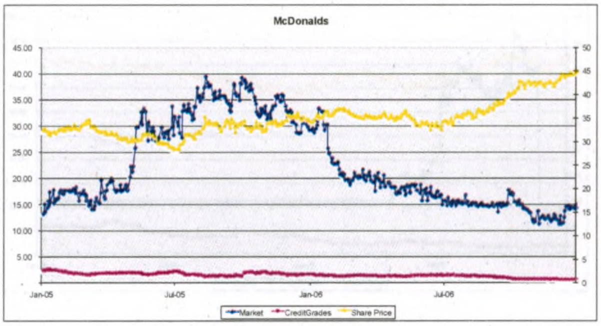


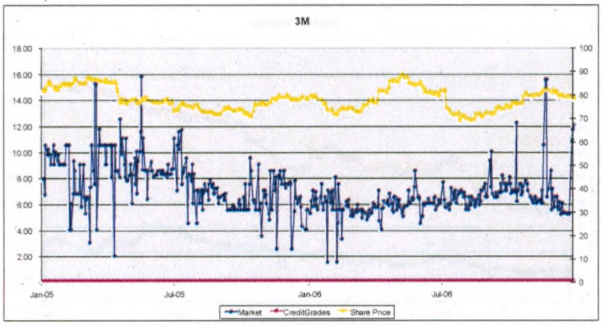


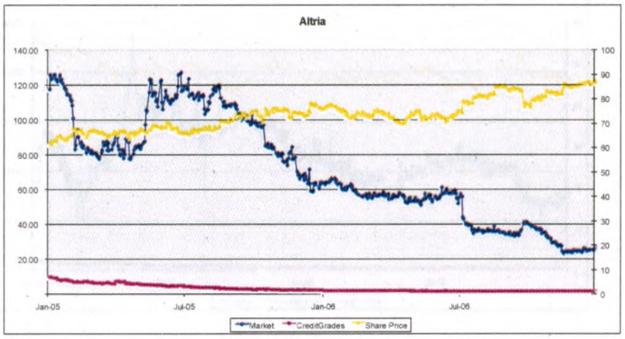

IBM
Jan-05
Jul-05
Jan-06
Jul-06
Market
CreditGrades
Share Price


Johnson & Johnson
Jan-05
Jul-05
Jan-06
Jul-06
Market
CreditGrades
Share Price

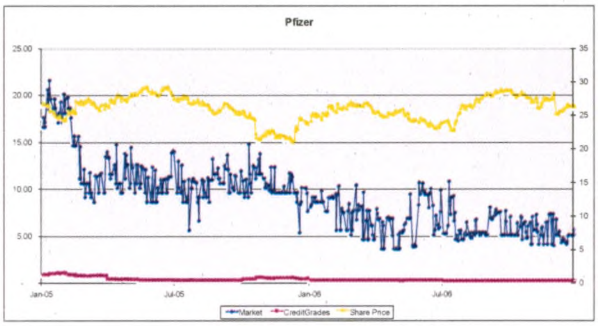

Coca Cola
Jan-05
Jul-05
Jan-06
Jul-06
Market
CreditGrades
Share Price

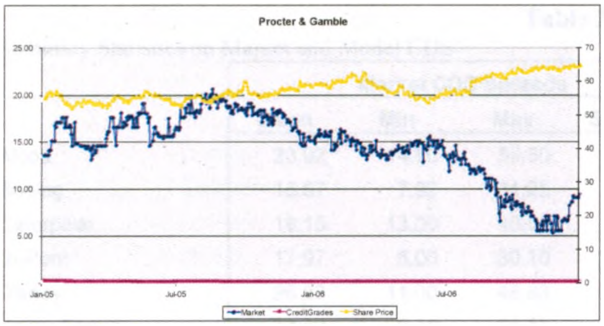

McDonalds
Jan-05
Jul-05
Jan-06
Jul-06
Market
CreditGrades
Share Price

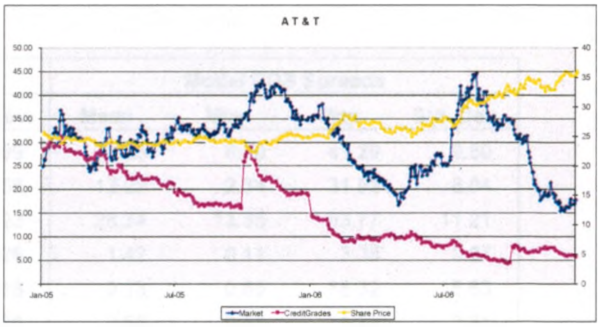

3M
Jan-05
Jul-05
Jan-06
Jul-06
Market
CreditGrades
Share Price

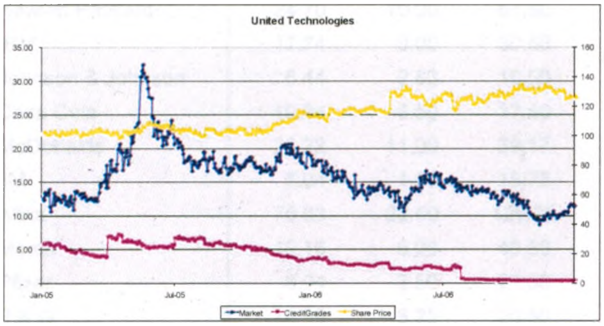

Altria
Jan-05
Jul-05
Jan-06
Jul-06
Market
CreditGrades
Share Price

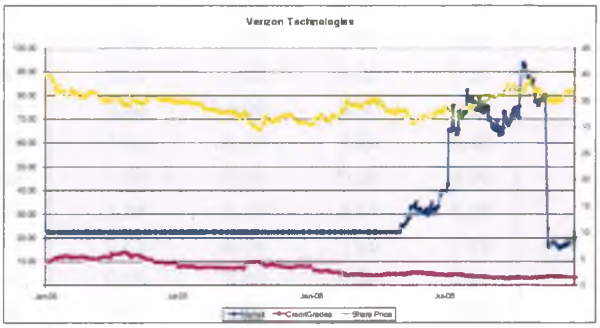

Merck
Jan-05
Jul-05
Jan-06
Jul-06
Market
CreditGrades
Share Price


Pfizer
Jan-05
Jul-05
Jan-06
Jul-06
Market
CreditGrades
Share Price


Procter & Gamble
Market
CreditGrades
Share Price


A T & T
Market
CreditGrades
Share Price


United Technologies
Market
CreditGrades
Share Price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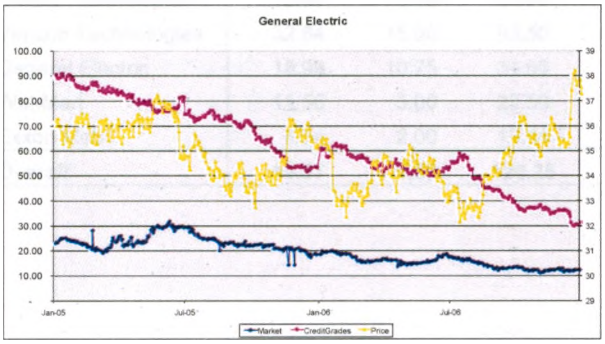
General Electric
Market
CreditGrades
Price


Walmart
Market
CreditGrades
Share Price

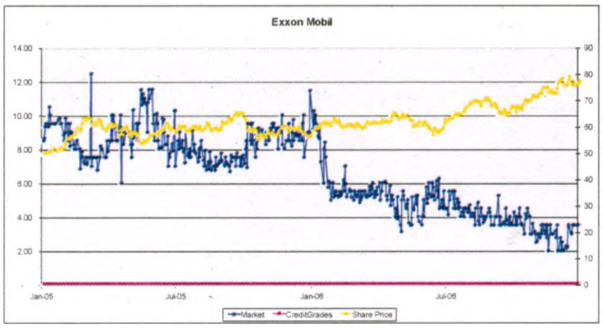
Exxon Mobil
Market
CreditGrades
Share Price

Table 2.2

Summary Statistics on Market and Model CDS

	Market CDS Spreads				Model CDS Spreads			
	Mean	Min	Max	Std. Dev.	Mean	Min	Max	Std. Dev.
Alcoa	23.92	14.50	59.50	6.99	20.56	8.50	41.29	9.50
Boeing	16.67	7.92	31.25	4.56	12.22	2.34	31.92	8.04
Caterpillar	19.15	13.00	40.50	4.23	28.24	13.35	53.77	11.21
DuPont	17.97	8.00	30.10	4.26	1.42	0.11	3.38	0.87
Disney	26.83	11.00	48.83	9.18	9.13	0.65	18.32	5.63
Home Depot	12.12	6.88	24.50	3.06	0.58	0.11	1.20	0.31
Honeywell	17.65	10.00	29.50	2.84	24.51	3.01	69.32	17.57
Hewlett Packard	24.70	10.00	61.50	8.89	31.97	2.69	93.73	27.81
IBM	17.71	8.00	30.50	4.34	2.68	0.36	9.05	2.45
Johnson & Johnson	5.44	2.83	10.50	1.97	0.00	0.00	0.00	0.00
Coca Cola	10.94	6.50	17.50	2.46	0.00	0.00	0.00	0.00
McDonalds	22.22	11.00	39.17	8.22	1.06	0.17	2.24	0.45
3M	7.04	1.50	15.75	1.92	0.00	0.00	0.00	0.00
Altria	70.03	22.50	126.25	29.94	1.84	0.16	8.44	2.06
Merck	19.16	6.00	40.50	9.42	0.62	0.09	1.90	0.46
Pfizer	8.94	3.50	21.50	3.58	0.15	0.00	0.89	0.21
P & G	14.35	5.25	20.50	3.66	0.02	0.00	0.13	0.03
A T & T	29.96	15.19	44.50	6.67	15.00	3.92	30.91	7.81
United Technologies	15.57	8.50	32.25	3.93	3.23	0.11	7.04	2.12
Verizon Technologies	32.64	15.00	93.50	20.85	6.20	1.99	13.30	3.17
General Electric	18.99	10.75	31.50	5.08	60.48	29.13	90.18	16.18
Wal-Mart	11.56	5.00	23.50	3.11	0.21	0.01	0.80	0.20
Exxon Mobil	6.54	2.00	12.44	2.32	0.00	0.00	0.00	0.00
Overall	**19.57**	**1.50**	**126.25**	**15.82**	**9.57**	**0.00**	**93.73**	**17.01**

Table 2.3

Mean Error of Difference between Market and Model CDS

	Mean Error	Min	Max	Std. Dev.
Alcoa	(3.36)	(25.84)	20.14	8.04
Boeing	(4.45)	(13.85)	14.59	4.92
Caterpillar	9.09	(3.81)	30.02	8.68
DuPont	(16.55)	(28.72)	(5.52)	4.35
Disney	(17.70)	(35.62)	(4.97)	5.96
Home Depot	(11.54)	(23.83)	(6.74)	3.02
Honeywell	6.86	(14.62)	52.22	16.47
Hewlett Packard	7.27	(16.36)	68.98	22.34
IBM	(15.03)	(23.17)	(7.20)	3.26
Johnson & Johnson	(5.44)	(10.50)	(2.83)	1.97
Coca Cola	(10.94)	(17.50)	(6.50)	2.46
McDonalds	(21.16)	(38.28)	(10.76)	8.06
3M	(7.04)	(15.75)	(1.50)	1.92
Altria	(68.20)	(122.60)	(22.32)	28.52
Merck	(18.55)	(39.22)	(5.90)	9.02
Pfizer	(8.78)	(20.73)	(3.47)	3.42
P & G	(14.33)	(20.46)	(5.25)	3.64
A T & T	(14.96)	(38.71)	3.41	8.69
United Technologies	(12.34)	(26.83)	(5.08)	3.05
Verizon Technologies	(26.44)	(90.92)	(8.70)	22.71
General Electric	41.49	17.13	67.04	12.08
Wal-Mart	(11.35)	(22.96)	(4.55)	3.03
Exxon Mobil	(6.54)	(12.44)	(2.00)	2.32
Overall	**(10.00)**	**(122.60)**	**68.98**	**21.38**

Table 2.4

Equity Volatility Root Mean Square Error *(using 22 and 250 day rolling windows)*

	22-Days			250-Days		
	Historical	CDS IV	Equity IV	Historical	CDS IV	Equity IV
Alcoa	0.067	0.128	0.073	0.038	0.093	0.042
Boeing	0.072	0.130	0.058	0.022	0.123	0.041
Caterpillar	0.126	0.087	0.081	0.034	0.022	0.028
DuPont	0.058	0.189	0.051	0.025	0.182	0.038
Disney	0.062	0.226	0.058	0.018	0.218	0.042
Home Depot	0.058	0.269	0.047	0.015	0.266	0.038
Honeywell	0.055	0.165	0.055	0.017	0.159	0.044
Hewlett Packard	0.128	0.191	0.099	0.051	0.183	0.083
IBM	0.068	0.229	0.060	0.034	0.221	0.040
Johnson & Johnson	0.050	0.379	0.055	0.022	0.377	0.047
Coca Cola	0.046	0.398	0.049	0.030	0.394	0.041
McDonalds	0.054	0.209	0.070	0.050	0.204	0.070
3M	0.093	0.287	0.068	0.021	0.272	0.033
Altria	0.076	0.321	0.108	0.026	0.317	0.096
Merck	0.128	0.241	0.094	0.101	0.226	0.039
Pfizer	0.119	0.229	0.088	0.033	0.208	0.054
P & G	0.042	0.240	0.047	0.012	0.237	0.035
A T & T	0.052	0.201	0.061	0.033	0.181	0.038
United Technologies	0.069	0.222	0.053	0.015	0.216	0.036
Verizon Technologies	0.055	0.224	0.057	0.017	0.208	0.038
General Electric	0.035	0.078	0.044	0.021	0.074	0.037
Wal-Mart	0.045	0.223	0.051	0.016	0.209	0.031
Exxon Mobil	0.062	0.238	0.058	0.038	0.238	0.042
Overall	**0.070**	**0.222**	**0.065**	**0.030**	**0.210**	**0.045**

Table 2.5

Regression of Mispricing and Liquidity

Contemporaneous (1) and 5-day lagged (2) regressions *(t-stats in italics)*

	Constant	Liquidity	Adj-R^2
1	(13.277)	12.294	0.013
	(50.22)	*13.04*	
2	(14.716)	17.871	0.017
	(45.18)	*14.93*	

Table 2.6

Variance Inflation Factors *(VIFs)*

	Market Spread	Stock Return	Model IV	Model Spread	Liquidity	Stock Index	3M Tbill	Bus. Sentiment	Risk Prem	Eq Option IV
Lag 0	-	1.30	1.28	1.01	1.80	1.32	1.18	1.16	1.36	1.32
Lag 1	4.30	1.39	4.46	1.04	2.03	1.43	1.12	1.07	1.48	1.44
Lag 2	4.28	1.33	4.56	1.04	2.05	1.38	1.10	1.06	1.48	1.45
Lag 3	4.29	1.33	4.58	1.04	2.05	1.39	1.11	1.05	1.48	1.45
Lag 4	4.27	1.33	4.56	1.04	2.04	1.39	1.15	1.05	1.47	1.44
Lag 5	4.09	1.33	4.54	1.04	1.82	1.37	1.19	1.15	1.24	1.32

Table 2.7

Univariate Regression of Market CDS and Risk Factors *(5-day Lagged FE Regression; t-stats in italics)*

			Model Variables		Firm Level Variables			Stock Market Variables		Macroeconomic Variables				
	Constant	Market Spread	CDSIV	Model Spread	Liquidity	Stock Return	EOIV	Index Returns	Index Volatility	Business Sentiment	3M Tbill	Risk Premium	Term Premium	Adj-R^2
1	0.007	(0.635)												0.120
	7.02	*(21.39)*												
2	0.005	(0.188)	(5.475)											0.161
	5.04	*(5.05)*	*(17.14)*											
3	0.007	(0.636)		(0.002)										0.120
	7.07	*(21.41)*		*(2.00)*										
4	(0.127)	(0.610)			0.077									0.125
	(3.77)	*(20.39)*			*6.22*									
5	0.008	(0.641)				(0.506)								0.120
	7.16	*(21.55)*				*(3.22)*								
6	0.007	(0.639)					0.155							0.120
	6.93	*(21.48)*					*2.02*							
7	0.008	(0.647)						(2.239)						0.122
	7.89	*(21.75)*						*(5.53)*						
8	(0.003)	(0.641)							1.736					0.120
	(0.74)	*(21.55)*							*2.44*					
9	0.008	(0.637)								(0.495)				0.120
	7.20	*(21.42)*								*(2.12)*				
10	0.008	(0.635)									(0.150)			0.120
	7.05	*(21.39)*									*(1.63)*			
11	0.009	(0.675)										(1.933)		0.126
	8.26	*(22.37)*										*(6.88)*		
12	0.007	(0.635)											0.001	0.119
	6.99	(21.38)											0.18	

Table 2.8

Multivariate Regression of Market CDS and Risk Factors *(5-day lagged FE Model; t-stats in italics)*

			Model Variables		Firm Level Variables			Stock Market Variables		Macroeconomic Variables				
	Constant	Market Spread	CDSIV	Model Spread	Liquidity	Stock Return	EOIV	Index Return	Index Volatility	Investor Sentiment	3M Tbill	Risk Premium	Term Premium	Adj-R^2
1	(0.022)	(0.654)		(0.002)	0.077				1.673	(0.055)		(1.687)		0.132
	(3.65)	*(21.48)*		*(2.09)*	*6.21*				*2.28*	*(2.30)*		*(5.75)*		
2	(0.025)		(6.541)		0.071				1.949			(2.040)		0.168
	(4.34)		*(25.79)*		*5.87*				*2.75*			*(7.21)*		
3	(0.024)	(0.214)	(5.533)		0.074				1.916			(2.178)		0.173
	(4.25)	*(5.73)*	*(17.33)*		*6.11*				*2.71*			*(7.68)*		

Chapter 3. Dealer Quotes and Their Impact on Price Discovery

3.1. Introduction

Credit default swaps are contracts on corporate or sovereign debt that insure investors against events of default on the underlying credit. While the CDS market grew at a rapid pace up until 2007 when it was valued at $58 tln (notional underlying exposure), the recent slowdown and issues with AIG and other financial institutions has led to a decline in the market size to $32.6 tln in Dec 2009[8]. As a result, the credit derivatives market has been receiving a lot of attention of late with demands to tighten regulations and move it to an exchange based environment from its current OTC structure.

Developing effective regulations for this market requires a sound understanding of the pricing practices for these instruments, the factors affecting trading activity in the market and the general behaviour of market participants. Unfortunately, this is an OTC market and data availability is an issue. Given this limitation, most of the research on CDS has focused either on the pricing of these instruments or on asset pricing models to study factors affecting CDS spreads.

In a typical CDS transaction, investors looking to hedge their credit exposure, contact dealers who quote bid and ask spreads. Once an agreement is reached, the dealers return to the market to close out the resulting short position on the underlying credit. In order to square his position, a dealer can either get into a long contract with other dealers at the prevailing ask rate or make his bid rate more attractive to investors looking to sell cover. Although we do not have access to data on internal dealer positions and intra-day quotes, we use the daily closing bid and ask

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[8] http://www.bis.org/statistics/otcder/dt1920a.pdf

spreads to develop a proxy that signals the combined position of the dealers in the market. While this may be a limitation in our data, our paper makes a contribution to literature by introducing a dimension not yet researched in the CDS market. Our initial findings are promising and this area should be researched further as more detailed data becomes available.

We look at changes in bid and ask spreads for 198 companies where a larger increase in bid when compared to the change in ask signals that dealers want to go long as they are making the bid quote relatively more attractive. This practice of "quote shading" is well documented in literature on foreign exchange markets which are also OTC like the CDS market.

Our analysis reflects quote shading in around 10% of the data but it would be wrong to conclude that dealers only have open positions 10% of the time. It is likely that instead of adjusting bid quotes, dealers typically cover their open short positions at prevailing market ask spreads so as not to reveal information about their positions. Unfortunately, without more detailed data, it is not possible to identify such occurrences.

Dealers do not like to carry open positions given the risk of credit deterioration and we expect to find a greater incidence of quote shading during periods of high risk. Using put-call ratios on equity options as a signal of market expectations about the firm's risk, we find a weak yet statistically significant correlation between quote shading and firm risk.

Using the premise that dealers do not like to hold short positions over extended periods of time, we also expect to find evidence of quote shading on Fridays or before the start of holidays i.e. on trading days before market closure. However, we find a negative yet statistically significant relationship between the two indicating that quote shading does not occur close to holidays.

Based on these initial results, we extend our analysis to see if there is any evidence of day-of-the-week effects on CDS liquidity, as measured by the bid-ask spread - a liquidity proxy developed by Amihud and Mendelson (1986). Our regression results show that liquidity decreases the most on Mondays and Fridays and least on Tuesdays which is similar to Chardia et al (2001) findings for equity markets.

Using an error correction model, we test price discovery with and without quote shading. To clarify, we do not focus on price discovery dynamics between the CDS and stock market but instead look at differences in price discovery in the CDS market with and without quote shading. While the average price discovery share of CDS is lower in the market with quote shading, we are unable to find a statistically significant difference between the price discovery levels for periods with and without quote shading.

We extend our tests of price discovery to high and low risk periods given evidence of quote shading during periods of high risk to analyse the impact a risk change has on price discovery in the CDS market. We find that while most of the price information comes from the equity market, CDS market contribution to price discovery is higher during low risk periods when there is less prevalence of quote shading.

Quote shading is just one explanation for this difference in price discovery dynamics and changes in liquidity levels during high and low risk periods could also be used to explain the price discovery changes. We therefore test the relationship between liquidity and firm risk levels but do not find any statistically significant relationship between the two.

Our main findings from this paper are that CDS dealers can modify quotes to manage their open position and that this practice can result in a loss of market informational efficiency. The contribution of this paper is to look at an area of the CDS market that has not been studied before. Furthermore, given data limitations, our results are encouraging and merit further investigation using more detailed data.

The remainder of the paper is organized as follows. The following section is a literature survey and our key test hypotheses while Section 3.3 looks at the data set and introduces some summary statistics. We define and test for evidence of quote shading and correlations in Section 3.4. In Section 3.5 we test day-of-the-week effects on CDS liquidity and present the price discovery tests in Section 3.6. The conclusion follows in Section 3.7.

3.2. Literature Review

In a working paper, Stulz (2009), explains how CDS dealers like to close out their exposure after getting into a short position as they are in the business of making a market for CDS and not of carrying risk on the underlying. It follows that when they sell protection to an investor, they try to book a matching long position as soon as possible using one of the following two routes:

1. buying protection from other dealers at the prevailing ask rate, or
2. offering attractive bid rates to investors looking to sell insurance.

The purpose of this paper is to look for evidence of the latter by CDS dealers and its impact on price discovery in the market. To the best of our knowledge, no other study has looked at this aspect of the CDS market. Therefore, to get some theoretical support for our hypotheses, we turn to the foreign exchange market, another OTC market, where the price shading phenomenon has been well documented.

Market microstructure theory looks at two models of order flow to explain price movements. The information or adverse selection models use information asymmetry between informed and uninformed traders to explain price movements. The underlying premise is that dealers adjust prices when they transact with informed traders to avoid being taken advantage of. However, as it is difficult to distinguish between informed and uninformed traders, dealers look to increase price if there is a buyer for the inventory and decrease price if the other party is selling.

The other model commonly used is the one we focus on and it draws on inventory management by dealers to explain price movements. Garman (1976) was one of the first to introduce the idea that dealers adjust the price to avoid bankruptcy and manage inventory. This idea was developed further by Amihud and Mendelson (1980) who built a multi-period model where dealers increase prices if their inventory is shrinking and reduce prices in case of an inventory build up. This was a key paper introducing price shading in the forex market and papers have followed-up by developing this concept further.

The important idea is that both models have the same result on prices i.e. buyer initiated trades result in an upward pressure on price and seller initiated trades result in a downward pressure on price.

From an empirical standpoint, Lyons (1995) looks at the DM/U$ market and finds evidence of both, information and inventory effects, on the part of the dealers quoting rates in the market. He finds that a dealer will not only increase the spread to protect himself against informed traders but also carry out quote shading to attract trades that help him manage inventory.

Bjonnes and Rime (2005) look at interbank dealers in the forex market to find that dealers actively control their inventory positions. As evidence of quote shading, they expect to see the forex quote dependent on existing inventory levels but fail to find a relationship between the two.

As a result, they argue that dealers use market orders to control their inventory and avoid adjusting price (i.e. quote shading) since it may reveal information about their position.

Cheung and Wong (2000) surveyed 392 practitioners in the interbank forex market in Hong Kong, Singapore and Tokyo to find that while bid-ask spreads are generally fixed in those markets, a small percentage of the respondents confirmed that they carried out quote shading to manage the risk of an adverse inventory position. Furthermore, they suggest that this inventory risk increases when markets are more volatile. As a result, we would expect to see quote shading occur more frequently in the CDS market when the overall market and firm risk are higher, leading to our first hypothesis:

H_1: There is a positive relationship between quote shading and firm risk.

Based on the premise that a dealer's CDS position has an impact on the quote he provides, we also test if the quote is affected by the dealer's ability to close out his position. Unfortunately as we do not have access to intra-day quotes, we can only use daily spreads to see if there is a pattern to spread movements close to the end of the week. Chordia et al (2001) look at the US equities market to find that trading activity and liquidity are low on Fridays and high on Tuesdays. As CDS dealers would not like to carry open short or long positions over weekends when trading is not possible, we expect CDS market liquidity to be high (i.e. tighter bid-ask spreads) on Fridays as they try to close out their positions prior to the start of the weekend.

H_2: The bid-ask spread is smallest on Fridays when compared to the other days of the week.

There has been a fair amount of research on price discovery in the CDS market when compared to the stock and bond markets. The general findings of Longstaff et al. (2005), Norden and Weber (2007), Blanco et al. (2005) and others is that while both CDS and stocks lead the less liquid bond markets, stocks typically lead CDS except in cases of higher risk firms where CDS lead. In another paper, we test price discovery in the stock and CDS markets before and after the financial crisis to find that the stock market continues to be the primary market where information is revealed.

However, none of the studies we found looked at CDS price discovery in the backdrop of price adjustment made by dealers to manage their risk positions. Therefore, if CDS dealers rely on quote shading to manage short CDS positions, they would narrow bid-ask spreads when net short and increase them if they hold a net long position. This adjustment may put pressure on spreads that is contrary to the direction of market pressure. As a result, we expect to find price discovery to be lower when dealers resort to quote shading i.e. during high risk periods.

H_3: Price discovery will be lower during periods of quote shading.

3.3. Data

We use daily CDS mid-spreads on 5-year senior, unsecured corporate bonds from the Thomson DataStream database for the period 1 Jan 2005 to 30 October 2009 as these represent the most liquid instruments in the CDS market. The data represents the average of daily reported spreads from 13 key sellers in the CDS market. As a result, we may not be able to pick out quote shading by individual dealers but will observe it when the dealers collectively resort to it. We start with a database of over 600 firms but after eliminating firms without stock or option data or firms with CDS data that appears to be missing or is questionable, we are left with 198 firms representing a total of 249,480 data points.

We use adjusted daily share prices for the period under study to arrive at the share log returns. To capture the "risk" of the firm, we use a measure known as the put-call ratio. Pan and

Poteshman (2006) use the ratio of the volume of puts to the volume of calls and find it to be a good predictor of future share performance. A higher put-call ratio suggests that more investors are long puts than are long calls and the market is therefore bearish on the firm. As the CDS spread is also a reflection of the future risk associated with a business, we believe the two measures are well aligned in that they both reflect the market's risk expectations about a business. The options data is sourced through the Optionmetrics database.

Table 3.1 presents summary statistics for our daily data. The average of the average daily CDS spread for the 198 firms is 107 bppa, while the average annual share return is 2.2% and the average put-call ratio is 1.63. The average share return has been calculated as the annualized compounded growth rate and not as the mean of the average daily returns since positive and negative returns would cancel out leaving us with an incorrect estimate. With regards to the put-call ratio, the market generally considers a ratio of 0.8 or over as a bearish outlook signal and a ratio of 0.6 or below as a signal of bullish outlook. Therefore the average of 1.63 for our data may seem high but it should be pointed out that our data includes the period of the financial crisis.

3.4. Quote Shading

In a typical trade, a fund manager, looking to hedge his exposure on a company, will call a dealer to get a quote for buying CDS protection on his exposure. The dealer will quote both bid and ask spreads and if acceptable, the investor will purchase insurance cover through the dealer at the ask rate, resulting in a short position for the dealer. As the dealer is in the business of market making for CDS and does not take on credit exposure on his books, he subsequently returns to the market to get into a long position on the same risk to close out his position. Therefore, a completed CDS transaction results in a net-zero position for the dealer.

For the purpose of our study, we focus on the scale of change in the bid and ask spreads. In an initial review of daily spreads, we observe asymmetric changes in the bid and ask spreads for the same underlying asset e.g. ask spread on Company A may increase by 10 bps while the bid quoted for Company A increases by 15 bps on the same day. As we normally expect to see symmetric changes in the spreads, this liquidity change may point to some form of quote adjustment taking place where dealers with short (long) positions on Company A may be offering more attractive bid (ask) rates to investors to get themselves into a long (short) position and close out their exposure.

There are three types of spread movements possible in bid and ask quotes, i.e. increase, decrease or no change. Figure 3.1 displays all possible types of changes in the bid and ask quotes as well as the scale of change in these quotes.

		Change		
		Ch Ask > Ch Bid	Ch Ask = Ch Bid	Ch Ask < Ch Bid
Ask inc	Bid inc	-	-	I
	Bid same		-	
	Bid dec	-	-	-
Ask same	Bid inc		II	
	Bid Same		-	
	Bid dec		-	
Ask dec	Bid inc	-	-	III
	Bid Same		-	
	Bid dec	-	-	-

Figure 3.1 Quote Shading Defined

We define quote shading as one of the following set of movements in the bid and ask spreads (shaded cells in Figure 3.1 above):

I) Ask and bid both increase but bid increases by more than ask.

II) Ask remains unchanged but bid increases.

III) Ask decreases while bid increases and the absolute change in bid is greater than the absolute change in ask.

We should note that in all three instances, we see a tightening of the bid-ask spread i.e. an increase in market liquidity. In our data, we find liquidity increasing (bid-ask spread decrease) in 53,271 data points and decreasing (bid-ask spread increase) in 53,943 instances and no change in liquidity in the remaining 142,224 data points. Therefore, as quote shading would be evident in cases where liquidity increases, we are looking at a maximum possible 53,271 data points.

Based on our definition of quote shading, we find evidence of it in 24,384 instances i.e. in 45.7% of increased liquidity data points or 9.77% overall. We next look at the days characterised by high volatility i.e. put-call ratio in excess of 0.8 for a total of 113,831 data days. There are a total of 49,896 weekend and holidays in our entire data set.

Looking at quote shading on days when either the put-call ratio is more than 0.8 or the following day is a holiday. We find this occurring 16,198 times i.e. on 66% of the days that we find dealers offering relatively more attractive bid quotes, the market is either assigning a negative outlook to the firm or is before a holiday. A firmwise snapshot is given in Table 3.2.

To test if the relationship between quote shading and high volatility and weekends is statistically significant, we take the correlation between the variables (Table 3.3) and find a positive, significant relationship between quote shading and high volatility days. This suggests that if a dealer is in a net short CDS position, we are more likely to see him adjust the bid quote to attract sellers if the firm is higher risk.

Conducting the same test for quote shading and weekends, we find a negative, significant relationship reflecting that dealers are more likely to carry out quote shading during weekdays than weekends. This result is contrary to our expectations as it does not support the underlying premise for hypothesis #2 that dealers systematically close out their positions (increased liquidity) prior to weekends and holidays. To make sure that this relationship does not hold as suggested by our hypothesis, we extend our analysis to a day-of-the-week test as explained in the following section.

3.5. Liquidity and day-of-the-week effect

3.5.1 Methodology

Cross (1973) tests stock returns from 1953 to 1970 to find that Friday returns are higher than Monday returns. Gibbons and Hess (1981) also test stock returns to identify a day-of-the-week effect where returns on Monday are lower than returns on other days. Their research triggered off a series of papers looking at the similar trends in stock and other markets using returns, volatility and other parameters. While papers on CDS spreads have included day-of-the-week dummies in analysing spread changes, we have not found any that look at day-of-the-week effect on liquidity.

As a further test of hypothesis #2, we run the following regression on each firm in our panel to test for day-of-the-week effects. Based on the expected relationship between liquidity and quote shading, we expect to see increased liquidity, as measured by the bid-ask spread, close to the weekend.

$$Ch\_Liq_{i,t} = Ch\_Liq_{i,t-1} + \alpha_{i,1}D_1 + \alpha_{i,2}D_2 + \alpha_{i,3}D_3 + \alpha_{i,4}D_4 + \alpha_{i,5}D_5 + \varepsilon_i$$

Where:

$Ch\_Liq_{i,t}$ = Change in liquidity (%) on day t for firm i

$D_{1\text{-}5}$ = Dummy for each day of the week (i.e. dummy is =1 if it is Monday, else it is 0) where 1= Monday, 2=Tuesday and so on

$\alpha_{1\text{-}5}$ = Coefficients for each day of the week

ε_i = Error term

The lagged liquidity change term is added to the OLS regression to account for the possibility of autocorrelations in the error term. This regression is run for the firms in our database and the results are presented in the following section.

3.5.2 Results

Table 3.4 presents a summary of our findings which reflect that on average, liquidity decreases throughout the week. More importantly, it decreases the most on Mondays and Fridays while it decreases by the least amount on Tuesdays. Interestingly, our results are in line with the findings from Chordia et al. (2001) where they study the equity markets to find trading activity peaking on Tuesdays and at the lowest on Fridays.

In the case of CDS, this means that traders typically avoid trading or taking up positions close to holidays or just after holidays and prefer trading during the week. While this result does not support our hypothesis #2 that quote shading (increased liquidity) occurs close to holidays, our regression results confirm the findings from our quote shading analysis where we find a negative, statistically significant relationship between quote shading and weekends. Based on the results from both tests, we can conclude that CDS dealers trade and square their positions during the week and then reduce trading activity close to weekend to avoid taking up a position just before a holiday.

3.6. Price discovery and volatility

3.6.1 Methodology

Literature on price discovery for the CDS market looks at price efficiency differences amongst CDS, stock and equity markets and none of the papers we found has looked at a market while focusing on changes in risk. Martens (1998) looks at price discovery in the bond futures market during periods of high volatility and low volatility. Studying bond futures traded on the London International Financial Futures Exchange (LIFFE) and Deutsche Terminborse (DTB) he finds that during periods of high volatility, share of price discovery in the LIFFE floor trading market increases although its trading volume decreases while during quiet periods, the DTB generates a higher share of price discovery with a lower transaction volume.

We draw on his methodology and extend the tests to our dataset. We separate our data into "Quote Shading" (QS) and "No Quote Shading" (NQS) sets based on our findings from Section 3.4. Having divided our data into QS and NQS series, we conduct Augmented Dickey-Fuller tests to check the time series for stationarity and find evidence of unit-roots present. One way of accounting for the presence of unit-roots is to take the first difference i.e., use share returns and CDS spread changes. However, the use of first difference results in a loss of information on the long run equilibrium characteristics of the data. An Error Correction Model (ECM) provides an alternative to using first difference for non-stationary data.

To use the ECM, we first need to identify cointegrated relationships. We therefore test the data for cointegration using the Johansen test. Although two variables may be non-stationary, if they are driven by the same underlying factors they could drift together so that their linear combination becomes stationary. This means that when an I(1) variable is regressed against another I(1) variable and the residuals are I(0), the variables are said to be cointegrated.

While cointegration suggests a long term relationship between the two variables, they are likely to deviate from equilibrium in the short term. When that happens, the variables will eventually move to close out the gap between them. This adjustment in the short term between the two can be captured through an ECM as shown below.

$$\Delta\ CDS_{i,t} = \alpha_1 + \lambda_1(CDS_{i,t-1} - \delta_0 - \delta_1\ Price_{i,t-1}) + \Sigma_{i=1 to 5}\ \beta_{1,i}\ \Delta Price_{i,t-i} + \Sigma_{i=1 to 5}\ \gamma_{1,i}\ \Delta CDS_{i,t-i} + \varepsilon_{1,t}$$

$$\Delta\ Price_{i,t} = \alpha_2 + \lambda_2(CDS_{i,t-1} - \delta_0 - \delta_1\ Price_{i,t-1}) + \Sigma_{i=1 to 5}\ \beta_{2,i}\ \Delta Price_{i,t-i} + \Sigma_{i=1 to 5}\ \gamma_{2,i}\ \Delta CDS_{i,t-i} + \varepsilon_{2,t}$$

Where

$CDS_{i,t}$	=	CDS spread for firm *i* at time *t*
$Price_{i,t}$	=	Share price for firm *i* at time *t*
$\alpha,\beta,\lambda,\delta,\gamma$	=	Regression coefficients
ε	=	i.i.d. shocks

When the two variables (Price and CDS) are cointegrated the variables $\delta_0 = 0$ and $\delta_1 = 1$. A negative and statistically significant value of λ_1 shows the stock market contributes to the price discovery. If the CDS market is contributing to price discovery, we will find λ_2 to be positive and statistically significant. In case both markets are contributing to the price discovery process, we will find both coefficients to be statistically significant.

As the purpose of our test is to compare price discovery in two separate regimes, we need a measure that allows us to compare price discovery during the two periods. Hasbrouck (1995, 2003) argues that given random walk in markets, new information gets reflected through price volatility. Therefore, whichever market contributes more to the variance of innovations is the one where price discovery takes place. However, as the different markets are often correlated, he uses an "information share" measure to find out where price discovery occurs, where

$$\text{Hasbrouck Lower Limit (HLL)} = \frac{\lambda_2^2\left[\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right]}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}$$

$$\text{Hasbrouck Upper Limit (HUL)} = \frac{\left[\lambda_2\sigma_1 - \lambda_1\frac{\sigma_{12}}{\sigma_1}\right]^2}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}$$

While we get the λ_1 and λ_2 values from our ECM, we also need to compute the values for σ_1, σ_2 and σ_{12} which are the residual variance-covariance values from our ECM. As the innovations in the markets may be correlated, we use Cholesky factorization to arrive at a lower-triangular matrix with the variance and covariance. In terms of the lag, we use data from 5 prior days to ensure that the entire week is taken into account.

3.6.2 Results

Results are presented in tables 3.5 and 3.6. In the absence of quote shading there is evidence of cointegration in 99 cases with the share market contributing to price discovery in 51 cases and the CDS market contributing in 18 cases. There are 30 firms where both the CDS and stock markets contribute to price discovery. Using the Hasbrouck Lower Limit as a price discovery measure, on average 41.5% of price discovery comes from the CDS market when there is no quote shading.

When we find evidence of quote shading, there are 45 cointegrated firms with the stock market contributing to price discovery in 30 instances while the CDS market contributes in 11 cases and both in only 4 instances. Furthermore, there is only 36.7% of price discovery coming, on average, from the CDS market. Looking at the two results, we find that price discovery is better when dealers do not adjust quotes.

In order to highlight the difference in price discovery between QS and NQS periods, we identify 33 cases where the prices display cointegration in both periods and also have statistically significant ECM parameters. We recognize that while we have 99 cases of cointegration for the NQS period and 45 for QS, the number declines drastically when we look for instances where cointegration is present in both QS and NQS periods. A possible reason is that cointegration draws on the long term relationship between variables and by splitting our database into subperiods, we are losing some information on the long term relationship between CDS spreads and share price. To ensure that our methodology yields correct cointegration results, we test the complete dataset for cointegration and find these 33 cases to be cointegrated.

Comparing the price discovery for QS and NQS data, we find that the CDS market's average contribution to price discovery is 41.8% with quote shading which increases to 46.4% without quote shading. This seems to support our hypothesis that quote shading by dealers reduces the informational efficiency in the market.

Using the price discovery contributions for the 33 firms, we compare the results for QS and NQS and test to see if they are significantly different from each other. However, we do not find statistically significant evidence showing that the NQS price discovery contribution is greater than that with QS. We therefore cannot use our results as conclusive support of hypothesis #3 and need to use an alternative approach.

3.6.3 Price discovery and volatility - Alternative Tests

Given that the price discovery differences between QS and NQS time series are not statistically significant, we turn to another set of tests to identify differences in price discovery. As our previous results have shown that quote shading is more likely to occur during higher risk periods, we use put-call ratio as a factor to split our dataset into high risk and low risk periods.

We take a 5-day moving average of the put-call ratio as an indicator treating a score of over 0.8 as high risk and a score below 0.6 as low risk. Unlike quote shading as an indicator that changes frequently, risk levels are more sticky and do not change as often. Also, quote shading was observed in only 10% of the data points while risk levels are spread out much more evenly. The data can therefore be split along risk levels and provide us with longer stretches of data for analysis.

We find cointegration in 51 cases in the high risk period and 67 cases in low risk (summary results in Table 3.7). For the high risk period, we find the stock market contributing to price discovery in 36 cases while CDS contributes in only 7 instances. There are 8 cases where both stock market and CDS contribute to price discovery. Using the Hasbrouck lower limit as a measure of price discovery, we find 32.1% price discovery in the CDS during high risk periods.

In the 67 cases of cointegration during low risk, we find that the stock market contributes in 50 cases and CDS in 11 cases while they both contribute in 6 instances. The Hasbrouck measure shows 36.1% contribution to price discovery from the CDS market in low risk periods.

The above results represent the summary of all cointegrated firms. However, our focus is on identifying differences between the two and therefore, we need to compare the mean price discovery levels for statistical significance.

We identify 26 cases where the prices display cointegration in both periods and also have statistically significant ECM parameters (detailed results in Table 3.8). As before, we also test these 26 firms for cointegration using the full dataset to ensure that no incorrect relationships come up due to the splitting of the database. We find the same firms to be cointegrated when the complete dataset is considered.

While the CDS market's average contribution to price discovery is 17.25% (median 3%) in periods of high risk, it increases to 28.3% (median 17.9%) when risk is low. When risk is high, the CDS market contributed to price discovery in one case and the stock market accounted for price discovery in 21 cases while the CDS and stock markets were jointly responsible for price discovery in 3 cases. During low risk periods, the stock market was significant in price discovery in 18 instances, with the CDS market in 5 cases and both markets in 2 instances.

The initial results support Hypothesis #3 that price discovery in the CDS market is lower during periods of high risk which is where we find a greater prevalence of quote shading. However, to be certain, we take the series of price discovery levels we computed for high and low risk periods and test the difference between the two to find it to be statistically significant.

Based on the above, we can conclude that price discovery is slower in the CDS market during high risk periods when there is a greater probability of quote shading. Therefore, if the true market spreads should be decreasing, dealers could be putting upward pressure on quotes to encourage investors to sell cover. This would adversely impact price discovery during high risk periods. While this practice of quote shading, i.e. adjusting quotes to modify investor behaviour, could be reducing market informational efficiency, it is equally likely that the OTC CDS market simply breaks down during high risk periods and pricing efficiency drops. Without more detailed data, it is difficult to identify the exact driver behind these results.

3.6.4 Liquidity and volatility - An alternative explanation

Since liquidity can have a direct impact on price discovery, a case can also be made for a liquidity based explanation for the change in price discovery between low and high risk periods. If liquidity increases in the CDS market when risk is low and decreases during high risk periods, it could be argued that changes in liquidity are driving our test results.

To confirm that liquidity is not the reason for our results, we extend our analysis to test for a relationship between liquidity changes and changing volatility levels by running the following regression:

$$Ch\_Liq_{i,t} = \alpha_i + \beta_i \, Ch\_Volatility_{i,t-1} + \varepsilon_i$$

Where:

$Ch\_Liq_{i,t}$ = % change in % liquidity on day *t* from day *t-1* for firm *i*.

$Ch\_Vol_{i,t}$ = % change in risk (using put-call ratio) on day *t* from day *t-1* for firm *i*.

α_i, β_i = Regression coefficients

ε_i = Error term

Our regression results (Table 3.9) reflect volatility change coefficients that are statistically significant in only 15 cases out of 198 while the constant remains significant for all firms, suggesting omitted factors. We therefore fail to establish a relationship between changes in CDS market liquidity and firm risk level for our dataset. These findings therefore support our results that price discovery is impacted by the risk level in the market and is independent of liquidity changes in the markets.

3.7. Conclusion

The OTC market for CDS is currently going through a period of great scrutiny with demands for regulatory reforms. Despite a growing stream of literature on this market, there is no published research that analyses dealers and their position/inventory management strategies. Drawing from literature on the foreign exchange markets, we know that sell side dealers are likely to cover their short positions either through getting into a long position at the market ask rate or by making the bid quotes attractive to investors i.e. quote shading.

Using changes in bid and ask rates, we find evidence of quote shading being carried out to cover short positions. Further, our initial analysis shows that traders prefer providing liquidity to the market during the week and tighten liquidity close to holidays or just after holidays.

We test price discovery with and without quote shading but do not find a statistically significant explanation for the changes. Instead, using the put-call ratio as a signal of market expectation of firm risk going forward, we look at the price discovery process to identify differences when market risk levels are high and low since there is a positive relationship between riskiness and quote shading.

Our findings show that most of the price discovery occurs primarily in the stock market. However, the contribution of CDS to the price discovery process in low volatility times is greater than during high risk periods.

We also look at liquidity levels and risk expectation to test if liquidity changes are driving the difference in price discovery process but find no evidence to support this premise. Given the fact that dealers indulge in quote shading to cover their positions especially during high risk periods, we conclude that this behaviour is actually detrimental to the price discovery process and results in lower price discovery taking place in a higher risk CDS market. This paper establishes the need to extend this analysis using more detailed information to improve our understanding of how CDS dealers behave and the impact their quote strategy has on price discovery.

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Table 3.1

Summary statistics on CDS, Shares and Put-call ratios *(average spreads and returns)*

Firm	CDS spread	Share Return	Put-Call Ratio
Alcoa	149	-17.25%	0.79
Amerisourcebergen	67	9.79%	2.16
Abbott Laboratories	30	1.68%	0.82
Archer-Danls.-Midl.	47	6.76%	0.78
Amer.Elec.Pwr.	44	-2.42%	1.28
AES	352	-0.74%	1.76
Aetna	49	-3.36%	1.07
Allergan	37	7.22%	1.36
American Intl.Gp.	351	-53.23%	1.16
AK Steel Hldg.	421	3.42%	0.83
Allstate	68	-10.75%	1.06
Advanced Micro Devc.	934	-27.27%	0.88
Amgen	39	-3.68%	0.91
American Tower 'A'	162	15.76%	1.60
Apache	44	14.82%	0.77
Anadarko Petroleum	72	14.97%	0.87
Avalonbay Commns.	131	-1.61%	4.29
Avon Products	34	-3.56%	1.92
American Express	116	-6.79%	1.12
Allegheny En.	151	3.46%	4.25
Autozone	75	8.62%	1.56
Bank Of America	69	-21.33%	0.91
Baxter Intl.	24	9.67%	1.08
Baker Hughes	36	0.36%	1.04
Ball	152	2.70%	3.56
Bristol Myers Squibb	26	-3.14%	0.78
Boston Scientific	113	-25.79%	1.27
Peabody Energy	210	17.59%	0.83
Boston Properties	155	-0.95%	2.57
Citigroup	108	-40.01%	0.96
CA	131	-7.71%	1.94
Cardinal Health	46	-7.39%	1.58
Caterpillar	62	3.09%	1.06
Chubb	40	5.10%	1.23
Carnival	91	-13.08%	2.10
Chesapeake Energy	271	9.99%	0.52
Cigna	74	0.89%	1.31
Colgate-Palm.	27	9.82%	1.33
Clorox	41	0.31%	1.57
Comcast 'A'	78	-8.19%	1.33
Cummins	90	16.51%	1.46
CMS Energy	182	5.24%	2.75
Centerpoint En.	104	2.74%	2.01
Costco Wholesale	36	3.61%	1.33
Campbell Soup	25	1.38%	2.82
Computer Scis.	64	-1.88%	1.69
CSX	68	16.82%	1.23
Chevron	29	8.81%	0.82
Dominion Res.	46	0.21%	1.17
E I Du Pont De Nemours	40	-8.60%	0.91
Deere	47	4.71%	1.11
Dell	55	-19.74%	1.19
Dean Foods New	264	-8.12%	4.02
D R Horton	234	-18.54%	1.96

Danaher	40	4.09%	1.33
Walt Disney	37	-0.08%	0.85
Dover	41	-1.82%	2.55
Dow Chemical	96	-14.29%	0.83
Darden Restaurants	100	2.25%	2.82
Duke Energy	39	1.70%	0.73
Devon Energy	44	12.14%	0.78
Conoco Phillips	38	3.72%	0.74
Eastman Kodak	447	-36.04%	2.01
Eastman Chemical	64	-1.79%	1.66
Emerson Electric	41	1.97%	0.70
El Paso	326	-0.70%	0.85
Eaton	66	-3.31%	1.40
Entergy	142	3.02%	2.13
Exelon	107	1.73%	0.87
Ford Motor	1,516	-14.25%	1.40
Fedex	67	-5.88%	1.26
First Energy	68	1.99%	1.67
Fortune Brands	95	-11.91%	2.04
Gannett	260	-35.43%	2.65
General Dynamics	30	4.36%	0.93
General Mills	39	6.38%	1.10
Corning	83	4.69%	0.64
Genworth Financial	463	-17.62%	3.27
Gap	91	0.36%	1.63
Goodrich	46	11.45%	1.88
Goldman Sachs Gp.	92	10.52%	0.91
Goodyear Tire & Rub.	454	-2.97%	1.63
Halliburton	38	9.30%	0.89
Hasbro	69	7.65%	2.63
Health Care Reit	193	3.75%	1.32
Home Depot	73	-10.60%	0.94
Hartford Finl.Svs.Gp.	166	-19.23%	1.60
HJ Heinz	44	0.82%	2.70
Honeywell Intl.	34	0.34%	0.81
Starwood Htls.& Rsts. Worldwide	215	-9.15%	1.68
H&R Block	92	-5.70%	2.48
The Hershey Company	35	-7.25%	1.04
Humana	115	5.39%	1.16
International Bus.Mchs.	33	4.45%	1.01
Intl.Game Tech.	99	-12.42%	0.98
Intl.Paper	149	-12.28%	1.10
Interpublic Gp.	488	-15.33%	10.49
Johnson Controls	124	2.80%	1.66
Penney JC	156	-4.52%	1.46
Johnson & Johnson	18	-1.30%	0.93
JP Morgan Chase & Co.	57	1.35%	1.05
Nordstrom	113	6.73%	1.35
Kellogg	34	3.15%	2.25
Kraft Foods	49	-4.79%	1.98
Kimco Realty	184	-15.64%	2.12
Kimberly-Clark	32	-1.11%	1.27
Coca Cola	27	5.30%	0.73
Kroger	62	6.39%	1.54
Kohl's	80	3.15%	1.59
Lennar 'A'	294	-26.57%	1.66
Eli Lilly	21	-9.89%	1.32

Lockheed Martin	29	5.06%	1.05
Lincoln Nat.	216	-12.77%	1.17
Southwest Airlines	106	-12.57%	1.05
Marriott Intl.'A'	128	-4.33%	2.02
Masco	164	-20.95%	8.84
Mattel	71	-0.26%	1.52
McDonalds	28	13.48%	0.83
McKesson	40	14.09%	1.44
Medtronic	40	-6.52%	0.83
Massey En.	392	-3.02%	1.32
Metlife	154	-3.37%	1.67
Medco Health Sltn.	74	22.84%	1.11
Marsh & Mclennan	60	-6.76%	1.28
3M	28	-2.32%	1.32
Altria Group	69	5.43%	0.72
Motorola	135	-13.28%	0.77
Merck & Co.	27	-0.22%	0.99
Marathon Oil	85	12.26%	0.71
Meadwestvaco	100	-7.62%	1.67
Nabors Inds.	82	-3.28%	0.82
Newmont Mining	83	0.53%	0.72
Nike 'B'	31	6.75%	1.20
Northrop Grumman	33	-1.40%	1.07
Norfolk Southern	42	5.79%	0.99
Northeast Utilities	51	4.66%	1.23
Nucor	48	9.93%	1.08
Newell Rubbermaid	78	-9.91%	1.93
Office Depot	372	-19.45%	1.63
Owens Illinois New	302	7.30%	2.18
Oneok	73	5.57%	0.86
Omnicom Gp.	67	-4.26%	2.15
Occidental Ptl.	40	22.67%	0.81
Pitney-Bowes	42	-12.15%	3.19
PepsiCo	28	3.23%	0.89
Pfizer	26	-8.71%	0.81
Procter & Gamble	37	1.03%	0.94
Pulte Group	187	-22.89%	2.37
Prologis	336	-23.98%	2.46
Pepco Holdings	97	-6.63%	1.06
PPG Industries	65	-3.57%	1.25
Praxair	38	13.02%	1.08
Qwest Comms.Intl.	291	-3.99%	0.97
Ryder System	101	-2.89%	3.71
Republic Svs.'A'	56	3.30%	1.37
Radioshack	153	-12.78%	3.21
Raytheon 'B'	35	3.67%	0.69
Sealed Air	108	-6.68%	5.03
Sherwin-Williams	57	5.46%	4.28
Sara Lee	52	-11.55%	1.05
SLM	370	-30.09%	2.28
Simon Pr.Gp.	141	1.25%	1.95
Staples	91	-0.19%	1.47
Sempra En.	51	7.49%	1.51
Sunoco	114	-4.67%	1.06
Supervalu	186	-14.41%	2.94
Safeway	64	2.76%	1.83
AT&T	38	0.06%	0.87

Teco Energy	116	-1.25%	1.74
Target	52	-1.38%	1.16
Tenet Hlthcr.	579	-14.17%	2.18
Tjx Cos.	48	8.80%	2.85
Tyson Foods 'A'	154	-7.25%	3.06
Tesoro	227	-1.12%	0.79
Time Warner	74	-7.12%	0.75
Textron	176	-13.67%	1.34
United Health Gp.	87	-10.06%	0.89
Unum Group	150	2.73%	2.43
Union Pacific	48	10.72%	1.29
United Parcel Ser.	29	-9.08%	0.85
United Technologies	36	3.72%	0.86
V F	50	5.66%	4.14
Valero Energy	100	-3.53%	0.70
Vornado Realty Tst.	179	-4.92%	3.84
Wisconsin Energy	49	5.51%	0.82
Wells Fargo & Co	58	-2.41%	2.21
Whirlpool	118	0.75%	2.18
Wellpoint	87	-3.75%	1.36
Williams Cos.	138	4.09%	0.73
Wal Mart Stores	31	-1.46%	0.96
Weyerhaeuser	111	-11.90%	1.15
US.Steel	257	-7.13%	1.12
Xcel Energy	52	0.95%	1.18
Xl Cap.'A'	207	-27.29%	3.40
Exxon Mobil	20	7.70%	0.80
Xerox	157	-15.51%	1.14
XTO En.	82	17.54%	0.70
Yum! Brands	67	7.33%	1.36
Overall Average	**107**	**2.20%**	**1.63**

Table 3.2

Summary of Quote Shading (QS) Results

Firm	QS days	High Risk days	Holidays	QS days when high risk or holiday
Alcoa	175	425	252	105
Amerisourcebergen	106	746	252	79
Abbott Laboratories	94	461	252	60
Archer-Danls.-Midl.	141	418	252	77
Amer.Elec.Pwr.	111	518	252	78
AES	143	439	252	86
Aetna	123	575	252	76
Allergan	106	632	252	69
American Intl.Gp.	133	656	252	94
AK Steel Hldg.	109	404	252	66
Allstate	134	524	252	79
Advanced Micro Devc.	115	465	252	74
Amgen	124	495	252	65
American Tower 'A'	31	564	252	17
Apache	107	468	252	66
Anadarko Petroleum	129	545	252	91
Avalonbay Commns.	134	781	252	105
Avon Products	99	729	252	71
American Express	135	648	252	105
Allegheny En.	168	481	252	107
Autozone	110	953	252	93
Bank Of America	115	593	252	80
Baxter Intl.	107	546	252	68
Baker Hughes	120	589	252	79
Ball	32	562	252	17
Bristol Myers Squibb	123	418	252	69
Boston Scientific	147	529	252	93
Peabody Energy	125	518	252	84
Boston Properties	128	687	252	88
Citigroup	127	592	252	88
CA	152	597	252	101
Cardinal Health	111	667	252	81
Caterpillar	146	765	252	111
Chubb	89	594	252	62
Carnival	155	843	252	110
Chesapeake Energy	150	212	252	71
Cigna	127	639	252	80
Colgate-Palm.	80	651	252	59
Clorox	129	564	252	80
Comcast 'A'	80	599	252	53
Cummins	138	741	252	110
CMS Energy	159	497	252	99
Centerpoint En.	140	430	252	86
Costco Wholesale	81	787	252	68
Campbell Soup	103	558	252	68
Computer Scis.	122	576	252	77
CSX	135	457	252	83
Chevron	119	550	252	79

Dominion Res.	111	532	252	67
E I Du Pont De Nemours	124	541	252	87
Deere	146	677	252	104
Dell	102	639	252	68
Dean Foods New	135	562	252	90
D R Horton	153	797	252	112
Danaher	108	657	252	77
Walt Disney	117	504	252	66
Dover	81	513	252	58
Dow Chemical	148	467	252	95
Darden Restaurants	144	711	252	105
Duke Energy	101	331	252	45
Devon Energy	124	471	252	77
Conoco Phillips	121	448	252	66
Eastman Kodak	148	680	252	103
Eastman Chemical	150	628	252	111
Emerson Electric	81	377	252	44
El Paso	128	360	252	68
Eaton	117	632	252	83
Entergy	148	586	252	96
Exelon	139	459	252	91
Ford Motor	152	628	252	106
Fedex	156	817	252	124
First Energy	129	433	252	70
Fortune Brands	130	547	252	77
Gannett	130	625	252	87
General Dynamics	136	537	252	96
General Mills	93	506	252	48
Corning	112	312	252	58
Genworth Financial	151	423	252	93
Gap	135	597	252	100
Goodrich	122	457	252	74
Goldman Sachs Gp.	120	740	252	86
Goodyear Tire & Rub.	138	598	252	91
Halliburton	114	560	252	79
Hasbro	123	544	252	78
Health Care Reit	117	708	252	80
Home Depot	138	608	252	98
Hartford Finl.Svs.Gp.	138	622	252	103
HJ Heinz	93	592	252	63
Honeywell Intl.	121	468	252	72
Starwood Htls.& Rsts. Worldwide	144	703	252	122
H&R Block	114	806	252	89
The Hershey Company	79	532	252	47
Humana	136	574	252	91
International Bus.Mchs.	106	750	252	83
Intl.Game Tech.	87	474	252	47
Intl.Paper	155	567	252	106
Interpublic Gp.	157	639	252	114
Johnson Controls	128	630	252	99
Penney JC	135	741	252	102
Johnson & Johnson	101	537	252	61
JP Morgan Chase & Co.	123	770	252	95

Nordstrom	127	655	252	88
Kellogg	118	595	252	71
Kraft Foods	119	640	252	76
Kimco Realty	143	644	252	100
Kimberly-Clark	109	607	252	71
Coca Cola	107	401	252	58
Kroger	115	534	252	80
Kohl's	128	825	252	109
Lennar 'A'	160	789	252	123
Eli Lilly	120	629	252	86
Lockheed Martin	121	611	252	90
Lincoln Nat.	128	504	252	93
Southwest Airlines	179	454	252	103
Marriott Intl.'A'	139	677	252	106
Masco	132	766	252	107
Mattel	112	583	252	84
McDonalds	99	519	252	60
McKesson	104	560	252	69
Medtronic	135	475	252	72
Massey En.	133	590	252	89
Metlife	149	669	252	107
Medco Health Sltn.	105	562	252	67
Marsh & McLennan	105	506	252	69
3M	93	709	252	67
Altria Group	129	404	252	72
Motorola	152	400	252	86
Merck & Co.	127	580	252	87
Marathon Oil	120	390	252	58
Meadwestvaco	132	670	252	95
Nabors Inds.	134	409	252	76
Newmont Mining	144	379	252	86
Nike 'B'	10	718	252	7
Northrop Grumman	116	509	252	67
Norfolk Southern	129	493	252	72
Northeast Utilities	63	697	252	41
Nucor	128	687	252	87
Newell Rubbermaid	137	505	252	82
Office Depot	94	513	252	64
Owens Illinois New	134	511	252	87
Oneok	113	342	252	64
Omnicom Gp.	134	741	252	100
Occidental Ptl.	119	480	252	66
Pitney-Bowes	105	535	252	64
PepsiCo	83	505	252	64
Pfizer	93	475	252	54
Procter & Gamble	103	581	252	71
Pultegroup	153	885	252	128
Prologis	140	585	252	79
Pepco Holdings	121	432	252	75
PPG Industries	133	540	252	85
Praxair	116	455	252	72
Qwest Comms.Intl.	52	297	252	31
Ryder System	148	713	252	110

Republic Svs.'A'	85	523	252	54
Radioshack	172	770	252	132
Raytheon 'B'	137	358	252	75
Sealed Air	115	653	252	78
Sherwin-Williams	131	855	252	108
Sara Lee	104	398	252	71
SLM	143	675	252	102
Simon Pr.Gp.	146	930	252	119
Staples	134	565	252	94
Sempra En.	119	459	252	68
Sunoco	151	618	252	96
Supervalu	145	562	252	102
Safeway	119	594	252	84
AT&T	132	437	252	90
Teco Energy	150	457	252	80
Target	121	737	252	94
Tenet Hlthcr.	119	532	252	83
TJX Cos.	83	520	252	54
Tyson Foods 'A'	137	647	252	93
Tesoro	136	412	252	76
Time Warner	142	401	252	73
Textron	152	534	252	83
UnitedHealth Gp.	125	443	252	67
Unum Group	127	564	252	88
Union Pacific	136	671	252	95
United Parcel Ser.	103	483	252	65
United Technologies	129	550	252	91
V F	103	568	252	63
Valero Energy	135	348	252	89
Vornado Realty Tst.	156	754	252	120
Wisconsin Energy	81	730	252	53
Wells Fargo & Co	114	948	252	100
Whirlpool	149	946	252	123
Wellpoint	107	636	252	65
Williams Cos.	133	360	252	86
Wal Mart Stores	100	601	252	62
Weyerhaeuser	168	599	252	104
US.Steel	82	673	252	57
Xcel Energy	110	307	252	64
XL Cap.'A'	136	756	252	102
Exxon Mobil	140	538	252	92
Xerox	184	442	252	118
XTO En.	126	378	252	70
Yum! Brands	119	659	252	81

Table 3.3

Correlation between Quote Shading, Risk Levels and Holidays

Quote shading and bearish outlook	
Correlation	0.0048
p-stat	0.0164
Quote shading and holidays	
Correlation	- 0.01
p-stat	0.00

Table 3.4

Regression of Liquidity and Day of Week

	Mean	Median	Significant relationship
Lag term	-32.70%	-34.02%	195
Monday	5.73%	4.79%	124
Tuesday	4.88%	4.57%	91
Wednesday	5.37%	4.69%	128
Thursday	5.43%	5.22%	136
Friday	5.89%	5.66%	151

Table 3.5

Price Discovery Results for Quote Shading and No-quote Shading

	Number of firms where			(%)	
	CDS market contributes	Stock market contributes	Both markets contribute	Mean CDS discovery	Median CDS discovery
Quote Shading	11	30	4	36.7%	30.7%
No Quote Shading	18	51	30	41.5%	33%

Table 3.6

Results from ECM and Hasbrouck Information Share *(for no-quote shading and quote shading periods)*

	No Quote Shading						Quote Shading					
	λ_1	λ_1 t-stat	λ_2	λ_2 t-stat	Hasbrouck - Lower Limit	Hasbrouck - Upper Limit	λ_1	λ_1 t-stat	λ_2	λ_2 t-stat	Hasbrouck - Lower Limit	Hasbrouck - Upper Limit
Amerisourcebergen	-2.1386	-2.3900	0.1256	1.1083	0.1694	0.2280	-0.3320	-3.0622	-0.0095	-0.9991	0.0955	0.1083
Apache	-7.8220	-3.7535	3.2068	2.5135	0.3400	0.3713	-0.2612	-3.1250	0.0449	0.6611	0.0219	0.0453
CA	-4.2094	-1.7872	-0.0739	-0.5999	0.1229	0.1377	0.1588	0.8122	0.0239	1.8094	0.8197	0.8396
Chubb	-2.6273	-1.8574	0.7627	2.5019	0.7257	0.8236	0.0235	0.1929	0.0873	3.0145	0.9879	0.9961
CMS Energy	1.0616	0.5398	0.1434	2.8052	0.9654	0.9748	0.5025	2.0860	0.0177	2.6912	0.6195	0.6503
Campbell Soup	-0.3626	-0.7444	0.5518	3.0754	0.9497	0.9846	-0.0756	-1.7529	-0.0368	-2.8228	0.6937	0.7336
Computer Scis.	-3.5443	-3.2342	-0.5267	-2.2252	0.3218	0.3376	-0.6990	-3.9328	-0.0089	-0.3164	0.0027	0.0067
CSX	-3.6426	-3.2751	-0.3057	-0.9062	0.0744	0.0873	-0.4461	-3.8969	-0.0137	-0.4374	0.0130	0.0328
Dominion Res.	-0.5928	-0.9684	-0.5365	-1.9645	0.7571	0.8607	-0.1657	-2.0800	-0.0384	-2.3657	0.5392	0.5917
Darden Restaurants	-4.8091	-2.4442	0.6128	3.7166	0.8296	0.8667	0.4052	2.2537	0.0499	1.8983	0.4163	0.4715
Duke Energy	0.7010	0.2537	0.3056	1.9288	0.9766	0.9850	-0.0795	-1.2494	-0.0197	-2.8403	0.7934	0.8506
Entergy	-3.0411	-1.7182	1.1469	3.3874	0.8053	0.8168	-0.3322	-1.7462	-0.0680	-1.4601	0.4071	0.4311
Ford Motor	-229.7377	-3.4522	0.0602	1.1530	0.1080	0.1083	22.1878	2.7699	0.0143	2.2208	0.3980	0.3986
General Dynamics	-1.1788	-2.9370	-0.3832	-0.9059	0.0978	0.1884	-0.1312	-2.2278	-0.0361	-1.0856	0.1821	0.2566
Gap	-3.1141	-3.4872	0.2898	2.5260	0.3489	0.3952	-0.4131	-3.1251	-0.0150	-1.3051	0.1485	0.1822
Kellogg	-1.6602	-2.9984	0.0541	0.4075	0.0085	0.0193	-0.0696	-1.2517	0.0419	2.5704	0.8032	0.8346
Kimco Realty	-12.4208	-1.8986	-0.6212	-2.4611	0.6952	0.7040	-0.7690	-2.1759	-0.0306	-1.1896	0.2368	0.2552
Kimberly-Clark	-1.2889	-2.2385	0.6341	2.7651	0.6773	0.8116	-0.0694	-1.2939	0.0723	3.4215	0.8712	0.9316
Lincoln Nat.	-37.8693	-2.1207	-0.0348	-0.0881	0.0023	0.0026	-5.6115	-4.0434	-0.0079	-0.2153	0.0030	0.0035
McKesson	-0.7999	-0.5359	2.2704	4.6132	0.9870	0.9907	-0.1918	-2.8398	-0.0523	-1.9749	0.3078	0.3859
Marsh & McLennan	-1.6525	-1.9563	-0.3325	-1.6141	0.3974	0.4133	-0.3369	-3.3696	-0.0120	-0.8193	0.0557	0.0747
Altria Group	-4.2922	-3.9994	0.1300	2.1246	0.2410	0.2928	-0.0845	-0.8879	0.0259	3.1778	0.9274	0.9486
Meadwestvaco	-5.2200	-3.0985	0.1939	0.9736	0.1039	0.1326	-0.3057	-1.8277	0.0483	3.1709	0.7624	0.8170
Newmont Mining	-9.3268	-3.1418	-0.1834	-0.6587	0.0508	0.0581	0.6763	3.5518	0.0724	2.0976	0.2569	0.2714
Norfolk Southern	-1.0370	-1.5393	1.1945	3.8195	0.8621	0.8851	-0.2464	-2.9913	0.0296	0.8415	0.0373	0.0816
PepsiCo	-3.0333	-4.1813	0.5448	1.0989	0.0346	0.0777	-0.0979	-2.1209	0.0456	2.1130	0.4590	0.5476

Procter & Gamble	-2.0980	-1.7364	0.3535	1.5472	0.4451	0.4716	-0.1216	-2.4967	0.0463	2.0306	0.3733	0.4169
Staples	2.7327	0.9859	-0.3539	-3.1361	0.9339	0.9446	0.0860	0.4586	0.0489	3.4482	0.9736	0.9836
Sempra En.	-2.6206	-3.0267	0.3963	1.4729	0.1846	0.2279	-0.1209	-1.1295	-0.0468	-1.9458	0.7021	0.7932
Safeway	0.9794	1.3994	-0.6056	-3.3440	0.8579	0.8968	-0.2508	-2.8102	-0.0355	-2.3084	0.3877	0.4401
AT&T	-1.7436	-2.5555	0.3339	2.1309	0.4125	0.4745	-0.4405	-4.3678	-0.0109	-0.7327	0.0273	0.0352
Union Pacific	-1.5957	-1.6658	-0.2060	-0.7119	0.2112	0.2972	-0.2860	-3.3449	0.0050	0.1311	0.0018	0.0084
United Parcel Ser.	-2.9375	-2.0546	0.6782	2.3987	0.6030	0.6406	-0.1551	-2.2810	-0.0758	-2.5459	0.5114	0.6104
Vornado Realty Tst.	-10.3775	-2.4708	-0.1968	-0.4942	0.0797	0.0924	-0.4322	-1.1555	-0.1418	-2.0732	0.7639	0.7865
Wells Fargo & Co	0.2997	0.1646	0.5731	3.2734	0.9950	0.9979	0.5882	2.8191	0.0172	0.6368	0.0586	0.0985
XTO En.	-11.9600	-4.4221	0.9315	2.5949	0.3403	0.3723	-0.3099	-2.0078	0.0564	1.6611	0.3937	0.4336
Mean					46.4%	49.9%					41.8%	45.4%
Median					37.3%	40.4%					39.6%	43.2%

Table 3.7

Price Discovery Results for High and Low Risk Periods

	Number of firms where			**(%)**	
	CDS market contributes	**Stock market contributes**	**Both markets contribute**	**Mean CDS discovery**	**Median CDS discovery**
High Risk	7	36	8	32.1%	18.1%
Low Risk	11	50	6	36.1%	30.9%

Table 3.8

Results from ECM and Hasbrouck Information Share *(for high risk and low risk periods)*

	High Risk						Low Risk					
	λ_1	λ_1 tstat	λ_2	λ_2 tstat	Hasbrouck - Lower Limit	Hasbrouck - Upper Limit	λ_1	λ_1 tstat	λ_2	λ_2 tstat	Hasbrouck - Lower Limit	Hasbrouck - Upper Limit
Amerisourcebergen	-0.3550	-2.7485	-0.0151	-1.2406	0.1673	0.2018	-0.8338	-2.2589	-0.0368	-1.4293	0.2985	0.3490
American Intl.Gp.	-26.9827	-6.4223	0.9346	0.7891	0.0155	0.0163	-22.0262	-4.0607	0.5251	0.5808	0.0201	0.0203
Chubb	-0.6435	-2.5047	-0.0269	-0.5987	0.0580	0.0858	0.1943	0.7655	0.1407	3.0543	0.9274	0.9446
CMS Energy	0.8248	1.5882	0.0385	2.6413	0.7428	0.7743	0.4543	1.1077	0.0288	2.6913	0.8520	0.8805
Campbell Soup	-0.1034	-1.4252	-0.0707	-3.2126	0.8082	0.8420	-0.1548	-1.8253	-0.0712	-2.8005	0.6179	0.7609
Computer Scis.	-1.0589	-3.6471	-0.0221	-0.4712	0.0146	0.0165	-1.2818	-3.8544	-0.0173	-0.3583	0.0053	0.0089
CSX	-1.5042	-3.8567	-0.0550	-0.6303	0.0282	0.0441	-0.6448	-4.0290	-0.0009	-0.0230	0.0000	0.0081
Devon Energy	-1.8459	-4.5350	0.0969	0.4065	0.0026	0.0085	-0.2262	-2.6216	-0.0101	-0.1469	0.0032	0.0175
Entergy	-0.7035	-2.3850	-0.0068	-0.0948	0.0016	0.0046	-0.8488	-2.0783	-0.1201	-1.3654	0.3005	0.3082
Ford Motor	-27.0531	-3.7918	0.0417	3.6705	0.5696	0.5732	49.3996	2.9700	0.0256	2.3125	0.3825	0.3828
Gap	-0.6931	-3.0872	-0.0191	-0.9665	0.0912	0.1157	-1.0058	-3.6775	0.0208	0.9475	0.0470	0.0698
Interpublic Gp.	-9.7043	-3.9393	-0.0036	-0.4572	0.0133	0.0134	-24.6010	-3.9392	-0.0093	-0.5201	0.0172	0.0172
Lincoln Nat.	-18.6930	-4.5573	0.0408	0.5052	0.0128	0.0137	-13.3579	-5.2210	0.0000	0.0004	0.0000	0.0000
McKesson	-0.6834	-4.6954	-0.0473	-0.8624	0.0335	0.0641	-0.3138	-2.5653	-0.0727	-1.5291	0.2543	0.3223
Marsh & McLennan	-0.6242	-2.9836	-0.0479	-1.5728	0.2153	0.2366	-0.4926	-3.2614	-0.0276	-1.1132	0.1039	0.1286
Merck & Co.	-0.2051	-1.7779	-0.1519	-2.8396	0.6668	0.7515	-0.1432	-1.7525	-0.0572	-1.8437	0.4725	0.6132
Meadwestvaco	-1.1513	-3.6074	0.0897	2.4051	0.3202	0.3969	-0.3245	-1.2732	0.0706	3.0307	0.8670	0.9081
Newmont Mining	-12.4008	-3.2948	0.0655	0.4174	0.0154	0.0171	0.5017	2.9355	0.0880	2.4121	0.4003	0.4085
Newell Rubbermaid	-1.0142	-3.6139	-0.0098	-0.3984	0.0144	0.0364	-0.9182	-3.6635	-0.0071	-0.3476	0.0095	0.0194

PepsiCo	-0.3600	-2.5558	-0.0335	-0.5194	0.0405	0.0944	-0.1898	-2.7114	0.0588	2.1030	0.3185	0.4357
Procter & Gamble	-0.6456	-3.4232	0.1073	1.8418	0.1942	0.2461	-0.2074	-2.7390	0.0700	2.4485	0.4146	0.4764
Radioshack	-0.7948	-2.9297	-0.0032	-0.1612	0.0034	0.0102	-2.7359	-2.4538	0.0191	0.2803	0.0104	0.0189
Sempra En.	-0.6362	-2.6538	0.0775	1.4475	0.2101	0.2850	-0.2081	-1.1169	-0.0539	-1.5705	0.6461	0.7327
AT&T	-2.0347	-6.2896	-0.0213	-0.2827	0.0023	0.0140	-0.6216	-4.6372	-0.0162	-0.9167	0.0375	0.0434
Union Pacific	-0.6103	-3.5653	0.0007	0.0115	0.0000	0.0090	-0.5350	-2.9980	0.0157	0.2236	0.0025	0.0073
XTO En.	-3.6959	-4.3207	0.1194	0.5963	0.0117	0.0252	-0.4498	-2.5554	0.0283	0.7516	0.0623	0.0869
Mean					16.4%	18.8%					27.2%	30.7
Median					3.1%	5.4%					17.9	21.8

Table 3.9

Regression of Liquidity and Risk Levels

	α	α - t_stat	β	β - t_stat	adj R-square
Alcoa	0.05	4.83	-0.01	-1.15	0.00
Amerisourcebergen	0.03	3.49	0.00	0.42	-0.00
Abbott Laboratories	0.02	3.60	-0.00	-1.82	0.00
Archer-Danls.-Midl.	0.03	3.61	-0.00	-1.05	0.00
Amer.Elec.Pwr.	0.03	3.50	0.00	0.03	-0.00
AES	0.03	3.76	-0.00	-0.14	-0.00
Aetna	0.02	3.30	-0.00	-0.62	-0.00
Allergan	0.03	3.79	-0.00	-1.40	0.00
American Intl.Gp.	0.04	4.43	-0.00	-0.60	-0.00
AK Steel Hldg.	0.03	4.01	-0.00	-0.45	-0.00
Allstate	0.03	3.87	-0.00	-0.29	-0.00
Advanced Micro Devc.	0.03	3.67	-0.00	-1.99	0.00
Amgen	0.03	4.18	-0.01	-1.63	0.00
American Tower 'A'	0.02	2.83	0.00	0.08	-0.00
Apache	0.03	3.53	-0.00	-1.51	0.00
Anadarko Petroleum	0.03	3.49	0.00	0.25	-0.00
Avalonbay Commns.	0.02	2.74	-0.00	-1.33	0.00
Avon Products	0.03	3.95	-0.00	-0.45	-0.00
American Express	0.03	4.00	-0.00	-0.38	-0.00
Allegheny En.	0.06	5.23	0.00	0.47	-0.00
Autozone	0.04	3.88	0.00	0.55	-0.00
Bank Of America	0.03	3.88	-0.00	-0.27	-0.00
Baxter Intl.	0.02	3.25	-0.00	-0.19	-0.00
Baker Hughes	0.02	3.32	0.00	0.14	-0.00
Ball	0.03	2.47	-0.00	-0.38	-0.00
Bristol Myers Squibb	0.02	3.16	0.00	0.38	-0.00
Boston Scientific	0.03	3.49	0.00	0.00	-0.00
Peabody Energy	0.38	4.09	0.01	0.18	-0.00
Boston Properties	0.03	3.68	0.00	0.17	-0.00
Citigroup	0.05	4.55	0.00	0.00	-0.00
CA	0.05	4.35	-0.00	-0.02	-0.00
Cardinal Health	0.02	3.52	-0.00	-0.16	-0.00
Caterpillar	0.03	3.81	0.00	0.13	-0.00
Chubb	0.02	3.31	-0.00	-0.75	-0.00
Carnival	0.04	4.14	0.00	0.01	-0.00
Chesapeake Energy	0.13	4.45	-0.00	-0.17	-0.00
Cigna	0.02	2.78	-0.00	-0.80	-0.00
Colgate-Palm.	0.03	3.42	-0.00	-0.06	-0.00
Clorox	0.04	4.33	-0.00	-0.83	-0.00
Comcast 'A'	0.01	2.15	-0.00	-0.29	-0.00

Cummins	0.03	4.15	0.00	0.43	-0.00
CMS Energy	0.04	3.07	-0.00	-0.34	-0.00
Centerpoint En.	0.03	3.69	-0.00	-0.31	-0.00
Costco Wholesale	0.02	2.59	-0.00	-0.23	-0.00
Campbell Soup	0.03	3.54	-0.00	-1.58	0.00
Computer Scis.	0.04	3.70	0.00	1.72	0.00
CSX	0.03	4.10	0.00	0.35	-0.00
Chevron	0.03	3.55	-0.00	-0.05	-0.00
Dominion Res.	0.02	3.67	-0.00	-0.48	-0.00
E I Du Pont De Nemours	0.03	3.27	0.00	0.02	-0.00
Deere	0.04	3.57	0.00	0.17	-0.00
Dell	0.02	2.91	-0.00	-0.10	-0.00
Dean Foods New	0.06	2.36	-0.00	-0.28	-0.00
D R Horton	0.05	3.99	-0.00	-0.89	-0.00
Danaher	0.03	3.72	0.00	0.26	-0.00
Walt Disney	0.04	3.72	-0.00	-0.08	-0.00
Dover	0.02	2.49	0.00	0.58	-0.00
Dow Chemical	0.03	3.48	0.00	0.24	-0.00
Darden Restaurants	0.04	3.85	-0.00	-0.16	-0.00
Duke Energy	0.02	3.00	0.00	0.79	-0.00
Devon Energy	0.03	4.13	-0.00	-0.98	-0.00
Conoco Phillips	0.03	3.28	0.00	2.03	0.00
Eastman Kodak	0.04	4.51	-0.00	-0.64	-0.00
Eastman Chemical	0.03	3.69	0.00	2.79	0.01
Emerson Electric	0.02	2.60	0.00	3.19	0.01
El Paso	0.04	4.22	0.00	1.23	0.00
Eaton	0.03	3.77	-0.00	-0.47	-0.00
Entergy	0.03	3.72	-0.00	-0.32	-0.00
Exelon	0.02	3.11	-0.00	-0.07	-0.00
Ford Motor	0.07	4.94	0.00	0.18	-0.00
Fedex	0.03	3.77	0.00	0.24	-0.00
FirstEnergy	0.03	3.57	-0.00	-0.03	-0.00
Fortune Brands	0.03	3.57	-0.00	-0.83	-0.00
Gannett	0.04	3.43	-0.00	-0.91	-0.00
General Dynamics	0.03	3.75	0.00	0.85	-0.00
General Mills	0.02	3.29	-0.00	-1.97	0.00
Corning	0.05	3.91	0.00	0.00	-0.00
Genworth Financial	0.04	4.22	-0.00	-0.08	-0.00
Gap	0.04	4.44	-0.00	-0.91	-0.00
Goodrich	0.03	3.39	-0.00	-0.02	-0.00
Goldman Sachs Gp.	0.04	4.36	0.00	0.19	-0.00
Goodyear Tire & Rub.	0.03	3.75	0.00	0.17	-0.00
Halliburton	0.03	3.50	0.00	0.59	-0.00

Hasbro	0.04	2.87	-0.00	-0.92	-0.00
Health Care Reit	0.01	1.42	0.00	0.21	-0.00
Home Depot	0.04	3.83	0.00	0.78	-0.00
Hartford Finl.Svs.Gp.	0.03	3.40	0.00	0.83	-0.00
HJ Heinz	0.03	3.48	-0.00	-0.96	-0.00
Honeywell Intl.	0.04	4.16	0.00	0.02	-0.00
Starwood Htls.& Rsts. Worldwide	0.06	3.32	0.00	0.41	-0.00
H&R Block	0.03	3.55	-0.00	-0.41	-0.00
The Hershey Company	0.02	2.56	0.00	1.24	0.00
Humana	0.01	2.18	0.00	2.54	0.00
International Bus.Mchs.	0.03	3.46	0.00	0.10	-0.00
Intl.Game Tech.	0.02	3.01	0.00	1.87	0.00
Intl.Paper	0.04	4.08	-0.00	-0.12	-0.00
Interpublic Gp.	0.05	4.21	-0.00	-0.76	-0.00
Johnson Controls	0.04	3.54	-0.00	-0.31	-0.00
Penney JC	0.03	3.33	0.00	1.11	0.00
Johnson & Johnson	0.03	3.34	0.00	1.30	0.00
JP Morgan Chase & Co.	0.04	4.26	-0.00	-1.69	0.00
Nordstrom	0.03	3.38	-0.00	-0.46	-0.00
Kellogg	0.03	3.87	-0.00	-0.87	-0.00
Kraft Foods	0.03	3.41	0.00	0.06	-0.00
Kimco Realty	0.02	3.11	-0.00	-0.16	-0.00
Kimberly-Clark	0.03	3.58	0.00	0.13	-0.00
Coca Cola	0.03	3.69	-0.00	-0.42	-0.00
Kroger	0.02	3.34	-0.00	-0.82	-0.00
Kohl's	0.03	2.98	-0.00	-1.03	0.00
Lennar 'A'	0.06	5.42	-0.00	-1.36	0.00
Eli Lilly	0.03	4.19	-0.00	-1.45	0.00
Lockheed Martin	0.02	2.51	0.01	3.65	0.01
Lincoln Nat.	0.03	4.05	0.00	1.05	0.00
Southwest Airlines	0.06	4.93	-0.00	-0.30	-0.00
Marriott Intl.'A'	0.04	4.06	0.00	2.04	0.00
Masco	0.03	3.57	-0.00	-0.31	-0.00
Mattel	0.03	4.08	-0.00	-0.25	-0.00
McDonalds	0.02	3.13	0.00	2.41	0.00
McKesson	0.02	3.19	0.00	0.97	-0.00
Medtronic	0.04	3.97	-0.00	-1.12	0.00
Massey En.	0.02	3.50	-0.00	-1.03	0.00
Metlife	0.03	3.55	-0.00	-0.64	-0.00
Medco Health Sltn.	0.03	3.63	0.00	0.34	-0.00
Marsh & McLennan	0.03	3.39	-0.00	-0.10	-0.00
3M	0.02	3.25	-0.00	-0.08	-0.00
Altria Group	0.05	3.90	-0.00	-0.94	-0.00

Motorola	0.03	3.60	0.00	1.19	0.00
Merck & Co.	0.04	4.13	-0.00	-0.59	-0.00
Marathon Oil	0.02	2.59	0.01	3.62	0.01
Meadwestvaco	0.07	3.67	-0.00	-0.53	-0.00
Nabors Inds.	0.02	3.13	0.00	0.50	-0.00
Newmont Mining	0.03	3.70	0.02	1.94	0.00
Nike 'B'	0.02	2.11	-0.00	-0.01	-0.00
Northrop Grumman	0.02	3.24	0.00	1.36	0.00
Norfolk Southern	0.03	3.62	0.00	0.13	-0.00
Northeast Utilities	0.02	0.78	-0.00	-0.47	-0.00
Nucor	0.03	3.68	0.00	0.72	-0.00
Newell Rubbermaid	0.03	4.00	-0.00	-0.72	-0.00
Office Depot	0.03	3.52	0.00	0.53	-0.00
Owens Illinois New	0.05	3.42	0.00	0.13	-0.00
Oneok	0.04	3.83	-0.00	-0.25	-0.00
Omnicom Gp.	0.03	3.79	-0.00	-0.81	-0.00
Occidental Ptl.	0.03	3.39	0.00	1.24	0.00
Pitney-Bowes	0.02	2.54	-0.00	-0.07	-0.00
PepsiCo	0.03	3.33	0.00	0.41	-0.00
Pfizer	0.04	4.33	-0.00	-0.95	-0.00
Procter & Gamble	0.04	3.90	0.00	0.77	-0.00
Pultegroup	0.04	4.45	-0.00	-1.22	0.00
Prologis	0.02	2.75	-0.00	-0.10	-0.00
Pepco Holdings	0.02	1.55	0.00	0.27	-0.00
PPG Industries	0.03	3.46	0.00	0.88	-0.00
Praxair	0.03	3.14	-0.00	-0.17	-0.00
Qwest Comms.Intl.	0.03	2.26	-0.00	-0.10	-0.00
Ryder System	0.03	3.29	0.00	1.19	0.00
Republic Svs.'A'	0.03	3.19	-0.00	-2.05	0.01
Radioshack	0.04	4.37	-0.00	-0.42	-0.00
Raytheon 'B'	0.03	3.55	0.00	1.33	0.00
Sealed Air	0.04	3.18	-0.00	-0.33	-0.00
Sherwin-Williams	0.04	3.54	0.00	0.70	-0.00
Sara Lee	0.02	3.38	-0.00	-0.46	-0.00
SLM	0.06	3.63	-0.00	-0.89	-0.00
Simon Pr.Gp.	0.04	4.06	-0.00	-0.30	-0.00
Staples	0.03	3.93	-0.00	-0.08	-0.00
Sempra En.	0.03	3.49	-0.00	-1.32	0.00
Sunoco	0.03	3.57	0.00	0.34	-0.00
Supervalu	0.04	3.74	-0.00	-0.01	-0.00
Safeway	0.03	3.49	0.00	1.12	0.00
AT&T	0.06	4.35	-0.00	-0.57	-0.00
Teco Energy	0.10	3.84	0.00	0.04	-0.00

Target	0.04	4.03	-0.00	-0.53	-0.00
Tenet Hlthcr.	0.04	4.28	-0.00	-0.10	-0.00
TJX COS.	0.02	2.79	0.00	1.82	0.00
Tyson Foods 'A'	0.03	3.46	0.00	0.26	-0.00
Tesoro	0.05	3.37	-0.00	-0.16	-0.00
Time Warner	0.04	4.52	0.00	0.58	-0.00
Textron	0.03	3.78	-0.00	-0.02	-0.00
UnitedHealth Gp.	0.03	3.57	-0.00	-0.91	-0.00
Unum Group	0.03	4.00	-0.00	-0.74	-0.00
Union Pacific	0.04	3.72	0.00	0.43	-0.00
United Parcel Ser.	0.05	4.52	-0.00	-1.03	0.00
United Technologies	0.03	3.71	-0.00	-0.50	-0.00
V F	0.02	2.29	-0.00	-0.17	-0.00
Valero Energy	0.03	3.38	0.01	1.19	0.00
Vornado Realty Tst.	0.02	2.50	0.00	2.97	0.01
Wisconsin Energy	0.01	0.47	0.00	1.24	0.00
Wells Fargo & Co	0.03	3.45	0.00	0.27	-0.00
Whirlpool	0.04	4.12	0.00	0.83	-0.00
Wellpoint	0.02	3.28	0.00	0.59	-0.00
Williams Cos.	0.04	4.00	0.00	0.60	-0.00
Wal Mart Stores	0.03	3.29	0.01	3.72	0.01
Weyerhaeuser	0.04	4.47	-0.00	-1.96	0.00
US.Steel	0.02	2.98	0.00	0.29	-0.00
Xcel Energy	0.03	3.02	0.00	0.04	-0.00
Xl Cap.'A'	0.04	3.74	-0.00	-0.75	-0.00
Exxon Mobil	0.04	4.22	-0.00	-0.40	-0.00
Xerox	0.10	3.57	-0.00	-0.65	-0.00
XTO En.	0.03	3.85	-0.00	-0.32	-0.00
Yum! Brands	0.03	3.58	0.00	1.83	0.00

Chapter 4. Market Quality and the Financial Crisis

4.1. Introduction

"Bond and derivative traders, who tend to focus on balance-sheet risks and ignore management happy talk, were way ahead of stock investors in picking up on problems in the subprime mortgage market and elsewhere. And they remain more bearish."[9]

Business Week, March 2008

The above quote from Business Week is a comment on the quality of the CDS market with regards to assimilating information into prices. Taken in the backdrop of the subprime crisis, it suggests that the CDS market has displayed a higher level of efficiency than other markets in recognizing risk and incorporating it into spreads.

CDS and stocks present the chance to study two different markets for the same underlying asset but with different price discovery dynamics. While the stock market has a relatively large number of retail investors, the less liquid CDS market consists primarily of banks, hedge funds and other financial institutions that may be considered relatively well informed especially when compared to investors in the stock market. Due to this possible information asymmetry between the two markets, we expect to see differences in the price discovery process between the two.

Although a number of research papers have looked at the CDS market price discovery and a few at CDS market misreaction, most of them use data prior to 2007 and thus do not provide any insights into how the market may have changed since the sub-prime crisis. We believe that there is reason to test the market for changes since the crisis due to the following reasons:

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[9] "Bonds are saying nasty things about stocks", Coy, Peter; March 17, 2008, *Business Week*. New York: Issue 4075; pg. 70

1) Given the low default probabilities in the pre-subprime world, hedge funds were active players in the CDS market, providing insurance cover to investors in return for a quarterly premium. However, as the general risk levels have increased and these funds have been driven out of the market, we expect the CDS market focus to shift from income generation to pricing of risk based on credit events.
2) At the same time, we are cognizant of the fact that with the financial crisis and issues at some large CDS trading financial institutions, liquidity and growth in the CDS market has suffered significantly and the market is still going through a slow period. This would seem to suggest a weakening of efficiency in the CDS market.

While the first reason may suggest that CDS markets have become more efficient, the second factor points to drying up of liquidity in this market, thereby reducing informational efficiency. Given demands to introduce more regulations in this OTC market, we are interested in testing for any changes that may have occurred in this market from a price efficiency perspective.

Our contribution to literature is along two dimensions. We analyze the CDS market price discovery vis-à-vis the stock market as well as look for possible evidence of over-reaction or under-reaction by CDS investors. Further, splitting the time frame for our study into pre and post crisis allows us to identify any changes that may have taken place in the CDS market due to the global financial sector meltdown.

Using a Granger causality lead-lag test on the stock and CDS markets, we find that the stock market remains the main market for price discovery both before and after the crisis even in the case of the higher risk firms. Examining share trading volume, CDS liquidity proxy and analyst coverage, we conclude that an increased share trade volume is the most likely reason for the increase in price discovery in the stock market.

As a test of the CDS market quality, we use Variance Ratios to analyze how well the CDS market is able to incorporate information into spreads. Using the variance in spread changes, we compare the long term variance to a time-scaled short term variance with a ratio close to 1 reflecting the market's ability to price information accurately. Our results are quite interesting as they show the CDS market over-reacting to information in the pre-crisis period and then under-reacting in the post-crisis scenario. We look at possible factors like industry concentration and risk levels but do not find any conclusive relationship. Further, contrary to existing literature where lower liquidity translates to over-reaction, we find lower liquidity in the CDS market accompanied by under-reaction.

Note that we use the terms "pre-crisis" and "post-crisis" in this study to define two distinct periods in our dataset i.e. Jan 2005 – Jun 2007 (pre-crisis) and Jul 2007 – Oct 2009 (post-crisis). It can be argued that the global financial crisis is still ongoing and we recognize that the latter term may suggest otherwise. However, we wish to highlight that the term "post-crisis" is simply used to define a period where the CDS market has gone through a transformation with generally higher risk and lower liquidity levels and does not suggest an end to the financial crisis.

The remainder of the paper is organized as follows. The following section presents the literature survey and our key test hypotheses while Section 4.3 looks at the data set. Section 4.4 talks about the price discovery test while Section 4.5 covers the variance ratio test for misreaction. The conclusion follows in Section 4.6.

4.2. Literature Review
4.2.1 Price Discovery

Longstaff et al. (2005) examine the stock, bond and CDS markets to conclude that while both CDS and stocks lead the bond market, no clear results emerge when the CDS and stock markets are compared. Norden and Weber (2007) find that bonds and CDS have little impact on stocks in terms of price discovery.

Blanco et al. (2005) examine the CDS and bond markets to conclude that there is greater price discovery in the CDS markets than in the bond markets. Forte and Pena (2009) find the stock market leading CDS and both CDS and shares leading the bond market. Therefore, while it is generally accepted that the bond market lags CDS and stocks, it is unclear how the CDS would perform against the stock market given mixed results.

Acharya and Johnson (2007) and Berndt and Ostrovnaya (2008) look at the CDS and stock markets to find that CDS spreads contain information ahead of the stock markets in case of adverse news. Acharya and Johnson find evidence of insider trading in the CDS markets which results in the CDS leading the stock market.

Forte and Lovreta (2008) look at the stock and CDS markets for the period 2002-2004 to find that CDS spreads lead the price discovery process for the higher risk (lower rating) credits thereby supporting the Acharya and Johnson findings. More importantly, they find evidence suggesting the informational dominance of the stock market declining over the period 2002-2004.

Norden and Weber (2010) examine the informational content of CDS for subordinated and senior debt of 20 financial institutions from seven countries. They find that while CDS on both subordinated and senior bank debt contribute to price discovery in the pre-crisis scenario, subordinated debt CDS offer an advantage in terms of lower transaction costs. However, they find that in the post-crisis scenario, the senior debt CDS reflects information first and the transaction cost benefit of subordinated debt also disappears.

Given the mixed results when comparing the CDS and stock markets as well as the evidence of market dynamics changing over time, we update the literature by extending this analysis to the post crisis scenario. To the best of our knowledge, Norden and Weber (2010) is the only paper that looks at CDS informational efficiency in a pre and post scenario. However, their focus is on differences in price discovery between senior and subordinated debt while we are looking at identifying any changes in informational efficiency that may have taken place in the CDS and stock market as a result of the sub-prime crisis. Our contribution to literature is therefore twofold. Given mixed results from previous studies, our paper updates the literature to include the recent financial crisis as well as increase the study sample size to almost 199 firms as previous papers were all limited to a much smaller sample size.

4.2.2 Market Misreaction

Other than the papers looking at stock market returns (DeBondt and Thaler (1985), Daniel et al. (1998)) and equity derivative prices (Stein (1989), Poteshman (2001)), there are relatively few studies examining the CDS markets from the perspective of market misreaction. In our search, we only found 3 papers on market misreaction that looked at the CDS market spreads.

Norden and Weber (2004) and Hull et al. (2004) both look at rating events to conclude that that the markets are informationally efficient with CDS adjusting in advance of credit downgrades.

Greatrex (2008), using data upto 2006, looks at earnings announcements to find evidence of over-reaction to negative news and under-reaction to positive earnings announcements.

Our focus in this paper is slightly different in that we do not conduct an event time study but instead, look at the entire dataset using variance ratio. This measure of long term variance to short term variance was introduced by Lo and MacKinlay (1988) as a random walk test and adapted by many including Bessembinder (2003) and Kaul and Sapp (2009) as a test of market quality. Using this measure allows us to study a large sample of firms over a long period of time which is something that has been absent from CDS market literature.

4.2.3 Key Hypotheses

The underlying premise in our paper is that there has been a shift in CDS market dynamics since June 2007 and we expect to see the CDS markets lead the price discovery process across all risk levels (contrary to the Acharya and Johnson findings). We therefore test the following hypotheses in the two markets from Jan 2005 – Jun 2007 (pre-crisis) and from Jul 2007 – Oct 2009 (post-crisis):

H_1: Stocks lead the price discovery process in the first sub-period.

Our first hypothesis tests our data to ensure that it supports findings from previous studies.

Given the change in market dynamics due to the financial sector crisis, there is a greater focus on risk management. We therefore expect to see the CDS market reacting ahead of stocks in the price discovery process and more importantly, we do not expect to see this lead to be confined to higher credit risks as has been seen in previous studies (Forte and Lovreta (2008)).

H_2: CDS spreads lead the price discovery process in the second sub-period.

With the Chicago Board Options Exchange Market Volatility Index (VIX) reaching a historical peak of 80.86 on 20 November 2008, we have seen the financial markets experience extremely high volatility levels. Given that Greatrex (2008) finds the CDS market over-reacting to bad news, we expect to find evidence of a general market over-reaction as the post-crisis period has been characterized by a period of significantly higher market risk levels.

H_3: The CDS market reflects over-reaction in the post-crisis period.

4.3. Data

We use daily and weekly stock and CDS data for 198 US firms available through DataStream for the period Jan 2005 – Oct 2009. While our initial database for CDS consisted of 242 firms, we removed firms that are missing data or have suspect data. While CDS are available for terms from 1 to 10 years, we use CDS spreads with a 5-year term for underlying senior, unsecured corporate debt as this represents the tenor with the highest liquidity levels.

A snapshot of the average CDS spreads for all firms for both periods is given in Table 4.1 reflecting an increase in the general risk level in the overall market. While the highest risk firm in the pre-crisis period only attracts an average premium of 636 bppa, the maximum average CDS spread has jumped up to 2,655 bppa since the start of the financial market meltdown. A comparison of the mean of the average CDS spreads for all firms in both periods reflects an increase of over 3.7 times.

Using the firm SIC codes, we assign the firms into 8 industry classifications (Table 4.2) and find that Mining, Services and Financial sectors reflect the highest levels of average CDS spreads in the post-crisis period. Interestingly, we find that the wholesale trade sector experienced a decline in CDS spreads.

The main take away from the two tables is that there has been a general marked increase in risk levels from the pre-crisis to post-crisis period. Given that previous research has found that CDS market quality is different for high risk firms than it is for low risk firms, we expect to see a general shift in the CDS market dynamics as almost all firms have experienced higher risk levels.

4.4. Price Discovery Test

4.4.1 Methodology

We start with an Augmented Dickey-Fuller test to check both sub-periods for stationarity. We find evidence of unit-roots in all cases and therefore use the first difference. Having a stationary data series, we conduct a Granger-causality test using a VAR model on daily as well as weekly data. For the daily data, we use 5 period lags to ensure that the entire week is taken into account while we use 4 period lags in our weekly data to capture the entire month. The following tests are conducted for both sub-periods on daily and weekly data:

$$\Delta CDS_{i,t} = \alpha_1 + \alpha_2 \Delta CDS_{i,(t-1 \text{ to } t-n)} + \alpha_3 \text{Share Return}_{i,(t-1 \text{ to } t-n)} + \varepsilon_{1,t}$$

$$\text{Share Return}_{i,t} = \beta_1 + \beta_2 \Delta CDS_{i,(t-1 \text{ to } t-n)} + \beta_3 \text{Share Return}_{i,(t-1 \text{ to } t-n)} + \varepsilon_{2,t}$$

Where,

$\Delta CDS_{i,t}$ = Change in CDS Spread for firm *i* at time *t*;

$\text{Share Return}_{i,t}$ = Log share price return for firm *i* at time *t*;

n = lag value where n=5 for daily data and n=4 for monthly data;

α,β = Regression coefficients;

ε = Stochastic error terms

Previous literature shows that CDS markets lead the price discovery process for higher risk firms. We therefore split our sample into 3 groups of 66 firms each, representing low, medium and high risk firms. To assign a firm to a group, we use the firm's average CDS spread for the period and mark it as a low, medium or high risk credit based on the criteria in Table 4.3.

An issue with this classification method is that a firm with relatively stable CDS spreads could appear to move from a high risk level to a lower one given the increase in the relative classification bracket e.g. a firm with a spread level of 30 bppa in both periods would move from medium risk to a low risk group simply due to the definition of the groups while the true risk level for the firm has remained unchanged.

To account for such cases, we also classify firms on the basis of the level of change in the average CDS spreads between the two periods. Therefore, in the above example, the firm with a stable CDS spread would remain in the low risk group as defined in Table 4.4.

4.4.1 Results

We conduct causality tests on daily and weekly data to understand where price discovery occurs. The following analysis provides a summary of our findings.

Pre-crisis

In line with findings from previous studies, we find stocks leading the price discovery process in 63 cases while CDS leading in only 14 instances in the pre-crisis period (Table 4.5).

The Risk Group classification shows that in 7 (50%) of the cases where CDS leads the price discovery process, the firm is placed in the high risk group which confirms findings from prior studies. Our results for stock market leading price discovery are more interesting as we find that

27 cases (out of 63) represent firms in the high risk group where CDS would be expected to lead. The evidence therefore supports H_1 that the stock market leads the price discovery process in the pre-crisis period.

We also consider the results on a weekly basis (Table 4.6) where we find 14 instances of CDS leading and 45 cases of stocks leading price discovery. For stocks, weekly data reflects fewer occurrences as compared to daily data. This can be explained as markets are efficient and therefore market news in most cases would be priced in during the first 5 trading days and thus not reflected in weekly data. Looking at the cases where price discovery occurs, our results are similar to what we find using daily data.

Post-crisis

Based on the premise that the crisis has led to a change in the CDS market with a higher level of price discovery in the CDS market, we expect to find the CDS leading the stock market. Our results (Table 4.7) show 24 cases where CDS leads price discovery and 144 cases of stocks leading. While we find an increased level of price discovery in the CDS market from the pre-crisis scenario, our findings are still overwhelmingly in favour of the stock market leading the process.

Looking at the cases where CDS leads the stock market, we again find only 50% of cases are high risk. Furthermore, we find 3 companies carrying through from our pre-crisis list while the remaining 21 in this category are new.

Examining the 12 firms in the high risk group, we find that in 11 cases where the firms have previously been lower risk and have recently moved into the higher risk group (i.e. have CDS spreads that have increased by more than 4.5 times what they were before the crisis). This tells us that firms that may have previously been ignored by CDS traders due to low risk levels are now receiving more focus and have therefore greater information content than their respective shares in the stock market.

Looking at the cases where the stock market leads CDS, we find that the largest group comprises of high risk firms, which is contrary to our expected results. Looking at the movement in spread levels for these firms, we find that stocks lead in cases that reflect some of the largest relative credit spread increases.

Using weekly data (Table 4.8), we again find fewer instances of price discovery occurring in the two markets compared to using daily data; 10 for CDS leading stocks and 32 for stocks leading CDS. We find that in most cases when CDS leads the stock market, the firm is mid-risk rather than high risk which is a result that is difficult to explain.

Our post-crisis results from the Granger causality test fail to support our H_2 as we find the stock market still leading the price discovery process with this relationship holding across risk levels.

4.4.3 Further Analysis

Our results from the price discovery tests can be explained by one of two possible reasons. Informational efficiency could be driven either by the higher liquidity levels in the stock market or by the more savvy investors/traders in the CDS market. As the idea of this paper is to identify any changes in the CDS and stock market price discovery mechanism due to the financial sector meltdown, we focus on the post-crisis scenario results in our analysis.

Our general finding is that, since the start of the crisis, stocks have started contributing even more to the price discovery process. We therefore try to isolate some key factors that could impact informational efficiency in the two markets:

1) CDS Liquidity: With a higher level of liquidity, we would expect to see faster dissemination of information in this market. Given that the CDS instruments are traded over-the-market, there is little information available on their actual trading volumes. We use the Amihud and Mendelson (1986) measure represented by the bid-ask spread as a proxy for liquidity.

The average bid-ask spread for our data increases from 5.35 bps in the pre-crisis period to 13.75 bps in the post-crisis period reflecting a decrease in liquidity in the overall CDS market - except for one firm where the bid-ask spread remains almost unchanged, we find a widening of spreads in all cases.

In a recent working paper, Dragon and Yan (2007) proxy CDS liquidity by a scaled measure as well i.e. the percentage spread (bid-ask spread divided by the mid spread). Using this we find that the scaled bid-ask spread decreases from 16.3% to 9.3% in the post-crisis period showing an increased liquidity situation in the post-crisis world.

To understand this contradiction between the two measures, we must consider actual CDS spread levels (i.e. the scaling factor) and we find that while the average bid-ask spreads have increased, the increase in average CDS spreads has been from 52bps to 194 bps. This more than proportional increase in CDS spread levels results in a reduction in scaled bid-ask spread levels.

Given that the CDS market liquidity decreased during the crisis, especially given the AIG issues, the bid-ask spread measure makes more sense as a liquidity proxy and we use it in our paper. This measure shows that the average CDS liquidity decreased in the post-crisis period.

2) Stock Volume Traded: In line with our focus on liquidity, we also look at the average level of trading activity in the stock market. An increase in the average trade volume in the post-crisis period may be able to explain the increased level of price efficiency in the stock markets. Our data shows that the average daily stock trading volume increased from around 485,000 shares in the pre-crisis period to 1.05 million shares in the post-crisis world with 143 firms registering an increase and 55 companies showing a decline in traded volume. As a result, we can conclude that, unlike in the CDS market, liquidity in the stock market has increased during the post-crisis period.

2) Analyst estimates: As an additional measure, we consider analyst coverage of the firms in our database. Research firms assign analysts to a firm depending on the level of public interest or investment potential in that company. Therefore an increase in the number of analysts covering a firm can be used as a proxy for heightened investor awareness about or interest in a firm and would lead to faster absorption of firm related news.

Given the higher level of trading volume in the post-crisis period, we expect to see an increase in the number of analysts covering these firms. However, we find that the average number of analysts covering the firms decreases from 14.6 in the pre-crisis scenario to 13.6 in the post-crisis world with only 62 of the 198 firms showing an increase in analyst coverage (we could not find analyst coverage data for 3 firms). The declining analyst coverage should be seen in the backdrop of the financial crisis where significant layoffs occurred in financial institutions, including equity research units.

We therefore use these three measures of liquidity and information coverage to understand the change in price discovery dynamics since the start of the financial crisis.

Looking at the firms where the CDS market leads, we find a widening of bid-ask spreads from 6 bps to 27 bps in all cases (Table 4.9) reflecting lower CDS liquidity for these firms. We also find a decrease in analyst coverage in 16 of the 24 cases while traded share volumes increase in 16 cases.

Focusing on the 144 cases where the stock markets lead the CDS market, we find that average bid-ask spreads increase from 6 bps to 15 bps; an increase in almost all cases. We also find an increase in the traded share volumes and a small decline in analyst coverage.

We now consider the CDS or risk levels as an alternative explanation for our price discovery results. We find that CDS levels (Table 4.7) for firms where the CDS market leads, have increased from an average of 89 bps to 411 bps while firms where price leads have also increased but only increased from 59 bps to 211 bps.

The above shows that the stock market liquidity is primarily driving price discovery while only in instances where risk levels are very high, price discovery occurs in the CDS markets. This is in line with findings from previous studies and our paper finds that despite the upheaval in the financial sector, price discovery dynamics have remained unchanged.

4.5. Variance Ratio Test

4.5.1 Methodology

Taking the random walk test measure developed by Lo and MacKinlay (1998) and used by Bessembinder (2003) and Kaul and Sapp (2009), we compute the Variance Ratio for each firm (*i*) as follows:

$$Variance\ Ratio_i = \frac{Var_{i,weekly}}{5 \times Var_{i,daily}}$$

Since variance is linear in time, we adjust the variance of daily spread changes by a factor of 5 to make it comparable to the weekly spread change variance. If CDS spreads follow a random walk, all spread movements will be permanent and we would see a ratio close or equal to 1. However, a ratio that is systematically less than or greater than 1 would imply that the spread movements are following a correction pattern as the market is mis-reacting.

If the market systematically over-reacts (under-reacts) to information, we are likely to see higher (lower) volatility in short term spread movements than in the long term. As a result, over-reaction (under-reaction) would lead to a variance ratio that is significant and less (greater) than 1.0 and a ratio close to 1.0 reflects high market quality. Once the ratios are computed for the pre and post periods, we use the Z-statistic to check if the ratio is significantly different from 1.0.

4.5.2 Results

Looking at the pre-crisis period, we find the variance ratio to be significantly less than 1.0 for 147 firms showing the CDS market systematically over-reacting to information. In 34 cases, this ratio is above 1 i.e. under-reaction, while the ratio is indistinguishable from 1 in only 17 instances. Therefore, the results (Table 4.10) for the pre-crisis period point to a systematic over-reaction in the CDS market.

Looking at the results for the same firm in the post-crisis period, we find the situation completely reversed (Table 4.11). There is over-reaction in only 27 cases while there is evidence of under-reaction in 162 firms. We are therefore unable to support our H_3 that the CDS market systematically over-reacts to information since the crisis.

We are comparing daily variance against weekly variance and it is possible that we need to consider a longer time frame. Therefore, we also run the same test on daily to monthly data but our key results remain unchanged i.e. the market has moved from over-reacting before the crisis to under-reacting since the crisis.

We look at firm risk level as well as industry classification to check if this shift can be ascribed to any particular industry or risk group. If that is the case, we would investigate further to see if any unique changes occurred in those groups during the crisis but do not see any common theme emerge. As a result, this shift from over-reaction to under-reaction is a general industry trend and must explained by factors common the entire CDS market.

We next turn to liquidity to look for a possible explanation as Cox and Peterson (1994) and Larson and Madura (2001) both show that lower liquidity results in over-reaction in stocks and currencies. We have already seen evidence of a reduction in liquidity in the CDS market with the start of the financial crisis suggesting markets should over-react. Therefore our finding that the market is under-reacting is contrary to expectations and should be investigated further.

4.6. Conclusion

This paper looks at the CDS market quality both, before and since the financial crisis. We test for any changes to the price discovery dynamics and for evidence of any over or under reaction in the CDS market. Compared to existing literature in this area, the study allows us to expand the sample size to almost 200 firms as well as update findings to include the period since the financial crisis began in 2007. Our findings also have implications on policy decisions regarding CDS given discussion about taking the market from an OTC structure to an exchanged based environment.

Looking at daily and weekly data for CDS and stock prices for before and after the crisis, we get mixed results showing that while stock markets lead CDS in more cases, there is no real change in how the two markets have behaved before and since the crisis. Our results show that despite the financial crisis and the subsequent focus on credit, players in the CDS markets are still not capturing credit events ahead of the stock market.

Our results regarding possible market mis-reaction are much more interesting as we find the CDS market has shifted from an overall over-reaction before the crisis to under-reaction since the start of the crisis. This is especially puzzling as existing literature finds a tightening of liquidity usually associated with over-reaction which is contrary to our findings. This implies that there are other factors that may have to be considered and provides the opportunity for further investigation.

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Table 4.1

CDS Spread Snapshot - Pre-crisis and Post-crisis

(bppa)	**Overall**	**Pre-crisis**	**Post-crisis**
Average	116	52	194
Median	70	31	110
Min	19	6	29
Max	1,542	636	2,655

Table 4.2

Sectoral CDS Spreads

Sector/Spread (*bppa*)	**Pre-crisis**	**Post-crisis**
Mining	102	239
Construction	81	184
Manufacturing	111	148
Transportation & Utilities	97	145
Wholesale Trade	115	75
Retail	73	154
Finance Insurance Real Estate	89	220
Services	88	233

Table 4.3

Firm Classification Basis - I

bppa	**Pre-crisis**	**Post-crisis**
Group 1	0 - 23	0 - 71
Group 2	23 - 41	71 - 169
Group 3	41 - 636	169 - 2,655

Table 4.4

Firm Classification Basis - II

	Change from pre to post crisis average spreads
Group 1	Upto 2.4x
Group 2	2.4x - 4.5x
Group 3	4.5x - 34.3x

Table 4.5

Pre-crisis Results (Daily)

CDS Leads Stock (Daily)				
Count	Risk group	*(bppa)*	Pre	Post
Low	3	Average	78	335
Mid	4	Min	13	52
High	7	Max	387	1,020
Stock Leads CDS (Daily)				
Count	Risk group	*(bppa)*	Pre	Post
Low	17	Average	80	278
Mid	19	Min	7	40
High	27	Max	636	2,655

Table 4.6

Pre-crisis Results (Weekly)

CDS Leads Stock (Weekly)				
Count	Risk group	*(bppa)*	Pre	Post
Low	5	Average	57	173
Mid	2	Min	7	46
High	7	Max	249	775
Stock Leads CDS (Weekly)				
Count	Risk group	*(bppa)*	Pre	Post
Low	7	Average	51	192
Mid	18	Min	17	43
High	20	Max	330	651

Table 4.7

Post-crisis Results (Daily)

CDS Leads Stock (Daily)					
Count	Risk group	Group change	*(bppa)*	Pre	Post
Low	4	8	Average	89	411
Mid	8	5	Min	17	40
High	12	11	Max	636	2,655
Stock Leads CDS (Daily)					
Count	Risk group	Group change	*(bppa)*	Pre	Post
Low	39	38	Average	59	222
Mid	51	53	Min	6	31
High	54	53	Max	636	2,655

Table 4.8

Post-crisis Results (Weekly)

CDS Leads Stock (Weekly)					
Count	Risk group	Group change	*(bppa)*	Pre	Post
Low	1	1	Average	33	211
Mid	6	3	Min	6	36
High	3	6	Max	81	961
Stock Leads CDS (Weekly)					
Count	Risk group	Group change	*(bppa)*	Pre	Post
Low	5	11	Average	98	362
Mid	13	13	Min	14	43
High	14	8	Max	636	2,655

Table 4.9

Post-crisis Factor Analysis

CDS Leads Price (Daily)				
Average	Pre-crisis	Post-crisis	Increase cases	Decrease cases
Bid-Ask Spread (bps)	6	27	-	24
Share Volume Traded	400,665	1,216,544	16	8
Analyst coverage	15.9	16	7	16
Price Leads CDS (Daily)				
Average	Pre-crisis	Post-crisis	Increase cases	Decrease cases
Bid-Ask Spread (bps)	6	15	143	1
Share Volume Traded	458,984	1,158,689	107	37
Analyst coverage	14.5	13.8	46	97

Table 4.10

Variance Ratio Summary Result

	Pre-Crisis	**Post-Crisis**
Variance Ratio	0.79	1.25
# of firms - under-reaction	34	162
# of firms - over-reaction	147	27

Table 4.11

Results of Mis-reaction

Firm_id	Firm_Name	Pre-Crisis	Post-Crisis
1	Alcoa	Over	Under
2	Amerisourcebergen	Over	-
3	Abbott Laboratories	Over	Under
4	Archer-Danls.-Midl.	Over	Under
5	Amer.Elec.Pwr.	Under	Under
6	AES	Over	Under
7	Aetna	Over	Under
8	Allergan	Over	Over
9	American Intl.Gp.	Over	Under
10	AK Steel Hldg.	-	Under
11	Allstate	Over	Under
12	Advanced Micro Devc.	Under	Over
13	Amgen	Over	Under
14	American Tower 'A'	Over	Over
15	Apache	Over	Under
16	Anadarko Petroleum	Over	Under
17	Avalonbay Commns.	Over	Under
18	Avon Products	Over	Over
19	American Express	Over	Under
20	Allegheny En.	Over	Under
21	Autozone	Under	Under
22	Bank Of America	Over	Under
23	Baxter Intl.	Over	Over
24	Baker Hughes	Over	Under
25	Ball	Over	Over
26	Bristol Myers Squibb	Over	Under
27	Boston Scientific	Over	Under
28	Peabody Energy	Over	Under

29	Boston Properties	Over	Under
30	Citigroup	Over	Under
31	CA	Under	Under
32	Cardinal Health	-	Under
33	Caterpillar	Over	Under
34	Chubb	Over	Under
35	Carnival	Over	Under
36	Chesapeake Energy	-	Under
37	Cigna	Over	Under
38	Colgate-Palm.	Over	Over
39	Clorox	Over	Under
40	Comcast 'A'	Under	Under
41	Cummins	Over	Under
42	CMS Energy	Under	Under
43	Centerpoint En.	Over	Over
44	Costco Wholesale	Over	Over
45	Campbell Soup	Over	Over
46	Computer Scis.	-	Under
47	CSX	Over	Under
48	Chevron	Over	Over
49	Dominion Res.	Under	Under
50	E I Du Pont De Nemours	Over	Under
51	Deere	Over	Under
52	Dell	Over	Under
53	Dean Foods New	Over	Under
54	D R Horton	Under	Under
55	Danaher	Over	Under
56	Walt Disney	Over	Under
57	Dover	Over	Under
58	Dow Chemical	Over	Under

59	Darden Restaurants	Over	Under
60	Duke Energy	Over	Under
61	Devon Energy	Under	Under
62	Conoco Phillips	Over	Under
63	Eastman Kodak	Over	Under
64	Eastman Chemical	-	Under
65	Emerson Electric	Over	Under
66	El Paso	Under	Under
67	Eaton	Over	-
68	Entergy	Over	Under
69	Exelon	Under	Under
70	Ford Motor	Under	-
71	Fedex	Over	Under
72	FirstEnergy	Under	Under
73	Fortune Brands	Over	Under
74	Gannett	Over	Under
75	General Dynamics	Over	Under
76	General Mills	Over	Under
77	Corning	Over	Under
78	Genworth Financial	-	Under
79	Gap	Under	Under
80	Goodrich	-	Under
81	Goldman Sachs Gp.	-	Under
82	Goodyear Tire & Rub.	Under	Under
83	Halliburton	Over	Under
84	Hasbro	Over	Under
85	Health Care Reit	Over	Over
86	Home Depot	Over	Under
87	Hartford Finl.Svs.Gp.	Over	Under
88	HJ Heinz	Over	Under

89	Honeywell Intl.	Over	Under
90	Starwood Htls.& Rsts. Worldwide	Over	Under
91	H&R Block	-	Under
92	The Hershey Company	Over	Over
93	Humana	Over	Over
94	International Bus.Mchs.	Over	Under
95	Intl.Game Tech.	Over	Under
96	Intl.Paper	Under	Under
97	Interpublic Gp.	Under	Under
98	Johnson Controls	Over	Under
99	Penney JC	Under	Under
100	Johnson & Johnson	Over	Under
101	JP Morgan Chase & Co.	Over	Under
102	Nordstrom	Over	Under
103	Kellogg	Over	Over
104	Kraft Foods	Over	Under
105	Kimco Realty	Over	Under
106	Kimberly-Clark	Over	Under
107	Coca Cola	Over	Over
108	Kroger	-	Under
109	Kohl's	Over	Under
110	Lennar 'A'	Under	Under
111	Eli Lilly	Over	Over
112	Lockheed Martin	Over	Under
113	Lincoln Nat.	Over	Under
114	Southwest Airlines	Over	Under
115	Marriott Intl.'A'	Over	Under
116	Masco	Over	Under
117	Mattel	Over	-
118	McDonalds	Over	Under

119	McKesson	Under	Under
120	Medtronic	Over	Under
121	Massey En.	Over	Under
122	Metlife	Over	Under
123	Medco Health Sltn.	Over	Over
124	Marsh & McLennan	-	Over
125	3M	Over	Over
126	Altria Group	-	Under
127	Motorola	Over	Under
128	Merck & Co.	Over	-
129	Marathon Oil	Over	Under
130	Meadwestvaco	Under	Under
131	Nabors Inds.	Over	Under
132	Newmont Mining	Over	Under
133	Nike 'B'	-	-
134	Northrop Grumman	Over	Under
135	Norfolk Southern	Over	Under
136	Northeast Utilities	Over	Under
137	Nucor	Over	Under
138	Newell Rubbermaid	Over	Under
139	Office Depot	Over	Under
140	Owens Illinois New	Over	Under
141	Oneok	Over	Under
142	Omnicom Gp.	Over	Under
143	Occidental Ptl.	Over	Under
144	Pitney-Bowes	Over	Under
145	PepsiCo	Over	Over
146	Pfizer	Over	-
147	Procter & Gamble	Over	Under
148	Pultegroup	Under	Under

149	Prologis	Over	Under
150	Pepco Holdings	Over	Under
151	PPG Industries	Over	Under
152	Praxair	Over	Under
153	Qwest Comms.Intl.	Over	-
154	Ryder System	Over	Under
155	Republic Svs.'A'	Over	Over
156	Radioshack	Under	Under
157	Raytheon 'B'	Over	Under
158	Sealed Air	Over	Under
159	Sherwin-Williams	-	Under
160	Sara Lee	Under	Under
161	SLM	Under	Under
162	Simon Pr.Gp.	Over	Under
163	Staples	Over	Under
164	Sempra En.	-	Under
165	Sunoco	Over	Under
166	Supervalu	Over	Under
167	Safeway	Over	Under
168	AT&T	Over	Over
169	Teco Energy	Over	-
170	Target	Over	Under
171	Tenet Hlthcr.	Under	Under
172	TJX Cos.	Over	Under
173	Tyson Foods 'A'	Under	Under
174	Tesoro	Over	Under
175	Time Warner	Under	Under
176	Textron	Over	Under
177	United Health Gp.	Over	Under
178	Unum Group	Under	Under

179	Union Pacific	-	Under
180	United Parcel Ser.	Over	Under
181	United Technologies	Over	Under
182	V F	Over	Under
183	Valero Energy	Under	Under
184	Vornado Realty Tst.	Over	Under
185	Wisconsin Energy	Over	Over
186	Wells Fargo & Co	Over	Under
187	Whirlpool	-	Under
188	Wellpoint	Over	Over
189	Williams Cos.	Under	Under
190	Wal Mart Stores	Over	Under
191	Weyerhaeuser	Under	Under
192	US.Steel	Under	Under
193	Xcel Energy	Over	Over
194	Xl Cap.'A'	Over	Under
195	Exxon Mobil	Over	Over
196	Xerox	Under	Under
197	XTO En.	Over	Under
198	Yum! Brands	Over	Under