2011

Lund University

DETERMINANTS OF CREDIT DEFAULT SWAP SPREADS: A REGIME-SHIFTING APPROACH

Course: Degree Project in Finance (BUSM26) – Master Level

Name: Dilan Hewavitharana

Johan Rahmqvist

Supervisor: Anders Vilhelmsson

Institution: Department of Business Administration

Date: 25th of May 2011

ABSTRACT

This thesis investigates the theoretical determinants of the credit default swap spread by employing a regime-shifting approach. The variables that are examined are leverage, stock return, volatility and interest rate. A sample of 47 companies was selected with daily mid-market quotes between Jan 2008-Dec 2010 in order to proxy the CDS spread. The research was conducted with the use of a linear regression analysis and the Markov Switching model. The results indicate problems with parameter stability justifying the implementation of the Markov model. We discover a positive relationship between the interest rate and the spread, insignificance of implied volatility and a mean-reverting behavior of the spread.

ACKNOWLEDGEMENT

Firstly, we would like to extend our gratitude to Anders Vilhelmsson, PhD at Lund University. His comments have been invaluable in crafting our Master thesis.

Johan would like to thank his parents for their ever present support and his brothers Martin and Erik.

Dilan thanks his mother and brother for continuously being his biggest supporters in all things in life.

He is grateful for all of his closest friends who eased the trials of the writing process.

Lastly, he would like to dedicate this work to the memory of his departed father and grandfather who always made him aspire to great achievements.

Finally, we want to give a special mention to Lenny Erlesand, Michael Bossetta and Axel Sylvan. We are appreciative for Lenny reserving time from his busy schedule to demonstrate his uncanny expertise and sharing some helpful advice. Thank you to Mike and Axel for unleashing the ninja English skills.

Thanks,

Johan and Dilan

25th of May 2011

TABLE OF CONTENTS

1 INTRODUCTION

The following chapter will outline the purpose of this thesis and provide a brief introduction to the background of credit default swap,. The methods implemented and pertinent delimitations will also be presented. The section will conclude with a disposition of the thesis.

1.1 BACKGROUND

Simply put, “risk” in finance is the uncertainty of a return. Yet, “risk” may be classified in a number of ways. An investor’s “credit risk” is associated with a borrower not meeting a payment on time. An event known as a default. Other ways a borrower may default include violating a loan covenant or neglecting to pay interest on time (Allen and Saunders, 2002).

In order to hedge credit risk exposure, credit derivatives have emerged. In recent times, the market for credit derivatives has seen a substantial increase in trading activity. In the realm of finance, there is protection against defaulting, a major credit derivative called credit default swap (CDS). A single-name CDS functions in such a fashion that a party pays a premium periodically to a protection seller. If a default event then occurs with a borrower, the lender receives a payment in a swap from the seller of the CDS (Allen and Saunders, 2002).

A CDS may be perceived as a form of insurance but there are certain distinguishing elements of a CDS. A CDS purchaser does not need to own the underlying asset or be exposed to any credit risk from it, and the seller does not need to be a regulated entity. The probability of default and the loss incurred by a default is reflected by the premium, also known as the “spread”. Having insight into the determinants of CDS spread is critical for financial analysts, economic policy makers and traders. The existing literature has explored these determinants; however, in light of the recent financial crisis, it is uncertain how the determinants behave during turbulent, as opposed to tranquil, times. Select portions of the literature have ascertained that the determinants exhibit varied influences on the CDS spread during periods of high or low volatility. Previously, literature examining the determinants’ behavioral pattern in contrasting periods, such as ‘Regime dependent determinants of credit default swap spreads’ by Alexander and Kaeck (2007), has exclusively utilized CDS indices for their analysis. The following thesis will instead employ single-name CDS – a regime-shifting approach to the study of CDS spread determinants.

1.2 PURPOSE

The purpose of this thesis is to investigate the determinants of the CDS spread by using single-name CDS. We will also analyze the regime-shifting behavior of the determinants.

1.3 METHOD

Firstly, we will explore a range of variables and to what extent each variable can explain the CDS spread by employing linear regression analysis. We will then apply a Markov Switching Model and observe the regime-shifting behavior of the variables.

1.4 DELIMITATIONS

We will limit our research to companies from S&P 500. 47 companies were selected and subsequently divided up into five sectors; consumer goods, industrials, financials, healthcare plus oil and gas. The data input will be restricted to the years 2008-2010 since we expect to capture a substantial part of the financial crisis within this sample period.

1.5 DISPOSITION

The disposition of the thesis will be as follows:

Chapter	Content
2	**Theoretical Framework** – This chapter will elaborate on the foundations of CDS and CDS spread, presenting the chosen variables (determinants). A section dedicated to the *Previous Research* will also supply the reader with an overview of the research that has previously been conducted relating to CDS spreads.
3	**Data** – A detailing of the data including where it is has been obtained from, the time span it refers to and a description of any performed transformations.
4	**Methodology -** This chapter will describe the methodology behind the Linear Regression Analysis and Markov Switching Model, investigate the characteristics of the data residuals and feature an econometric justification for implementing the Markov Model.
5	**Empirical Analysis and Results** – Results will be collected and interpreted from the Linear Regression Analysis and Markov Switching Model.
6	**Discussion** – The results will be discussed and contrasted with previous research.
7	**Conclusion** – A summary of the research and suggestions for future research.

2 THEORETICAL FRAMEWORK

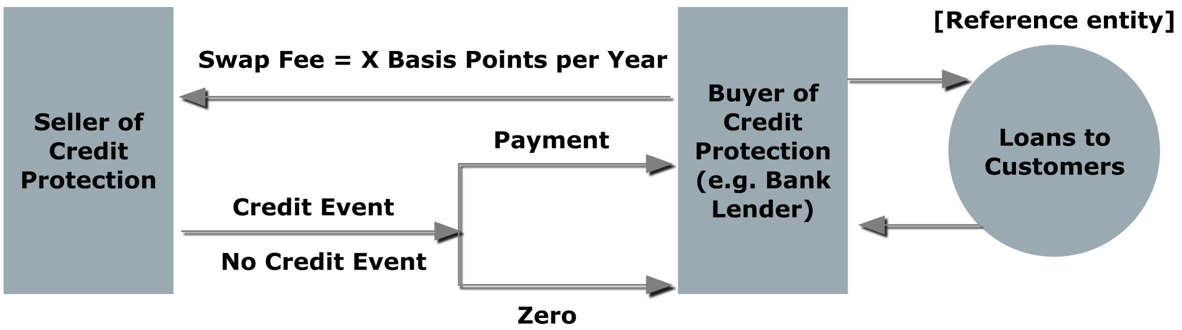
The following chapter will explain and develop fundamental theoretical concepts that will be addressed throughout this thesis.

2.1 CREDIT DEFAULT SWAP

A credit default swap is a credit derivative that enables the transferring of credit risk exposure between different entities. It is the most commonly traded credit derivative and has been responsible for magnifying the effects of the financial crisis according to scholars (Dickinson, 2008; Kress 2010; Stultz 2009). The inherent property of a CDS contract is to isolate and transfer credit risk, and therefore a CDS has strong appeal for both debt holders and shareholders.

The basic intuition of a CDS contract is illustrated in Figure 2.1:

FIGURE 2.1: CDS CONTRACT



The buyer of credit protection (usually a bank) pays a fee to the seller(usually commercial/ investment banks, insurance companies and speculative investors) (Hassan et.al, 2011). The fee paid by the buyer is referred to as the CDS spread and is often paid quarterly. In essence, the CDS spread is paid in exchange for protection against a credit event (i.e. default by a debtor), otherwise known as the reference entity. Understanding the determinants of spread may be crucial for financial analysts, economic policymakers and traders. Moreover, scholars have recently described the CDS spread as a measure of credit risk.

Different events may trigger default and lead to the execution of a CDS contract. For corporate borrowers, these generally fall into three main categories: bankruptcy, failure to pay and restructuring. Restructuring is often considered a 'soft' credit event and a CDS contract can be traded with different features in terms of restructuring. Modified restructuring contracts qualify any restructuring event except the restructuring of bilateral loans as a credit event. This study has looked to North America, where these contracts are most frequently traded (Packer and Zhu, 2005). In this scenario, if a pre-specified credit event occurs, payment of the CDS fee ceases and the protection seller is obligated to pay the par value of the loan minus the recovery value of the loan (Allen and Saunders, 2002).

2.2 DETERMINANTS

"For a given maturity, the risk premium is a function of two variables: (1) the variance (or volatility) of the firm's operations, σ^2 and (2) the ratio of the present value (at the riskless rate) of the promised payment to the current value of the firm." (Merton, 1974, p. 454-455)

The above description highlights the theoretical Merton model that acts as a measure for distance to default. Moody's Default Prediction Model extends the structural framework of the Merton model's distance to default with various key variables such as firm size, leverage and market sensitivity (Allen and Saunders, 2002). The variables applied in the analysis for this thesis are outlined below.

2.2.1 FIRM VALUE

The application of the firm value originates from the Merton model (1974), where the firm value is a component for obtaining the distance to default. Default events are triggered by the firm value decreasing below a threshold value. For example, ceteris paribus, the probability of default increases when firm value decreases and as a result, CDS spreads should also increase. Daily stock returns were acquired in order to proxy the firm value.

2.2.2 LEVERAGE

A firm with significant levels of debt on its balance sheet is considered highly leveraged. Ceteris paribus, higher debt equals higher probability of default. As a result, the literature states that leverage is one of the most frequently used variables for determining CDS spreads (Cossin and Hricko, 2001; Ericsson et al. 2001). According to Moody's Default Prediction Model, default is a function of the firm's capital structure (Allen and Saunders, 2002). In turn, Collin-Dufresne et al. (2001) posit that leverage is the principal explanatory variable for credit spreads and that credit spreads can be expected to increase with leverage.

Furthermore, Ericsson et al. (2004) conclude that leverage alone has an explanatory power of 13% on changes in CDS spreads and is on average more influential than equity volatility and the risk free interest rate.

2.2.3 VOLATILITY

Moody's Default Prediction Model attributes market sensitivity to stock volatility. This concurs with Merton's model, which takes variance (volatility) into account when determining the distance to default estimate. An increase in volatility should trigger a higher probability of default. In this thesis, we have opted to apply implied volatility as opposed to historical volatility for as inferred by Benkert (2004), implied volatility shares a closer relationship with CDS spread than historical volatility. This makes intuitive sense since CDS spreads are based on similar expectations to implied volatility, whereas historical volatility is solely based on past equity returns. The mechanics of how implied volatility is obtained will be detailed later in the *Data* section.

2.2.4 INTEREST RATE

In theory, raising the risk-free interest rate leads to a decrease in default probability. In fact, Collin-Dufresne (2001) states that this particular rate impacts the risk neutral drift in the firm value process, i.e. a higher risk-free rate increases the risk neutral drift, thereby reducing the probability of default. Subsequently, this reduction will decrease the CDS spread. In addition, Alexander and Kaeck (2007) note that the risk-free rate's future movement is dictated by the slope of the yield curve.

"The steeper the yield curve, the higher expected future interest rates and thus we expect a negative relationship between both the riskfree interest rate and the slope of the yield curve and the CDS spread." (Alexander and Kaeck, 2007, p.1010)

To explore the aforementioned relationship we execute a principal component analysis using interest rate swap rates retrieved from the US Federal Reserve database. Swap rates are deemed as a superior proxy for the unobservable risk-free interest rates opposed to government bond yields (Houweling and Vorst, 2005).

2.2.5 EXCLUSION OF CREDIT RATING

For a number of reasons, credit rating has been excluded from this thesis. We postulate that the rapid and volatile nature of the financial crisis could not be adequately captured by credit rating in the upcoming regressions. For example, Alexander and Kaeck (2007) choose to infer the effect of credit rating if significant changes in volatility occur simultaneously, instead of including it as a determinant. Löffler (2002) also asserts that there is an inherent informational loss in credit ratings as they are monitored only twice a year. Unlike credit rating, all the above theoretical determinants are quoted on a daily basis. The irregular activity of credit ratings would therefore likely not exhibit legitimate regime-shifting behavior and be unsuitable for the forthcoming Markov switching model (see section 2.7). The *Previous Research* section below will further highlight how credit rating has been consistently employed when exploring the determinants for the CDS spread.

2.3 PREVIOUS RESEARCH

The following section will provide the reader with an overview of previous research in this field.

The early theoretical development of default harks back to Robert Merton's article, *On the Pricing of Corporate Debt: the Risk Structure of Interest Rates*, where he introduced a framework for estimating the distance to default (Merton, 1974). Merton postulated that defaulting was intrinsically bound to the variables variance and firm value, an idea which has since been the main structural framework for distance to default in much of the literature. Merton's model has since been further expanded in certain academic and practical works. Moody's Default Prediction Model, for instance, adds key variables implied by Merton's model such as firm size and leverage. Greatrex (2008) develops the model further by adding business risk as a variable, utilizing credit ratings to proxy the business climate in the market.

2.4 CREDIT DEFAULT SWAP SPREAD

In the field of credit spread changes, the research by Collin-Dufresne et al. (2002) was pioneering in that it investigated the theoretical determinants of credit risk by applying bond spreads. However, empirical literature has since swayed away from using bond spreads as a proxy for credit risk instead opting to employ CDS spreads.

Cossin and Hricko (2001) initiated the movement towards CDS spreads by combining elements of the Merton model mentioned above with fundamental variables such as interest rate in their cross-sectional regression analysis. Ericsson et al. (2004) show that leverage, volatility and interest rates have significant explanatory power for CDS spreads. While Blanco et al. (2005) verify that CDS spreads are a superior proxy for credit risk than bond spreads, since CDS spreads adapt to new information more swiftly than bonds. Furthermore, Longstaff et al. (2005) find that a significant part of the default risk incorporated in bond spreads is influenced by illiquidity. Benkert (2004) examines the CDS spread by contrasting historical volatility with option implied volatility and concludes that option implied volatility has a greater influence.

Calibrations for the theoretical determinants for the CDS spread vary, particularly over how the risk-free interest rate is proxied (see also section 3.3 *Credit Rating*). Ericsson et al. (2004) apply government bonds to produce a risk-free interest rate for the level and generate a yield curve from the difference between a long and short rate. Blanco et al. (2005), however, use swap rates rather than government bonds as a proxy for the risk-free interest rate and, as established by Houweling and Vorst (2005), swap rates offer better proxy for the unobservable risk-free interest rate than government bonds. Alexander and Kaeck (2007) advocate the use of principal components as it precludes using two arbitrary points of the yield curve as a difference. In addition, principal components extinguish issues with collinearity when using the slope derived from an interest rate difference and the level as a single interest rate.

T wo primary theoretical frameworks have influenced the pricing of the credit default swap, namely the structural model and the reduced form model. The structural model is derived from the option pricing model developed by Black and Scholes (1973), where firms' structural variables are incorporated into the model and default is a function of endogenous elements. The reduced form model, on the other hand, treats default as an entirely exogenous event, unrelated to firm activity. Ennab and Gretarsson (2009) conducted research which employed the Merton Model (structural) and the Hull and White Model (reduced form) in pricing CDS spreads. They concluded that the reduced form model was superior as an empirical tool, yet it overestimated the CDS spread set by the market. This was attributed to a lack of a standardized and consistent method of pricing CDS spreads. Nevertheless, research by Li and Wright (2009) states that the reduced form model does not perform ideally due to the strict assumptions implied. There has also been criticism directed at the reduced form approach on the basis of a suggested weak economic justification (Alexopoulou et al., 2009). In the main, the structural model has been applied to explore the explanatory power of the determinants (Collins-Dufresne et al., 2001; Abid and Nader, 2006; Avramov et al., 2007; Blanco et al., 2005; Ericsson, 2004).

Other than the discussed (theoretical) determinants, a large number of other variables have been argued to influence the CDS spread. Gregory (2009) suggests the three variables included in the Fama-French three factor model:

- Market risk premium
- Small-minus-Big factor (market capitalization)
- High-minus-Low factor (book to market ratio)

Gregory (2009) aims to capture distress risk and liquidity risk through these factors and finds a positive relationship between CDS spreads and the small-minus-big factor together with ambiguous results for the high-minus-low factor for the U.S high yield CDS indices.

Zhang et al. (2008) include 'jump-risk' and observe a significantly negative relationship. Jump-risk refers to the reference entity's equity volatility and rests on the assumption that jumps are rare and large in financial markets. For a more detailed explanation of jump-risk see Zhang et al. (2008).

The studies in the previous research vary greatly in their ability to explain the variation of the CDS spread. Abid and Naifar (2006) account for to 66 % of the variation in CDS spreads, while Aunon-Nerin et al. (2002) explain up to 82 % and Blanco et al. (2005) 25 % of the variation (for an overview of the variables used and explanatory power of previous research see Table 45 in the Appendix).

2.5 SINGLE-NAME CDS VS. CDS INDICES

When empirically investigating CDS spreads, some previous researchers have focused on CDS indices such as iTraxx while others has used single-name CDS spreads. According to Alexander and Kaeck (2007), the main advantage of using indices is the greater liquidity as compared to single-name contracts. On the other hand, using single-name contracts allow us to detect patterns in our data based on different industry classifications and also examine the impact of firm-specific events on companies in our data. For example, one can observe the impact on different groups of companies in light of the Lehman Brothers bankruptcy on September 15, 2008.

In addition, there has to our knowledge not been any previous research on the regime-switching determinants on single-name CDS spreads.

2.6 CREDIT RATING

Part of the empirical literature in this subject argues that credit rating has an intricate connection with CDS spreads (Abid and Naifar, 2006) (Cossin and Hricko, 2001) (Czarnitzki and Kraft, 2007) (Daniels and Jensen, 2005). For example, Greatrex (2008) theorizes that a rating-based CDS index is the single best predictor of CDS. Also, Hull et al. (2004) discovered that CDS spreads predict negative rating events while also establishing that positive rating events were less significant. In addition, Ammer and Packer (2000) uncovered imperfections in credit ratings assigned for different sectors in the U.S. Löffler (2002) also points out that credit ratings suffer from informational loss due to less regular monitoring. This sentiment is echoed by Rom (2009), who partially attributes the credit rating system for the subprime crisis.

Some researchers have, contrastingly, encountered difficulties in verifying the relevance of credit rating. Bhar et al. (2008) received conflicting results regarding the significance of credit rating where the rating was deemed insignificant in a substantial part of their research. Likewise, Made and Olszamowski (2008) found that a downgrade announcement was statistically insignificant as well as determining that announcements from the rating agency Fitch were insignificant in relation to CDS spreads.

2.7 MARKOV-SWITCHING REGRESSIONS

In the field of econometrics, Goldfeld and Quandt are renowned for creating the heteroscedasticity test, i.e. the Goldfeld-Quandt test (1965). They made further scientific contributions by producing groundbreaking Markov-switching regressions (1973). In essence, the duo put the linear regression system in a framework whereby switching between equations or 'regimes' were permitted. For instance, Goldfeld and Quandt (1973) exemplified this with a linear regression system followed below:

$$y_i = \sum_{j=1}^{k} \beta_{1j} x_{ji} + u_{1i} = x_i' \beta_1 + u_{1i} \qquad \textit{Equation 3.1}$$

$$y_i = \sum_{j=1}^{k} \beta_{2j} x_{ji} + u_{2i} = x_i' \beta_2 + u_{2i} \qquad \textit{Equation 3.2}$$

The above equation system assumes that the y_i variable can be generated by either regression. The error terms u_{1i} and u_{2i} abide by the classical linear regression assumptions and additionally the terms are assumed to be normally distributed (N, σ^2). An additional assumption is made where:

$$(\beta_1, \sigma_1^2) \neq (\beta_2, \sigma_2^2)$$

Thus, the above assumption induces the 'switching' between the two equations. Subsequently, one would need to estimate the parameters and test the null hypothesis consisting of - $(\beta_1, \sigma_1^2) = (\beta_2, \sigma_2^2)$ in order to determine the existence of different regimes in the system. This presumes that the researcher has no prior knowledge on how to classify the data between the regimes. In such an instance, the null hypothesis may be conveniently tested with the Chow test (Goldfeld and Quandt, 1973). Obtaining the parameters is otherwise performed by applying Markov-switching regressions. The Markov model in itself is technical but the main tool employed is a log likelihood function, which was correctly ascertained by Cosslet and Lee (1985).

In fact, the research conducted by Alexander and Kaeck (2007) proposes that "the influence of theoretical determinants of credits spreads has a regime dependent, sector specific behavior". They also perform unconditional density estimates and find that the Markov switching model provides a better depiction of observed data than a linear regression model. Cont (2005) also concurs with the notion of the existence of regimes as time series data often exhibit volatility clustering. Consequently, researchers have increasingly started to accommodate for volatility clustering by utilizing regime switching models (Fong and See, 2001) (Vanden, 2006). Particularly demonstrated by

Marcucci (2005) who used a Markov Regime Switching GARCH to forecast stock market volatility and concluding that the Markov GARCH outperformed standard GARCH models.

3 DATA

The following chapter will detail the type of data used and pertinent data transformations.

3.1 TYPE OF DATA

Data for completing this thesis was collected via Datastream and the U.S Federal Reserve. The data consists of single-name CDS spreads for 47 companies from the S&P 500 index, stock returns, total debt and number of outstanding shares was also collected for each company. A complete overview over included companies and sectors can be found in the Appendix (Table 1).

The "spread mid" e.g. mid-market quotes in Datastream, was used to proxy the CDS spread. This measure is already expressed in basis points and shows the mid rate spread between the reference entity and relevant benchmark curve. Furthermore, only five year maturity spreads traded in U.S dollar with modified restructuring (MR) agreements where used. Five year CDS contracts are in the literature often argued to be most liquid and frequently used (Benkert, 2004). In addition, MR agreements are most commonly used in North America. Hence, aiming at minimizing the nonsynchronous trading problem resulted in the usage of these particular CDS spreads.

For stock data, the official closing price was used and the total debt represents all interest bearing debt including interest bearing lease obligations. The number of outstanding shares is the total number of ordinary shares that represent the capital of respective company.

VIX index is used as a proxy for implied volatility and was retrieved through Datastream. VIX is based on a wide range of options on the S&P 500 index and aims to anticipate the future (30 calendar days) volatility on the S&P 500. Bid quotes were used and VIX is already expressed on a yearly basis. The interest rate data was collected via Federal Reserve.

3.2 TIME PERIOD AND DATA TRANSFORMATION

We limit the time period in our research to 2008-01-02 to 2010-12-31. A longer time period could have been of interest but data availability was limited and resulted in the aforementioned time period. Additionally, some observations were unavailable due to non-trading days coinciding with weekends and holidays. These observations were consistently excluded from all the variables.

The change in stock price, volatility index and CDS spreads was performed directly in Excel by applying: $\frac{P_{t+1} - P_t}{P_t}$.

Firm specific leverage is defined as $\frac{Total\ Debt}{Total\ Debt + Equity}$, where equity is number of outstanding shares multiplied to the current stock price.

Principal component approach was used as a proxy for the interest rate based on U.S swap rates with different maturities. A more comprehensive description of principal components can be found in section 2.3.

4 METHODOLOGY

The following chapter will present the methodology behind the analytical parts.

4.1 PRINCIPAL COMPONENT APPROACH

When factors are not specified a priori using theoretical arguments, we can use statistical methods to determine factors. Hence, the principal component approach may be implemented in order to capture the level and spread of the yield curve for the swap rates that are used as a proxy for the risk-free interest rate. U.S swap rates with eight different maturities from 1 to 30 years were used as input for the principal component computation.

$$\boldsymbol{PC_1} = \mathbf{max}: \boldsymbol{X'\hat{V}X}$$

$$subject\ to\ X'X = 1$$

$$\boldsymbol{PC_2} = \mathbf{max}: \boldsymbol{X'\hat{V}X}$$

$$subject\ to\ X'X = 1, X'_1X = 0$$

The first principal component (PC_1) can be retrieved using:

$$PC_1 = X_1'R_t$$

X is an 8*1 vector solving the optimization problem: $X'VX$ subject to $X_1'X=1$. V is the sample covariance matrix of the swap rates. In order to solve for X, starting values was chosen to 0,125 (1/8) and then maximized with respect to the restrictions. X_1 is the eigenvector corresponding to the largest value of V and X' is the transpose of the 8*1 vector solving the optimization problem.

The second principal component was computed in the same fashion only by adding one restriction for PC_2 so that:

$$PC_2=X_2'R_t \text{ subject to } X'X=1 \text{ and } X_1'X=0$$

X_2 is the eigenvector corresponding to the second largest value of V. As a result, PC_1 enables the depiction of the level of the interest rate while PC_2 represents its yield curve.

4.2 LINEAR REGRESSION ANALYSIS

The objective of the linear time series regression is to explain changes in single-name CDS spreads. Financial time series modeling is typically subject to problems regarding autocorrelation, heteroskedasticity and non-normality in the residuals. These problems have to be addressed in order to obtain a best linear unbiased estimator (BLUE). Firstly, using first differences instead of level in our variables reduces the autocorrelation problem[1]. Secondly, heteroskedasticity is addressed by using HAC standard error which is more detailed in section 2.5. Finally, non-normality in the residuals is expressed as excess kurtosis and often caused by 'outliers' in the data. Brooks (2002) point out that for sufficiently large sample sizes, effects of non-normality are inconsequential.

Given the aforementioned factors determining the CDS spread, equation 2.1 is carried out for each company.

$$\Delta CDS_t = \alpha_t + \beta_{1t}LEV_t + \beta_{2t}RET_t + \beta_{3t}\Delta VIX_t + \beta_{4t}\Delta {PC_1}_t + \beta_{5t}\Delta CDS_{t-1} + \varepsilon_t \qquad \textit{Equation 2.1}$$

Where ΔPC_1 is the change in the first principal component based on U.S interest rate swaps with different maturities, ΔCDS_{t-1} is the first lag of changes in CDS spreads, LEV is the firm specific leverage, ΔVIX is the change in implied volatility based on the S&P 500 index and RET is the stock return.

Section 2.2.1-2.2.5 described the theorized behavior of the determinants. Taking the previously mentioned sections into account, following below in Figure 2.2 are the variables included in the linear regression analysis as well as their predicted sign:

[1] The Durbin-Watson statistic, which is near 2, in our sample data supplies this indication

FIGURE 2.2: PREDICTED SIGNS OF COEFFICIENTS IN LINEAR REGRESSION

Variable	Description	Predicted Sign
LEV_t	Leverage	+
RET_t	Daily stock return data	-
VIX_t	Volatility index	+
PC_{1t}	Proxy for the level of the risk-free interest rate (First principal component)	-
CDS_{t-1}	The first lag of the CDS spread	+

The predicted sign for the lag of the CDS spread is based on the findings of Byström (2005) who determined that there was positive autocorrelation in CDS index data.

4.3 RESIDUAL DIAGNOSTICS

Since a major financial crisis is included in our data, one might suspect that the residuals display heteroskedasticity. To investigate this further, White's test was performed in Eviews. The null hypothesis is that we have no heteroskedasticity and the alternative hypothesis is that we have heteroskedasticity of an unknown, general form. Since the underlying null hypothesis assume errors to be both homoskedastic and independent of the regressors, failure in linear specification of the model can cause a significant test. It is, however, in this case economically plausible to suspect heteroskedasticity and the results show that we can almost exclusively reject the null hypothesis.

The coefficient estimates are still accurate since the OLS estimator is unbiased; however, standard errors will be incorrect which makes both t- and F-tests incorrect. To prevent this from affecting our model, Newey-West HAC standard error was used. This approach estimates the covariance consistently even in the presence of any form of heteroskedasticity and autocorrelation[2].

4.4 CHOW'S BREAKPOINT TEST

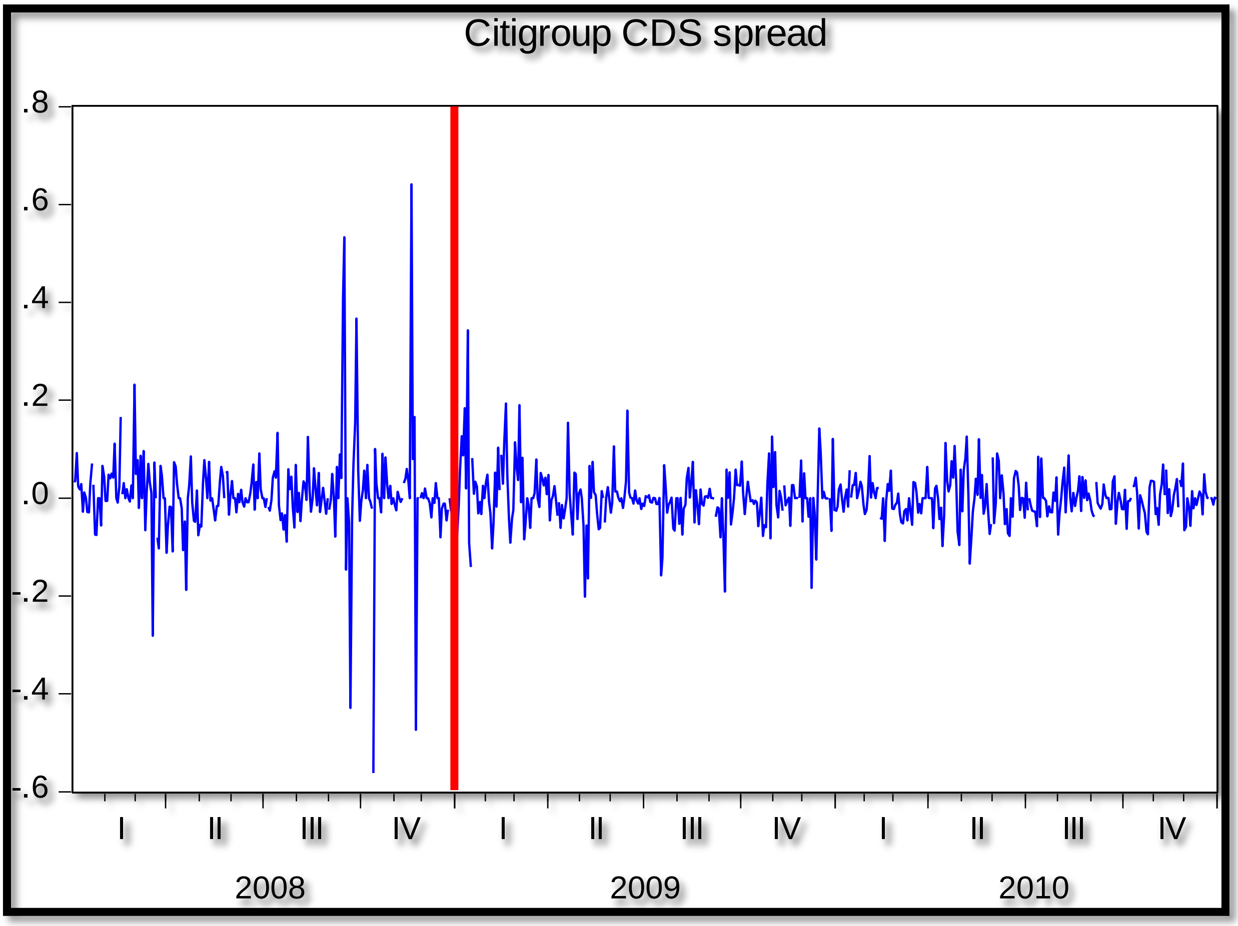
Since our data display a vastly changing economic environment, it is of importance to test the stability of the model. This is done by applying Chow's breakpoint test using 2009-01-01 as the breakpoint. The idea behind Chow's test is quite intuitive, for it suggests the fit to the model should not be significantly different in these two subsamples. When applying Chow's test, the sum of squared residuals are compared between fitting one equation to the whole data and fitting the

[2] Eviews 7 User Guide II p.36

equation on the subsamples separately. Hence, one tests for structural changes in all of the parameters[3]. The test runs three regressions, one over the whole time period and one for each sub-period. Comparing the sum of squared residuals in the following way yields the test statistic:

$$Chow\ test = \frac{RSS - (RSS_1 + RSS_2)}{RSS_1 + RSS_2} * \frac{T - 2k}{k}$$

Where RSS is the residual sum of squares for the whole period and RSS_1 and RSS_2 is the residual sum of squares for each sub-period respectively. T is number of observations while k is the number of explanatory variables in each regression[4]. Depending on the choice of breakpoint, results differ among companies and sectors. However, there is an obvious trend that the volatility of CDS spreads diminishes at the end of 2008 as the market stabilizes, see graph 2.6 below.



By consistently applying 2009-01-01 as breakpoint, approximately 65% of the companies display significance (see Table 5.1). We conclude that there are major problems with parameter stability

---

3 Eviews 7 User Guide II p.172
4 Introductory econometrics for finance (2002), p.199.

although it slightly differs in time among companies which motivates the use of a regime switching model.

4.5 MARKOV SWITCHING MODEL

Financial data might at times display drastic changes in its behavior. This can be caused by events such as regulatory changes or financial crises (Hamilton, 2005). Applying a Markov model allows the regression coefficients to change over time depending on the market regime at time t, which is a very suitable feature for this thesis since our data includes a financial crisis. The Markov model will also enable one to pinpoint the variables that have greater influence in for example a turbulent period against a tranquil period.

A typical behavior may be expressed by an AR (1) model:

$$y_t = c_{1t} + \emptyset\, y_{t-1} + \varepsilon_t \qquad \textit{Equation 2.2}$$

The above equation serves to describe the observed data for t = 1, 2, …. t_0 where the error term is normally distributed. In order to portray a sudden change in the variable y_t, one might opt to modify the equation into the following:

$$y_t = c_{2t} + \emptyset\, y_{t-1} + \varepsilon_t \qquad \textit{Equation 2.3}$$

The above modification accommodates a significant change in the average level of a series to some extent at t_0. By changing the value of the intercept from c_1 to c_2[5] better forecasts may be produced but fails to take into account the stochastic element of the generated data (Hamilton, 2005). Moreover, the former setup (Eq 1.2 and Eq 1.3) would imply that the change from c_1 to c_2 at t_0 is a deterministic event. Therefore one must construct a model encompassing the two states:

$$y_t = c_{st} + \emptyset y_{t-1} + \varepsilon_t \qquad \textit{Equation 2.4}$$

(s_t = 1 and s_t = 2)

As a result of drastic changes, s_t is a random variable where s_t appropriates the value of 1 for t = 1, 2, …. t_0 and 2 for $t = t_0 + 1$, t_0+2,…. Furthermore, a probabilistic model would be necessary to ascertain the change induced from s_t = 1 to s_t = 2. The realization of a two-state Markov chain (Hamilton, 2005) can thus be complemented with the following:

[5] Note that $c_1 \neq c_2$. The example is designed to illustrate how only changing the intercept is an insufficient measure to model the data.

$$\Pr(s_t = j | s_{t-1} = i) = p_{ij} \qquad \textit{Equation 2.5}$$

As a two-state Markov chain is assumed to be unobservable, one can only assign probabilities of being in a certain regime at time t. The Markov switching model retrieves the parameters by utilizing a maximum likelihood function under the restrictions that probabilities sum to one and standard deviations are greater than zero. The coefficient estimates' magnitude and sign can thus reveal if variables behave differently in different states. For further technical specification of the Markov switching model, the literature by Hamilton (2005) and Alexander and Kaeck (2007) is recommended.

4.6 IMPLEMENTATION OF MARKOV SWITCHING MODEL

Investigating the determinants regime dependent behavior over time requires complex mathematical calculations not possible in Eviews or Excel. Instead, MATLAB was used for estimating the Markov Switching model. This was possible due to a Markov Switching package[6] with codes ready for input in MATLAB. These codes were then modified to suit our specific model.

The number of regimes in the model was set to two. By doing so, we implicitly assume that the economic environment switches between two regimes. Specified in the model is also the number of variables that is allowed to change regime since we do not have any information indicating whether the variables change regimes. Hence, we allow all variables the possibility of switching regimes. Further discussion regarding the output of the switching behavior can be found in chapters 5-6.

[6] Perlin (2010) MS Regress - The MATLAB Package for Markov Regime Switching Models

5 EMPIRICAL ANALYSIS AND RESULTS

The following section contains the results from the empirical analysis of the linear regression and Markov switching regression. A significance level of 5 % will be assumed.

5.1 LINEAR REGRESSION RESULTS

FIGURE 5.1

Sector	***Constant***	***LEV***	***RET***	***ΔVIX***	***ΔPC_1***	***ΔCDS_{t-1}***	***R^2***
Consumer	-0.003	0.016	-0.129	0.079	-0.087	0.161	0.114
p-value	*0.358*	*0.328*	*0.051*	*0.023*	*0.172*	*0.004*	
Financial	-0.003	0.010	-0.151	0.116	-0.265	0.166	0.121
p-value	*0.425*	*0.391*	*0.221*	*0.002*	*0.046*	*0.018*	
Healthcare	-0.006	0.010	-0.085	0.095	-0.059	0.193	0.099
p-value	*0.490*	*0.504*	*0.221*	*0.000*	*0.126*	*0.009*	
Industrial	0.002	-0.003	-0.151	0.073	-0.111	0.195	0.118
p-value	*0.676*	*0.860*	*0.026*	*0.016*	*0.136*	*0.005*	
Oil and Gas	0.002	-0.001	-0.218	0.005	-0.052	0.178	0.058
p-value	*0.229*	*0.350*	*0.108*	*0.206*	*0.510*	*0.001*	

Figure 5.1 illustrates the median values for the different companies included in each sector (for a full presentation of the linear regressions see Table 2-6 in the Appendix). We chose to use the median due to outliers in the data, making the median reflect the results better than the averages. The financial, industrial and consumer sectors have the highest R^2 value indicating a better fit. Implied volatility and ΔCDS_{t-1} has the lowest p-values demonstrating greater influence on the CDS spread.

Leverage has a positive coefficient for all sectors except industrial and Oil & Gas (close to zero) and should be interpreted as increasing leverage leads to increasing CDS spread. This is in line with our expectations and seems plausible according to economic theory. However, leverage is the most insignificant variable which contradicts economic theory and will be addressed in more detail in chapter 6 *Discussion.*

Changes in stock return, which can be seen as a measure of changes in firms' equity value and is negative for all sectors. This is also in line with our expectations because decreasing equity value should lead to increasing D/E ratio and a higher probability of default. The change in implied volatility is positive meaning that higher future expected volatility has a positive relationship with the CDS spread.

The first principal component representing risk free interest rate is negative for all sectors. Initially, it can be intuitive to think that this variable should have a positive sign due to decreasing interest rates leading to lower debt payments and cheaper financing. But a decreasing interest rate signals a downturn in the overall economy and increases the probability of companies going bankrupt; hence a negative coefficient is expected.

Finally, the lagged CDS spread is positive and has a high explanatory power. This finding suggests a significant positive autocorrelation which in turn implies inefficiency in the market for single-name CDS spreads. Byström (2005) and Alexander (2007) support this finding for European CDS indices.

Generally, the determinants' explanatory power differs among companies and sectors. This comes as no surprise since there are many firm specific factors that might affect each individual CDS spread in contrast to analyzing CDS indices.

White's test was also performed resulting in that all companies show heteroskedasticity except Altria Group, Boston Scientific and Marathon Oil. These companies display a poor fit with a R^2 value of approximately 5% (see Table 2, 4 and 6 in the Appendix).

Table 5.1 illustrates the Chow breakpoint test using 2009-01-01 as the breakpoint.

TABLE 5.1

Average Chow Test		
Sector	Reject H_0	Accept H_0
Consumer Goods	50,0%	50,0%
Industrials	44.4%	55.6%
Financials	81.2%	18.8%
Oil & Gas	100,0%	0,0%
Healthcare	66.7%	33.3%
Total	**64.6%**	**35.4%**

Rejecting H_0 demonstrates the percentage of companies in each sector where the sub-periods are significantly different. "Total" reflects the weighted average depending on the number of firm's included in each sector. For a full overview over the significance of the parameter stability of the regressions, see Table 7 in the Appendix.

5.2 MARKOV SWITCHING REGRESSION RESULTS

The Markov model enables the parameters to transition into different states by assigning probabilities at a point of time. The model does not however reveal outright which state is the tranquil or turbulent according to our sample data. We have inferred from the variance exhibited in the model that Regime 1 is the tranquil period while Regime 2 is the turbulent period. The volatility is notably more pronounced in Regime 2 for all sectors in the Markov model (see Table 44 in the Appendix).

As a result of parameter instability, the use of a Markov model is justified. Hence, in theory coefficient estimates and statistical inferences are more reliable with this particular model.

By analyzing the median results from each sector[7], we find little evidence of implied volatility being significant. Furthermore, we find evidence supporting a negative autocorrelation indicating mean reversion in the CDS spread. Interestingly, the interest rate is positive for all sectors but overall only significant in the volatile regime. This suggests that the explanatory power of interest rates increases with market volatility. The same reasoning applies to leverage which unexpectedly has a negative coefficient. Finally, firm specific stock return does not seem to have a significant effect when treating the sectors as cross-sections of individual firms. It is noteworthy that the data contains outliers which distort the sectoral values. This distortion was amended by applying median values instead of mean.

Henceforth, the results will be interpreted by investigating select companies for the Markov switching model (for a full presentation of the Markov regressions see Table 8-44 in the Appendix).

We will exploit the benefits of using single-name CDS spreads by analyzing on a firm-specific level. Below we have a selection of companies that are well-known entities and represent two of the major sectors.

Following below will be an interpretation of the results retrieved from the Markov switching regressions on select companies (Figure 5.2):

[7] The reader is provided with a comprehensive presentation of the Markov Switching Regression results in Table 37-42 in the Appendix.

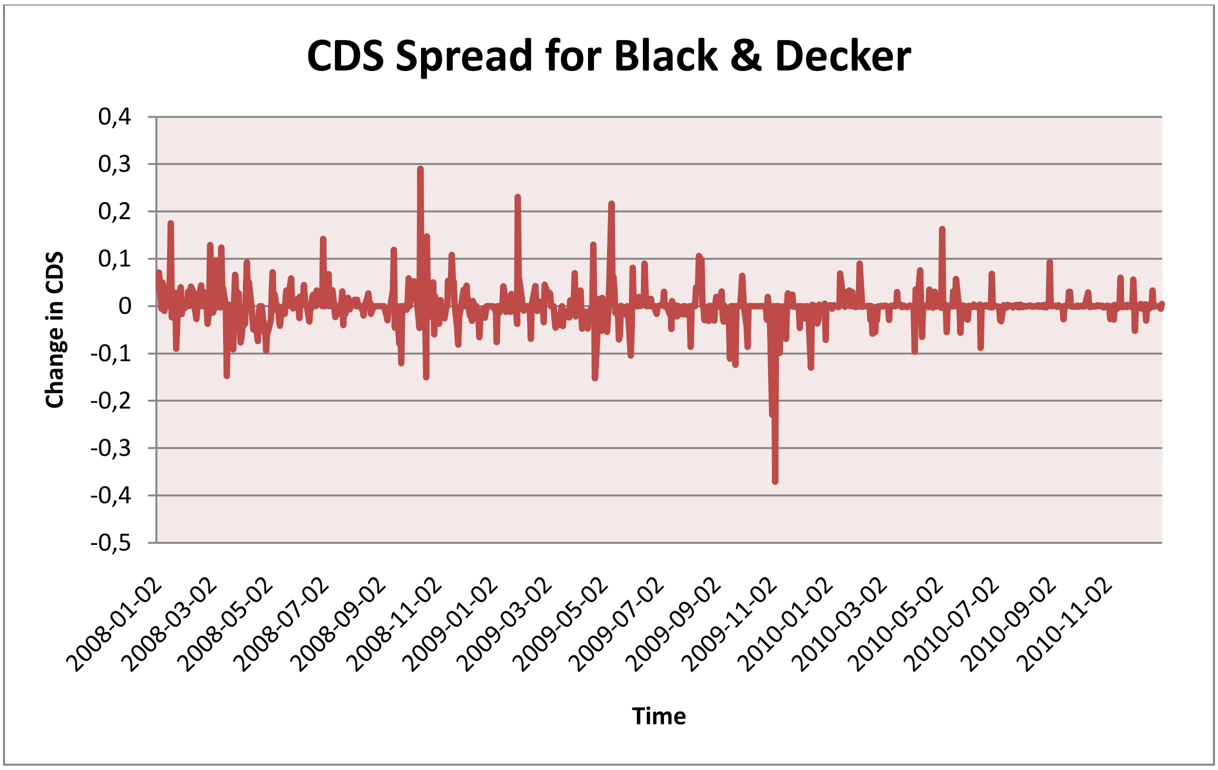
FIGURE 5.2

	LEV	*RET*	*ΔVIX*	*ΔPC₁*	*ΔCDS_t-1*	*Duration*
Black&Decker						
Regime 1	-0,001	0,0001	0,0001	0,000	0,009	2,710
	(0,75)	(0,89)	(1)	(1)	(0)	
Regime 2	-0,316	-0,028	0,117	0,193	-0,055	3,140
	(0)	(0,02)	(0,02)	(0)	(0,5)	
Ford						
Regime 1	-0,194	-0,032	0,038	0,074	-0,088	14,910
	(0)	(0)	(0)	(0)	(0,07)	
Regime 2	-0,305	-0,032	0,038	0,245	-0,093	9,250
	(0)	(0,4)	(0,37)	(0)	(0,51)	
Morgan Stanley						
Regime 1	-0,122	0,057	-0,062	0,200	-0,190	93,590
	(0)	(0,19)	(0,2)	(0)	(0)	
Regime 2	-1,658	1,080	-1,187	-0,325	-2,546	5,060
	(0,03)	(0,35)	(0,36)	(0,51)	(0,14)	

The duration in Figure 5.2 conveys the expected average time length of a certain regime after a switch. The frequency is expressed in days in accordance to our sample data. As mentioned above, Regime 2 has been identified as the volatile regime. According to Alexander and Kaeck (2007) "the price of a CDS becomes more sensitive to volatility when the firm value is close to the default-triggering barrier, so investors may become more concerned about future uncertainties once volatility has entered the CDS market". This phenomenon is exemplified by Black & Decker who displays significance in volatility in Regime 2. Furthermore, Alexander and Kaeck also point out that there is a strong relationship between firm value and credit spreads among low-rated companies. Again, the stock return is proven to be a significant determinant for Black & Decker in Regime 2[8]. Being a low-rated company Black & Decker experienced a surge in its stock on November 2 2009 during the announcement of a merger between Stanley Works and Black & Decker (Pepitone, 2009).

[8] Black & Decker was downgraded to a P3 by Moody's and A3 respectively by Standard & Poor's in 2009 (Black & Decker, Annual Report 2009)

FIGURE 5.3

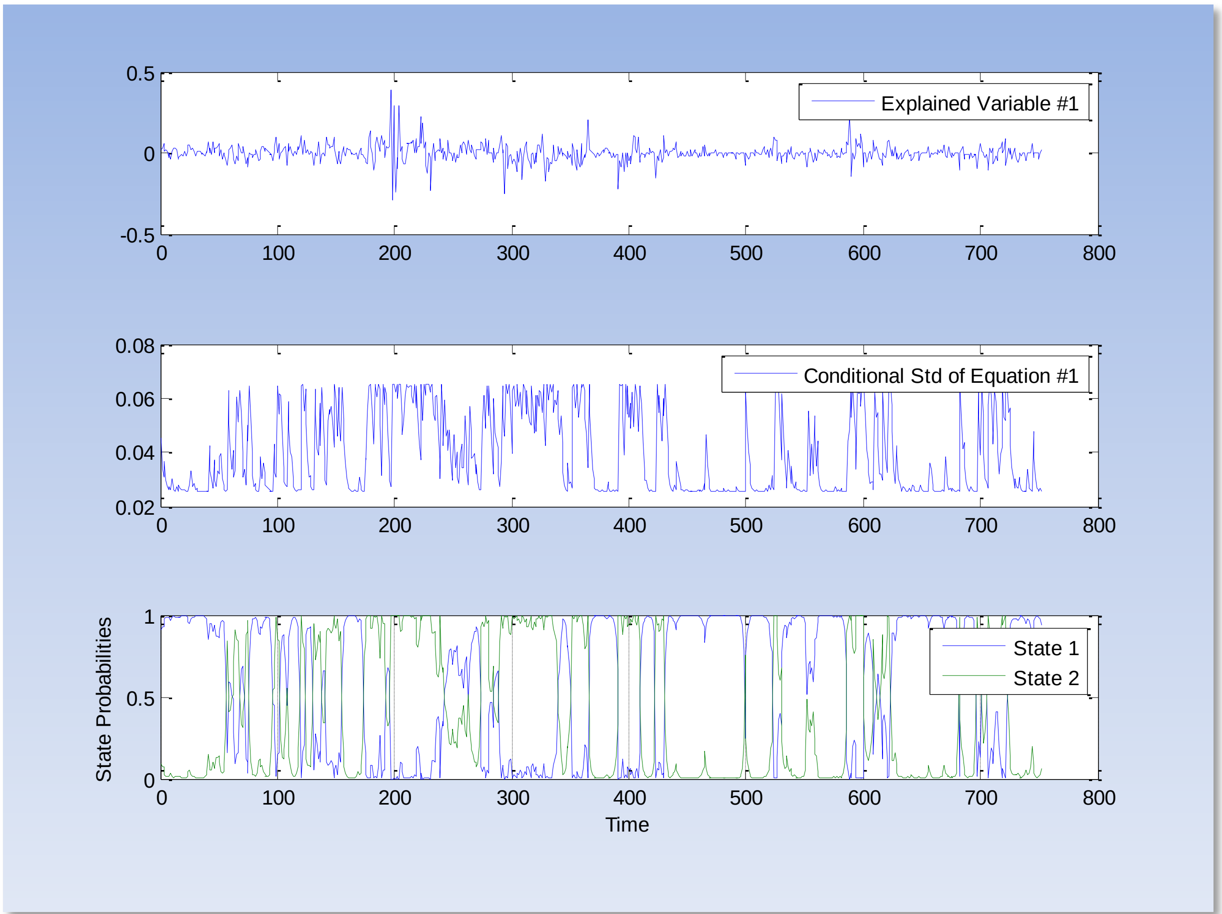


The negative spike on Figure 5.3 corresponds to the aforementioned stock increase with a two day delay. This affirms the theory that the CDS spread and stock return should be negatively correlated. Moreover, the lag suggests that the illiquidity in the single-name CDS market does not incorporate new information immediately.

For Ford, we observe a negative and highly significant coefficient for leverage in both regimes. The negative sign applies surprisingly for most companies which is counter-intuitive with regards to economic theory. Stock return on the other hand is negative and significant in regime 1 and negative but not significant in regime 2. VIX is almost significant (0.07) in regime 1 but insignificant in regime 2. This implies that the stock return and implied volatility has greater influence on Ford's CDS spread in low volatility periods. PC_1 displays a positive sign which is not in line with our predictions. It is however possible that increasing interest rates could contribute to triggering default during economic recessions through increased costs of short term financing. Gregory (2009) supports this finding stating that increases in interest rates often preceded increasing default events during the recent financial crises. Consequently, a positive relationship is contradictory to economic theory but during our sample period not unreasonable.

Graph 5.1 illustrates the explained CDS spread, conditional standard deviation and the regime switching behavior of Ford. When examining graph 5.3, one can see that the regime switching behavior is closely related to VIX illustrated in figure 6.1. Furthermore, Ford was downgraded by Fitch from B- to CCC on Oct 6, 2008 which corresponds to observation 194. It is possible to observe a regime switch at this point. By examining Ford in the above table, one can observe that the explanatory variables are more significant in the tranquil regime (Regime 1). This suggests that other economic variables have more influence on the CDS spread during volatile periods (such as a credit downgrade).

GRAPH 5.1 FORD REGIME-SHIFTING BEHAVIOUR



Ford can be deemed pro-cyclical and heavily dependent on the economic environment. In addition, the automobile industry experienced huge financial difficulties during the financial crisis which is reflected in the high expected duration in Regime 2.

The coefficient for leverage shows a negative sign, albeit being significant. This contradicts our own prediction and there is little economic rationale suggesting a negative relationship between leverage and the CDS spread. In theory, increasing leverage should increase the probability of default. Instead, this finding indicates the direct opposite. It puts the inclusion of leverage as a determinant for the CDS spread in a regime-shifting environment into doubt.

The financial firm Morgan Stanley exhibits the same negative relationship for leverage as discussed earlier. Interestingly, signs for stock return and implied volatility are reversed. Morgan Stanley has a negative relationship with implied volatility (however not significant), while most firms display a positive relationship. This is counterintuitive and not in line with economic theory or our prediction. Expected duration of regime 1 is surprisingly high indicating very few regime shifts during the sample period. This suggests that the explanatory variables are fairly stable over time.

6 DISCUSSION

The following section will contain a discussion of the results from the empirical analysis. It will contrast our findings with previous research.

6.1 COMPARISON TO PREVIOUS RESEARCH

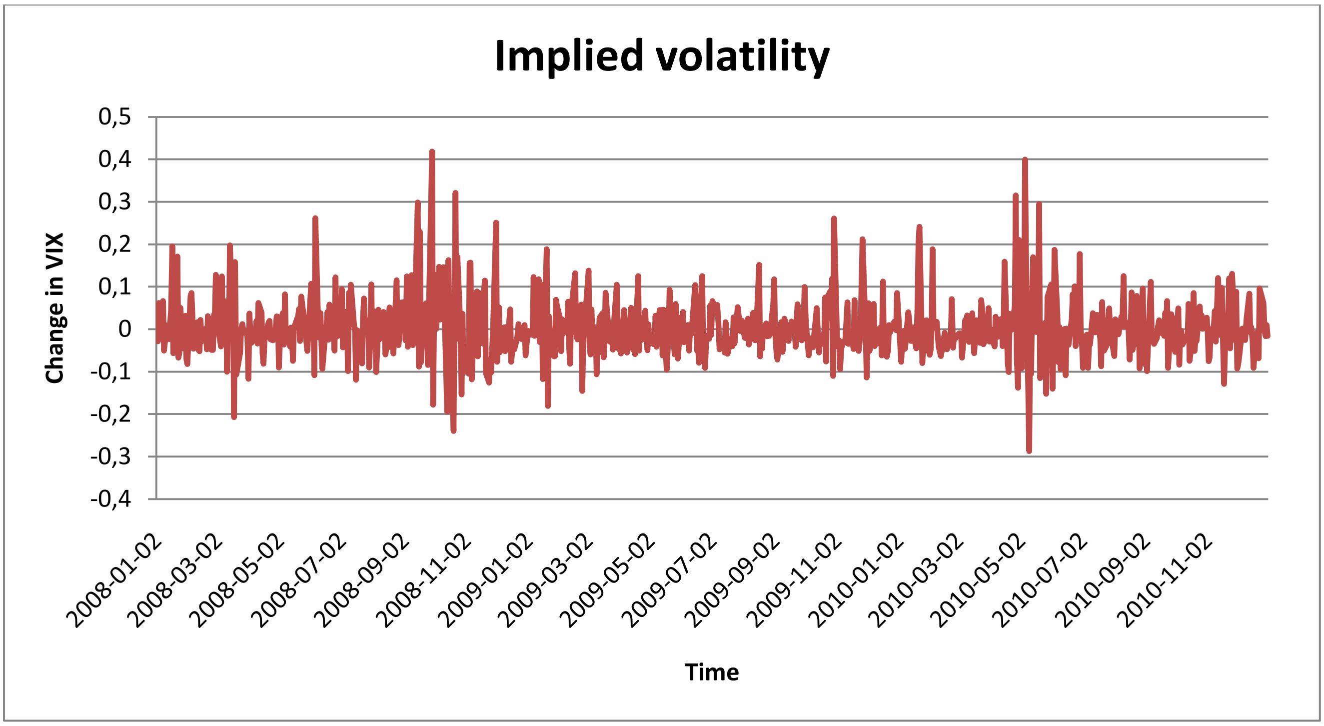
6.1.1 LINEAR REGRESSION ANALYSIS

When scrutinizing the linear regression analysis in our study compared to previous research certain aspects need to be considered:

- The turbulent sample period
- The difference between using single-name CDS and CDS index
- The theoretical determinants involved in the regression
- Performing the linear regression using levels and/or differences
- Frequency of the observed data

The sample period of our observed data encapsulates to a great extent the financial crisis. This introduces a number of issues. Most of the leading research in the field has a data selection which dates prior to the financial crisis. Arguably, this might make their conclusions erroneous compared to the present, but more importantly enhances the difficulty in comparing results from our study – that is, contrasting empirical results from a tranquil period against a turbulent period. Furthermore, as highlighted in the *Residual Diagnostics* chapter (section 2.5) the residuals of the data displayed heteroskedasticity, which was adjusted for by implementing the Newey-West HAC standard error. This violation of the general properties of BLUE may be attributed to volatility clustering as can be seen below in figure 6.1:

FIGURE 6.1: VOLATILITY CLUSTERING IN OBSERVED DATA



As Cont (2005) notes, attempts to model volatility clustering often result in low and high activity regimes with heavy-tailed durations of regimes. In order to reconcile the effects of volatility clustering, regime switching models has hence become a more common method in the field (Fong and See, 2001; Marcucci, 2005; Valden, 2006).

The most notable differences in our selection of theoretical determinants compared to previous research has been how the risk-free rate and its yield curve has been obtained and our exclusion of credit rating. Other variables that have been used to explain the CDS spread have been firm-specific variables such as jump-risk and the Fama-French factors. The composition of our model was based on the variables chosen by Alexander and Kaeck (2007) enabling a more convenient comparison. In addition, we added leverage as a determinant due to theoretical support as well as previous empirical research.

The explanatory power of our variables in the linear regression analysis is less compared to most previous research (see Table 45 in the Appendix). To be noted, though, is that most scholars have used bid/offer quotes as a proxy for their CDS spread for their research rather than mid-market quotes. Also, the set of variables included in the models have been vastly different compared to our study. Scholars who have used bid/offer quotes to proxy the CDS spread as the dependent variable attain inflated variation of the CDS spread ranging from approx. 50- 80 %. Conversely, Blanco et al. (2005) approach a variation explaining 25 % while our results explain roughly 11 % of the variation in the CDS spreads. Then again, Blanco et al. include the slope of the yield curve as a determinant, which Alexander and Kaeck (2007) firmly exclude as a significant variable. Nonetheless, Alexander and Kaeck (2007) find a variation, which explains approx. 17 % of the CDS spreads. This is presumably closer to our findings since we use a similar set of variables. Also, the implication of using single-name CDS in our research has been firm-specific events i.e. the unsystematic risk inflicting a worse fit on the regressions especially in comparison to Alexander and Kaeck. Our sample period, which includes the financial crisis, also exacerbates the process of obtaining a good fit. To exemplify, the financial crisis generates extreme outliers, which undoubtedly affects the fit of our linear regressions.

Greatrex (2009) underscores how inaccurate inferences might be made due to spurious regression with level analysis. Bearing this in mind, some of the determinants in our study have therefore been transformed into first differences. In addition, we have opted to use daily data opposed to weekly or monthly data, in effect yielding different results compared to some studies.

6.1.2 MARKOV SWITCHING REGRESSION ANALYSIS

This section will aim to compare our study with the most influential study regarding determinants exhibiting regime-shifting behavior for the CDS spread. The main difference between the research conducted by Alexander and Kaeck (2007) and ours is the use of single-name CDS spreads opposed to spreads with CDS indices. Our observed data (2008-2010) is also more current compared to their study (2004-2007). We also investigate the US market as opposed to the Euro market. While Alexander and Kaeck maintain that single-name CDS spreads are less liquid than CDS indices, single-name CDS spreads have permitted us though to explore firm-specific events.

"The size of all regression coefficients is much higher during the volatile regime, when the association between CDS spreads and their structural determinants is enhanced." (Alexander and Kaeck, 2007, p. 1015)

The above statement corresponds to our own findings (see Figure 5.2) as well as evidencing magnified traces of autocorrelation as shown in the CDS_{t-1} term in Regime 2 (see Table 28-32 in the Appendix). On the other hand, the CDS_{t-1} term is consistently negative contradicting research conducted by Byström (2005) and Alexander and Kaeck (2007) who discovered positive autocorrelation in their sample data. Both of these studies investigated CDS indices whereas the aforementioned negative autocorrelation could suggest mean reversion of the spread for the single-name CDS in the long run (Balvers et al., 2000). The variables transition in and out from a tranquil and turbulent regime (Alexander and Kaeck, 2007), which could support the existence of a mean-reverting behavior within this sample period.

As was previously established in section 5.2, our findings proposed an inverse relationship between leverage and the CDS spread. This is illogical from an economic standpoint and could imply that leverage is unsuitable for a regime-shifting approach. To illustrate, Alexander and Kaeck (2007) has a tested down[9] model that they acknowledge as statistically and economically significant: stock return, volatility, interest rate level and a lag. Collectively, these determinants could conceivably comprise the most parsimonious model for the CDS spread in a regime-shifting environment. The significance of our own findings differs though with respect to all the previously mentioned variables.

Our results from the Markov regressions show an overall insignificance for leverage, stock return and volatility when examining the sectors as cross-sections of individual firms (see Table 38-43 in the Appendix). Interest rate is the only remaining significant variable in this case. On a firm-specific level though one can clearly see a varying amount of significance amongst all the determinants. Possibly governing this behavior is that overall companies may response similarly to interest rate changes in times of distress. As Gregory (2009) explained, increased interest rates during the financial crisis preceded default events due to struggling with short-term interest payments. On the other hand, on a firm level the actions taken and behavior in terms of changes in the remaining determinants can vary greatly. This is exemplified by the way a CDS index classifies companies. A CDS index may classify companies in High Volatility, Investment Grade, Sub-Investment Grade etc. (Gregory, 2009) opposed to the simplistic nature of dividing companies into business sectors as conducted in this study. Additionally, if one were to cross-reference the instability in the parameters (see Table 7 in the Appendix) together with the insignificance of certain Markov estimations (see Table 8-37 in the Appendix) one would discover a pattern between the two. As a result, the application of single-name CDS when investigating the determinants for the CDS spread for entire business sectors becomes impractical.

7 CONCLUSION

7.1 CLOSING REMARKS

- Implied volatility is not significant in any regime.
- There is a positive and significant coefficient for interest rates in the volatile regime.
- CDS_{t-1} is positive in tranquil periods for the Consumer and Oil & Gas sectors, but negative otherwise indicating mean reversion in the CDS spreads.
- Stock return has no explanatory power in either regime.

[9] Interest rate slope was deemed insignificant and their original model was tested again by excluding the slope

- Leverage is negative and significant in the volatile regime.
- Explanatory power of the determinants fluctuates vastly between regimes and firms.

As we are using single-name CDS spreads, implied volatility might not be a good proxy for firm-specific volatility as indicated by the low explanatory power. It has been frequently used in the literature on CDS indices and on single-name spreads in linear regressions. It has, however, to our knowledge not been used on single-name CDS spreads in a regime switching approach. As a result, we recommend using a firm-specific measure of volatility instead.

Leverage is a backward looking measure collected from each firm's quarterly reports and does not seem suitable for the Markov model suggested by the sign and explanatory power. Today's ("true") leverage is unobservable which forces some kind of backward-looking measure of debt. In addition, the equity part of leverage $(P_t * NOSH)$[10] might already be captured by the stock return. To solve this problem we suggest a lagged leverage variable (1-3 months) while using book value of equity. This is likely a measurement problem since it seems economically plausible that leverage affects the probability of default.

However, the overall insignificance for stock return is unexpected and does not seem reasonable according to economic theory. This could be a result of inadequate classification with business sectors instead of the rigorous methodology behind a CDS index.

The fluctuation of explanatory power in the different regimes and the overall parameter instability indicate that a regime-shifting approach is suitable for analyzing determinants of single-name CDS spreads.

When implementing the Markov Switching Model we discover negative autocorrelation, which implies mean reversion of the CDS spread in this period.

The positive and significant relationship for interest rate in the volatile regime is perhaps the most interesting finding. We conclude that this is likely related to firm's inability to meet short term debt payments during economic recessions.

7.2 SUGGESTED FUTURE RESEARCH

Due to the existence of outliers in the sample period, it could be of interest to increase the sample size in certain sectors. This would enable a more thorough comparison between sectors. An alternate way of classifying the sectors, more in line with a CDS index, will probably lead to improved statistical

[10] NOSH= Number of outstanding shares. P= Stock price.

inferences. Moreover, a firm-specific volatility measure is preferable for single-name CDS spreads since implied volatility embodies volatility on a macroeconomic level.

Furthermore, performing a principal component analysis on the residuals of the model could be a relevant way to investigate if a systematic factor is influencing the variation. One could also perform statistical tests to compare the validity of the Linear Regression method against the Markov method. It is also possible to extend the Markov Switching Model with time varying transition probabilities and/or with a GARCH filter for conditional volatility.

BIBLIOGRAPHY

Abid, F., Nader, N., 2006, "The Determinants of Credit Default Swap Rates: An Explanatory Study" *International Journal of Theoretical and Applied Finance* 9(1), 23-42

Alexander, C., Kaeck, A., 2007, "Regime dependent determinants of credit default swap spreads", *Journal of Banking & Finance* 32, 1008-1021

Alexopoulou, I., Andersson, M., Georgescu, O.M., 2009, "An Empirical Study on the Decoupling Movements between Corporate Bonds and CDS Spreads", ECB Working Paper Series, August

Allen, L., Saunders, A., 2002, "Credit Risk Measurement: New Approaches to Value at Risk and Other Paradigms (2nd edition)" *John Wiley & Sons Inc*., New York

Ammer, J., Packer, F., 2000, "How Consistent Are Credit Ratings? A Geographic And Sectoral Analysis Of Default Risk" *International Finance Discussion Papers* 668

Avramov, D., Gergana, J., Alexander, P., 2007,"Understanding Changes in Corporate Credit Spreads" *Financial Analysts Journal* 63(2), 90-105

Balvers, A., Wu, Y, Gilliland, E., 2000,"Mean Reversion across National Stock Markets and Parametric Contrarian Investment Strategies", *Journal of Finance* 55, 745-772

Benkert, C., 2004, "Explaining credit default swap premia", *Journal of Futures Markets* 24 (1), 71–92

Bhar, R., Colwell, D.B., Wang, P., 2008, "Component Structure of Credit Default Swap Spreads and Their Determinants", *21st Australasian Finance and Banking Conference 2008 Paper*, Available at SSRN: http://ssrn.com/abstract=1263176

Black & Decker., *"2009 Annual Report"* Towson, MD., 2009, *Black & Decker Corp, 10-K*, Available at:

http://2009annualreview.stanleyblackanddecker.com/pdfs/Black_Decker_2009_10-K.pdf

Black, F., Scholes, M., 1973, "The pricing of options and corporate liabilities", *Journal of Political Economy* 81, 637-654

Blanco, R., Brennan, S., Marsh, I.W., 2005, "An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps", *Journal of Finance* 60 (5), 2255–2281

Brooks, C., 2002, "Introductory econometrics for finance", *Cambridge University Press*, Cambridge

Byström, H.N.E., 2005, "Credit default swaps and equity prices: The iTraxx CDS index market", Working Papers 2005:24, Lund University, Department of Economics

Collin-Dufresne, P., Goldstein, R.S., Martin, J.S., 2001,"The determinants of credit spread changes", *Journal of Finance* 56 (6), 2177–2207

Cont, R., 2005, "Volatility Clustering in Financial Markets: Empirical Facts and Agent-Based Models", Ecole Polytechnique, Centre de Mathématiques appliquées

Cossin, D. Hricko, T., 2001, "Exploring for the Determinants of Credit Risk in Credit Default Swap Transaction Data", Working Paper, University of Lausanne

Cosslett, S.R., Lee, L.F., 1985, "Serial Correlation in Discrete Variable Models", *Journal of Econometrics* 27, 79-97

Czarnitzki, D., Kraft, K., 2007, "Are credit ratings valuable information?", *Applied Financial Economics* 17 (13), 1061-1070

Daniels, K.N., Jensen, M.S., 2005,"The Effect of Credit Ratings on Credit Default Swap Spreads and Credit Spreads", *The Journal of Fixed Income* 15(3), 16-33

Dickinson, E., 2008, "Credit Default Swaps: So Dear To Us, So Dangerous", Fordham University – School of Law

Ericsson, J., Jacobs, K., Oviedo-Helfenberger, R., 2004, "The determinants of credit default swap premia", *SIFR Research Report Series* 32, Swedish Institute for Financial Research

Ennab, N., Gretarsson, I., 2009, "On the Pricing of Credit Default Swaps: A Comparative Study between the Reduced-Form Model and the Structural Model", Lund University, Department of Economics

Fong, W.M., See, K.H., 2001, "Modelling the conditional volatility of commodity index futures as a regime switching process. *Journal of Applied Econometrics* 16,133-163

Goldfeld, S.M., Quandt, R.E., 1965, "Some Tests for Homoscedasticity" *Journal of the American Statistical Association* 60 (310), 539-547

Goldfeld, S. M., Quandt, R.E., 1973, "A Markov Model for Switching Regressions," *Journal of Econometrics* 1, 3-16.

Gregory, R.P., 2009, “Factor determinants of credit default swap spreads”, East Tennessee State University.

Hamilton, J.D., 2005, “Regime-Switching Models”, Working Paper, University of California, Department of Economics

Hassan, M.K. Thiti S. Ngow and Jung Suk-Yu., 2011, “Determinants of Credit Default Swaps in International Markets”, Working paper, Indiana State University

Houweling, P., Vorst, T., 2005, “Pricing default swaps: Empirical evidence”, *Journal of International Money and Finance* 24 (8), 1200–1225

Hull, J., Predescu, M., White, A., 2004, “The relationship between credit default swap spreads, bond yields, and credit rating announcements”, *Journal of Banking & Finance* 28 (11), 2789–2811

Kress, J.C., 2010, “Credit Default Swap Clearinghouses and Systematic Risk: Why Centralized Counterparties Must Have Access to Central Bank Liquidity?” Available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1583912

Li, M., Wright, M., 2009, “An Application of the Hull-White Model on CDS Spread Pricing”, Lund University, Department of Economics

Longstaff, F.A., Mithal, S., Neis, E., 2005, “Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market”, *Journal of Finance* 60 (5), 2213–2253

Löffler, G., 2002, “Avoiding the rating bounce: why rating agencies are slow to react to new information”, *Journal of Economic Behavior & Organization* 56, 365-381

Made, O., Olszamowski, T., 2008, “The effect of changes in credit rating on CDS spreads – An empirical study of European companies rated by Standard & Poor’s, Moody’s and Fitch”, Stockholm School of Economics

Marcucci, J., 2005 “Forecasting Stock Market Volatility with Regime-Switching GARCH Models”, *Studies in Nonlinear Dynamics & Econometrics* 9(4), Article 6

Merton, R.C., 1974, “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates”, *The Journal of Finance* 29 (2), 449-470

Packer, F., Zhu, H., 2005, “Contractual terms and CDS Pricing”, *Bank for International Settlements*, Available at: https://www.bis.org/publ/qtrpdf/r_qt0503h.pdf

Pepitone, J., 2009, "*Tool time: Stanley buying Black & Decker*" Available at: http://money.cnn.com/2009/11/02/news/companies/stanley_black_decker_merger/index.htm

Perlin, M., 2010, MS Regress - The MATLAB Package for Markov Regime Switching Models. Available at SSRN: http://ssrn.com/abstract=1714016

Rom, M.C., 2009, "The Credit Rating Agencies and the Subprime Mess: Greedy, Ignorant, and Stressed?" *Public Administration Review* 69, 640-650

Stultz, R.N., 2009, "Credit Default Swaps and the Credit Crisis" Available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1475323

Vanden, J.M., 2006, "Portfolio Insurance and Volatility Regime Switching", *Mathematical Finance* 16, 387-417

Zhang, B, Zhou, H, Zhu, H., 2008, "Explaining Credit Default Swap Spreads With the Equity Volatility and Jump Risks of Individual Firms", *Review of Financial Studies, Forthcoming*, BIS Working Paper no. 181, Available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=713482

APPENDIX

TABLE 1: OVERVIEW OF COMPANIES SELECTED FOR STUDY

Company Name (A-J)	Sector	Company Name (J-W)	Sector
Aetna	*Healthcare*	J.P. Morgan	*Financials*
AIG	*Financials*	Kimco Reality	*Financials*
Altria Group	*Consumer*	Kraft	*Consumer*
American Express	*Financials*	Macy's	*Consumer*
Anadarko Petroleum	*Oil & Gas*	Marathon Oil	*Oil & Gas*
Apache	*Oil & Gas*	Marsh & McLennan	*Financials*
Avalonbay	*Financials*	Masco	*Industrials*
Avon Products	*Consumer*	Meadwestvaco	*Industrials*
Bank of America	*Financials*	Metlife	*Financials*
Berkshire Hathaway	*Financials*	Morgan Stanley	*Financials*
Boston Scientific	*Healthcare*	Nordstrom	*Consumer*
Caterpillar	*Industrials*	Norfolk Southern	*Industrials*
CBS	*Consumer*	Prologis	*Financials*
Citigroup	*Financials*	Prudential	*Financials*
Ford Motor	*Consumer*	Ryder System	*Industrials*
Fortune Brands	*Industrials*	Safeway	*Consumer*
Genworth Financial	*Financials*	StanleyBlack & Decker	*Consumer*
Goldman Sachs	*Financials*	Tenet Healthcare	*Healthcare*
Goodrich	*Industrials*	Textron	*Industrials*
Halliburton	*Oil & Gas*	Time Warner	*Consumer*
Home Depot	*Consumer*	WalMart	*Consumer*
Honeywell International	*Industrials*	Wells Fargo	*Financials*
Interpublic Group	*Consumer*	Whirlpool	*Consumer*
JC Penney	*Consumer*		

TABLE 2: CONSUMER SECTOR

	Constant	*LEV*	*RET*	*ΔVIX*	*ΔPC$_1$*	*ΔCDS$_{t-1}$*	*R^2*
Altria	0.013	-0.054	-0.199	0.071	-0.083	0.046	0.059
p-value	*0.100*	*0.138*	*0.034*	*0.005*	*0.160*	*0.379*	
Avon	0.002	-0.002	-0.123	0.009	-0.087	0.124	0.041
p-value	*0.824*	*0.970*	*0.147*	*0.789*	*0.113*	*0.053*	
Black&Decker	-0.016	0.052	-0.227	0.097	-0.001	0.113	0.115
p-value	*0.057*	*0.053*	*0.011*	*0.006*	*0.980*	*0.008*	
CBS	0.000	0.001	-0.067	0.079	-0.153	0.317	0.174
p-value	*0.964*	*0.955*	*0.202*	*0.076*	*0.005*	*0.000*	
Ford	-0.029	0.035	-0.283	0.157	-0.093	-0.023	0.171
p-value	*0.026*	*0.035*	*0.000*	*0.001*	*0.298*	*0.755*	
Home Depot	-0.025	0.130	-0.128	0.082	-0.023	0.191	0.114
p-value	*0.044*	*0.056*	*0.051*	*0.002*	*0.722*	*0.000*	
Interpublic	-0.016	0.042	0.004	0.031	-0.006	0.161	0.040
p-value	*0.103*	*0.141*	*0.961*	*0.199*	*0.953*	*0.004*	
JC Penney	-0.009	0.029	-0.165	0.111	-0.109	0.169	0.141
p-value	*0.358*	*0.328*	*0.004*	*0.006*	*0.075*	*0.003*	
Kraft	0.022	-0.065	-0.129	0.070	0.002	0.232	0.102
p-value	*0.228*	*0.224*	*0.279*	*0.026*	*0.967*	*0.001*	
Macy's	-0.015	0.029	-0.226	0.085	-0.078	0.199	0.177
p-value	*0.161*	*0.173*	*0.001*	*0.002*	*0.172*	*0.000*	
Nordstrom	-0.003	0.016	-0.225	0.081	-0.104	0.219	0.174
p-value	*0.683*	*0.581*	*0.000*	*0.023*	*0.171*	*0.000*	
Safeway	0.009	-0.020	-0.036	0.062	-0.129	0.140	0.063
p-value	*0.716*	*0.774*	*0.667*	*0.045*	*0.067*	*0.034*	
Time Warner	-0.005	0.016	-0.095	0.066	-0.111	0.194	0.083
p-value	*0.747*	*0.742*	*0.243*	*0.098*	*0.149*	*0.003*	
Walmart	0.007	-0.031	-0.069	0.071	-0.117	0.117	0.056
p-value	*0.627*	*0.663*	*0.697*	*0.042*	*0.204*	*0.157*	
Whirlpool	-0.002	0.011	-0.241	0.102	-0.080	0.139	0.129
p-value	*0.760*	*0.535*	*0.000*	*0.013*	*0.342*	*0.016*	

TABLE 3: FINANCIAL SECTOR

	Constant	*LEV*	*RET*	*ΔVIX*	*ΔPC$_1$*	*ΔCDS$_{t-1}$*	*R^2*
AIG	0.024	-0.026	-0.180	-0.040	-0.567	0.276	0.137
p-value	*0.067*	*0.048*	*0.221*	*0.729*	*0.096*	*0.041*	
American Express	-0.016	0.027	-0.063	0.163	-0.299	0.098	0.111
p-value	*0.551*	*0.532*	*0.384*	*0.005*	*0.030*	*0.189*	
Avalon Bay	-0.005	0.012	-0.055	0.115	-0.025	0.166	0.083
p-value	*0.712*	*0.719*	*0.351*	*0.001*	*0.738*	*0.010*	
Berkshire Hathaway	0.020	-0.065	-0.101	0.116	-0.102	0.194	0.121
p-value	*0.102*	*0.130*	*0.329*	*0.002*	*0.151*	*0.000*	
Bank of America	-0.040	0.051	-0.154	0.200	-0.320	0.110	0.184
p-value	*0.425*	*0.391*	*0.009*	*0.000*	*0.027*	*0.062*	
Citigroup	-0.037	0.045	-0.321	0.173	-0.375	0.054	0.227
p-value	*0.322*	*0.292*	*0.002*	*0.000*	*0.008*	*0.279*	
Genworth	-0.012	0.025	-0.052	0.018	-0.195	0.218	0.070
p-value	*0.547*	*0.456*	*0.239*	*0.706*	*0.046*	*0.002*	
Goldman Sachs	-0.001	0.005	-0.354	0.215	-0.397	0.170	0.223
p-value	*0.975*	*0.932*	*0.001*	*0.000*	*0.018*	*0.053*	
J.P. Morgan	-0.113	0.141	-0.027	0.276	-0.397	0.041	0.172
p-value	*0.112*	*0.108*	*0.833*	*0.000*	*0.013*	*0.542*	
Kimco	0.003	-0.007	-0.031	0.089	-0.112	0.159	0.084
p-value	*0.727*	*0.712*	*0.449*	*0.012*	*0.065*	*0.000*	
Marsh & McLennan	0.012	-0.052	-0.179	0.033	-0.163	0.192	0.103
p-value	*0.213*	*0.244*	*0.025*	*0.151*	*0.003*	*0.007*	
Morgan Stanley	0.069	-0.074	-0.282	0.154	-0.265	0.263	0.204
p-value	*0.284*	*0.297*	*0.042*	*0.001*	*0.050*	*0.018*	
ProLogis	-0.003	0.007	0.019	0.109	-0.071	0.063	0.028
p-value	*0.816*	*0.758*	*0.773*	*0.009*	*0.236*	*0.012*	
Prudential	-0.003	0.010	-0.151	0.090	-0.177	0.174	0.112
p-value	*0.867*	*0.768*	*0.010*	*0.031*	*0.107*	*0.004*	
Wells Fargo	-0.026	0.041	-0.182	0.210	-0.332	0.114	0.197
p-value	*0.111*	*0.104*	*0.025*	*0.000*	*0.018*	*0.020*	

TABLE 4: HEALTHCARE SECTOR

	Constant	*LEV*	*RET*	*ΔVIX*	*ΔPC$_1$*	*ΔCDS$_{t-1}$*	*R^2*
Aetna	0.000	0.004	-0.090	0.095	-0.050	0.216	0.099
p-value	*0.982*	*0.937*	*0.221*	*0.000*	*0.349*	*0.009*	
Boston Scientific	-0.006	0.019	-0.021	0.115	-0.059	-0.019	0.053
p-value	*0.460*	*0.476*	*0.725*	*0.000*	*0.126*	*0.723*	
Tenet	-0.007	0.010	-0.085	0.051	-0.116	0.193	0.141
p-value	*0.490*	*0.504*	*0.002*	*0.005*	*0.014*	*0.000*	

TABLE 5: INDUSTRIAL SECTOR

	Constant	*LEV*	*RET*	*ΔVIX*	*ΔPC$_1$*	*ΔCDS$_{t-1}$*	*R^2*
Caterpillar	-0.015	0.035	-0.219	0.037	-0.129	0.231	0.118
p-value	*0.245*	*0.222*	*0.023*	*0.333*	*0.148*	*0.000*	
Fortune	0.003	-0.005	-0.239	0.045	0.004	0.302	0.167
p-value	*0.783*	*0.860*	*0.026*	*0.083*	*0.931*	*0.000*	
Goodrich	0.008	-0.033	0.033	0.104	-0.111	0.224	0.109
p-value	*0.501*	*0.552*	*0.713*	*0.016*	*0.071*	*0.005*	
Honeywell	-0.005	0.029	-0.082	0.117	-0.140	0.154	0.106
p-value	*0.599*	*0.537*	*0.337*	*0.005*	*0.073*	*0.019*	
Masco	0.001	0.000	-0.151	0.102	-0.097	0.112	0.153
p-value	*0.917*	*0.991*	*0.005*	*0.005*	*0.126*	*0.023*	
Meadwestvaco	0.012	-0.028	-0.130	0.073	-0.089	0.183	0.111
p-value	*0.091*	*0.136*	*0.033*	*0.015*	*0.141*	*0.000*	
Norfolk	0.002	-0.005	-0.243	0.051	-0.132	0.219	0.133
p-value	*0.852*	*0.901*	*0.005*	*0.175*	*0.136*	*0.005*	
Ryder	0.001	-0.001	-0.207	0.108	0.028	0.095	0.127
p-value	*0.920*	*0.984*	*0.000*	*0.001*	*0.613*	*0.063*	
Textron	0.004	-0.003	-0.140	0.071	-0.164	0.195	0.110
p-value	*0.676*	*0.885*	*0.117*	*0.095*	*0.042*	*0.000*	

TABLE 6: OIL AND GAS SECTOR

	Constant	*LEV*	*RET*	*ΔVIX*	*ΔPC$_1$*	*ΔCDS$_{t-1}$*	*R^2*
Anadarko	-0.024	0.083	-0.587	-0.060	-0.087	0.235	0.177
p-value	*0.175*	*0.148*	*0.011*	*0.298*	*0.197*	*0.000*	
Apache	-0.002	0.019	-0.176	0.069	0.009	0.060	0.049
p-value	*0.835*	*0.697*	*0.155*	*0.047*	*0.906*	*0.529*	
Halliburton	0.006	-0.021	-0.260	-0.031	-0.094	0.171	0.063
p-value	*0.284*	*0.552*	*0.061*	*0.347*	*0.174*	*0.002*	
Marathon	0.014	-0.053	-0.025	0.040	-0.017	0.186	0.053
p-value	*0.080*	*0.110*	*0.641*	*0.115*	*0.823*	*0.000*	

TABLE 7: PARAMETER STABILITY FROM CHOW BREAKPOINT TEST

Company Name (A-J)	*p-value*	*Company Name (J-W)*	*p-value*
Aetna	*0.004*	J.P. Morgan	*0.000*
AIG	*0.009*	Kimco Reality	*0.008*
Altria Group	*0.519*	Kraft	*0.556*
American Express	*0.001*	Macy's	*0.134*
Anadarko Petroleum	*0.000*	Marathon Oil	*0.014*
Apache	*0.000*	Marsh & McLennan	*0.084*
Avalonbay	*0.000*	Masco	*0.459*
Avon Products	*0.000*	Meadwestvaco	*0.344*
Bank of America	*0.012*	Metlife	*0.009*
Berkshire Hathaway	*0.003*	Morgan Stanley	*0.074*
Boston Scientific	*0.033*	Nordstrom	*0.141*
Caterpillar	*0.002*	Norfolk Southern	*0.027*
CBS	*0.000*	Prologis	*0.001*
Citigroup	*0.000*	Prudential	*0.081*
Ford Motor	*0.000*	Ryder System	*0.135*
Fortune Brands	*0.060*	Safeway	*0.148*
Genworth Financial	*0.000*	StanleyBlack & Decker	*0.342*
Goldman Sachs	*0.037*	Tenet Healthcare	*0.118*
Goodrich	*0.142*	Textron	*0.001*
Halliburton	*0.034*	Time Warner	*0.503*
Home Depot	*0.069*	WalMart	*0.003*
Honeywell International	*0.033*	Wells Fargo	*0.002*
Interpublic Group	*0.000*	Whirlpool	*0.000*
JC Penney	*0.013*		

Under a significance level of 5 %, several of the companies above display parameter instability.

TABLE 8

	Consumer Sector: *LEV*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Altria	0.000	0.740	-0.332	0.070
Avon	0.000	0.920	-0.231	0.030
Black&Decker	-0.001	0.750	-0.316	0.000
CBS	0.000	0.490	-0.148	0.010
Ford	-0.194	0.000	-0.305	0.000
Home Depot	-0.001	0.140	-0.191	0.070
Interpublic	0.000	0.830	0.004	0.930
JC Penney	-0.061	0.050	-0.402	0.000
Kraft	-0.002	1.000	-0.296	0.080
Macy's	-0.032	0.140	-0.385	0.000
Nordstrom	0.000	1.000	-0.350	0.000
Safeway	-0.001	0.510	-0.162	0.260
Time Warner	0.000	0.770	-0.238	0.060
Walmart	-0.003	0.410	-0.049	0.790
Whirlpool	0.001	0.730	-0.357	0.000

TABLE 9

	Financial Sector: *LEV*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
AIG	-0.051	0.020	-1.072	0.000
American Express	-0.126	0.010	0.632	0.360
Avalon Bay	0.000	0.810	0.038	0.470
Berkshire Hathaway	-0.001	0.620	-0.209	0.070
Bank of America	-0.147	0.000	-0.230	0.020
Citigroup	-0.126	0.000	-0.565	0.000
Genworth	0.000	0.240	-0.133	0.020
Goldman Sachs	-0.264	0.000	-1.803	1.000
J.P. Morgan	-0.188	0.000	0.545	0.110
Kimco	0.001	0.210	-0.080	0.170
Marsh & McLennan	0.000	0.570	-0.527	0.000
Metlife	0.000	0.890	-0.164	0.020
Morgan Stanley	-0.122	0.000	-1.658	0.030
ProLogis	0.000	0.860	0.000	1.000
Prudential	0.000	0.640	-0.247	0.000
Wells Fargo	-0.071	0.090	-0.418	0.010

TABLE 10

	Healthcare Sector: *LEV*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Aetna	0.000	0.340	-0.219	0.030
Boston Scientific	0.000	0.900	-0.128	0.240
Tenet	0.000	0.460	-0.096	0.000

TABLE 11

	Industrial Sector: *LEV*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Caterpillar	0.000	0.650	-0.426	0.000
Fortune	0.001	0.360	-0.359	0.000
Goodrich	-0.002	0.250	-0.022	0.920
Honeywell	-0.003	0.100	-0.331	0.040
Masco	0.002	0.080	-0.225	0.000
Meadwestvaco	0.000	0.960	-0.269	0.010
Norfolk	-0.003	0.180	-0.464	0.000
Ryder	0.001	0.330	-0.317	0.000
Textron	0.001	0.400	-0.223	0.000

TABLE 12

	Oil & Gas *LEV*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Anadarko	-0.784	0.000	-0.001	0.170
Apache	-0.001	0.340	-0.233	0.060
Chevron	0.000	0.910	-0.023	0.930
Halliburton	0.000	0.900	-0.635	0.000
Marathon	0.000	0.870	-0.076	0.510

TABLE 13

	Consumer Sector: *RET*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Altria	0.000	1.000	0.023	0.090
Avon	0.000	1.000	-0.039	0.220
Black&Decker	0.0001	0.890	-0.028	0.020
CBS	0.000	1.000	0.003	0.630
Ford	-0.032	0.000	-0.032	0.400
Home Depot	0.000	0.520	-0.045	0.000
Interpublic	0.000	0.870	-0.018	0.020
JC Penney	-0.009	0.050	-0.006	0.820
Kraft	0.000	1.000	0.054	0.060
Macy's	-0.011	0.010	-0.016	0.370
Nordstrom	0.000	1.000	-0.004	0.610
Safeway	0.000	0.770	0.018	0.520
Time Warner	0.000	1.000	-0.003	1.000
Walmart	0.000	0.800	0.034	0.340
Whirlpool	0.000	0.760	-0.003	0.730

TABLE 14

	Financial Sector: *RET*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
AIG	0.0171	0	0.0707	0.4
American Express	0	0.95	-0.166	0.43
Avalon Bay	0	0.91	-0.0157	0.45
Berkshire Hathaway	0	1	0.0324	0.03
Bank of America	0.0012	1	-0.0633	0.39
Citigroup	-0.0043	0.84	-0.1959	0.54
Genworth	-0.0001	0.1	-0.0211	0.26
Goldman Sachs	-0.0088	1	-0.2208	1
J.P. Morgan	-0.0735	0.09	-0.3952	0.26
Kimco	0	0.87	0.0061	0.68
Marsh & McLennan	-0.0001	0.14	0.0294	0.14
Metlife	-0.0001	0.7	0.026	0.2
Morgan Stanley	0.0572	0.19	1.0804	0.35
ProLogis	-0.0002	0.04	-0.0079	0.7
Prudential	-0.0002	0.52	0.0018	1
Wells Fargo	-0.0096	0.4	-0.0761	0.32

TABLE 15

	Healthcare Sector: *RET*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Aetna	0.000	1.000	-0.002	1.000
Boston Scientific	0.000	0.370	-0.011	0.650
Tenet	0.000	0.280	-0.011	0.250

TABLE 16

	Industrial Sector: *RET*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Caterpillar	0.000	0.210	-0.024	0.120
Fortune	0.000	1.000	0.006	0.530
Goodrich	0.000	0.330	0.025	0.080
Honeywell	0.000	0.810	-0.003	0.860
Masco	0.000	0.260	0.000	1.000
Meadwestvaco	0.000	0.960	0.020	0.110
Norfolk	0.000	0.410	0.012	0.450
Ryder	0.000	0.690	0.001	1.000
Textron	0.000	0.070	0.007	0.580

TABLE 17

	Oil & Gas *RET*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Anadarko	-0.035	0.100	0.000	0.530
Apache	0.000	0.890	-0.004	0.810
Chevron	0.000	1.000	0.047	0.110
Halliburton	0.000	0.650	0.012	0.380
Marathon	0.000	0.890	0.037	0.060

TABLE 18

	Consumer Sector: *ΔVIX*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Altria	0.000	1.000	-0.097	0.120
Avon	0.000	0.760	-0.001	1.000
Black&Decker	0.000	1.000	0.117	0.020
CBS	0.000	0.470	-0.003	0.790
Ford	0.038	0.000	0.038	0.370
Home Depot	0.000	0.610	0.233	0.010
Interpublic	0.000	0.820	0.048	0.020
JC Penney	0.020	0.130	0.034	0.670
Kraft	0.000	1.000	-0.165	0.050
Macy's	0.017	0.010	0.033	0.300
Nordstrom	0.000	1.000	0.016	0.480
Safeway	0.000	0.760	-0.043	0.600
Time Warner	0.000	1.000	0.007	1.000
Walmart	0.000	0.910	-0.187	0.350
Whirlpool	0.000	0.840	0.016	0.530

TABLE 19

	Financial Sector: *ΔVIX*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
AIG	-0.022	0.000	-0.039	0.730
American Express	-0.004	0.170	0.356	0.280
Avalon Bay	0.000	0.810	0.038	0.470
Berkshire Hathaway	0.000	1.000	-0.106	0.050
Bank of America	-0.002	1.000	0.085	0.330
Citigroup	0.007	0.790	0.235	0.510
Genworth	0.000	0.070	0.043	0.150
Goldman Sachs	0.011	1.000	0.294	1.000
J.P. Morgan	0.089	0.100	0.504	0.250
Kimco	0.000	0.580	-0.017	0.610
Marsh & McLennan	0.001	0.110	-0.126	0.180
Metlife	0.000	0.680	-0.047	0.280
Morgan Stanley	-0.062	0.200	-1.187	0.360
ProLogis	0.000	0.010	0.016	0.650
Prudential	0.000	0.380	0.004	1.000
Wells Fargo	0.015	0.380	0.116	0.270

TABLE 20

	Healthcare Sector: *ΔVIX*			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Aetna	0.000	0.800	0.014	1.000
Boston Scientific	0.000	0.370	0.030	0.710
Tenet	0.000	0.220	0.017	0.210

TABLE 21

	Industrial Sector: ΔVIX			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Caterpillar	0.000	0.210	0.055	0.070
Fortune	0.000	1.000	-0.011	0.630
Goodrich	-0.001	0.470	-0.107	0.100
Honeywell	0.000	0.920	0.023	0.780
Masco	0.001	0.220	0.001	1.000
Meadwestvaco	0.000	0.980	-0.047	0.120
Norfolk	-0.001	0.400	-0.045	0.440
Ryder	0.000	0.520	0.001	1.000
Textron	0.000	0.040	-0.004	0.830

TABLE 22

	Oil & Gas ΔVIX			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Anadarko	0.121	0.060	0.000	1.000
Apache	0.000	0.870	0.034	0.740
Chevron	0.000	1.000	-0.693	0.140
Halliburton	0.000	0.700	-0.020	0.830
Marathon	0.000	0.470	-0.141	0.070

TABLE 23

	Consumer Sector: ΔPC_1			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Altria	0.000	0.550	0.117	0.000
Avon	0.001	0.100	0.049	0.200
Black&Decker	0.000	1.000	0.193	0.000
CBS	0.000	0.720	0.145	0.000
Ford	0.074	0.000	0.245	0.000
Home Depot	-0.001	0.000	0.168	0.000
Interpublic	0.000	0.790	0.046	0.120
JC Penney	0.058	0.000	0.230	0.000
Kraft	0.000	1.000	0.155	0.000
Macy's	0.035	0.000	0.164	0.000
Nordstrom	0.000	1.000	0.131	0.000
Safeway	-0.001	0.430	0.132	0.000
Time Warner	0.000	0.680	0.122	0.010
Walmart	0.001	0.440	0.176	0.000
Whirlpool	0.000	0.780	0.141	0.000

TABLE 24

	Financial Sector: ΔPC_1			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
AIG	0.097	0.000	-0.479	0.270
American Express	0.165	0.000	0.165	0.540
Avalon Bay	0.000	0.810	0.249	0.000
Berkshire Hathaway	0.000	0.080	0.189	0.000
Bank of America	0.143	0.000	0.237	0.000
Citigroup	0.194	0.000	0.412	0.090
Genworth	0.000	0.130	0.065	0.320
Goldman Sachs	0.187	0.000	-0.043	1.000
J.P. Morgan	0.149	0.000	0.535	0.000
Kimco	0.000	0.490	0.159	0.000
Marsh & McLennan	0.000	0.210	0.051	0.170
Metlife	-0.001	0.370	0.135	0.010
Morgan Stanley	0.200	0.000	-0.325	0.510
ProLogis	0.000	0.470	0.205	0.000
Prudential	0.000	0.840	0.168	0.000
Wells Fargo	0.163	0.000	0.384	0.000

TABLE 25

	Healthcare Sector: ΔPC_1			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Aetna	0.000	0.160	0.198	0.000
Boston Scientific	0.000	0.300	0.193	0.000
Tenet	0.000	0.000	0.082	0.000

TABLE 26

	Industrial Sector: ΔPC_1			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Caterpillar	0.000	1.000	0.064	0.140
Fortune	0.000	0.530	0.101	0.000
Goodrich	0.000	0.620	0.179	0.000
Honeywell	0.000	0.610	0.183	0.000
Masco	0.000	0.900	0.149	0.000
Meadwestvaco	0.000	0.670	0.110	0.010
Norfolk	0.000	0.640	0.092	0.040
Ryder	0.000	0.720	0.170	0.000
Textron	0.000	0.480	0.131	0.000

TABLE 27

	Oil & Gas ΔPC_1			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Anadarko	-0.080	0.140	0.000	1.000
Apache	0.000	0.920	0.135	0.020
Chevron	0.000	0.560	-0.024	0.760
Halliburton	0.000	0.850	-0.080	0.320
Marathon	0.000	0.760	0.113	0.040

TABLE 28

	Consumer Sector: ΔCDS_{t-1}			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Altria	0.000	0.550	-0.174	0.100
Avon	0.003	0.000	-0.206	0.020
Black&Decker	0.009	0.000	-0.055	0.500
CBS	0.000	0.390	-0.191	0.010
Ford	-0.088	0.070	-0.093	0.510
Home Depot	0.001	0.140	-0.044	0.590
Interpublic	0.000	0.940	-0.014	0.880
JC Penney	-0.080	0.040	-0.189	0.240
Kraft	0.003	0.000	-0.088	0.320
Macy's	-0.032	0.250	-0.190	0.060
Nordstrom	-0.001	0.790	-0.139	0.070
Safeway	0.001	0.750	-0.309	0.000
Time Warner	0.003	0.000	-0.176	0.060
Walmart	0.009	0.000	-0.266	0.010
Whirlpool	-0.003	0.150	-0.169	0.060

TABLE 29

	Financial Sector: ΔCDS_{t-1}			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
AIG	-0.074	0.180	-4.917	0.030
American Express	-0.101	0.060	-3.726	0.000
Avalon Bay	0.000	0.560	-0.039	0.730
Berkshire Hathaway	-0.004	0.000	-0.226	0.020
Bank of America	-0.032	0.510	-0.921	0.000
Citigroup	-0.158	0.000	-3.374	0.000
Genworth	0.002	0.000	-0.340	0.030
Goldman Sachs	-0.194	0.000	-4.296	1.000
J.P. Morgan	-0.126	0.010	-2.693	0.000
Kimco	-0.001	0.020	-0.199	0.050
Marsh & McLennan	0.000	0.940	-0.272	0.000
Metlife	0.001	0.690	-0.346	0.000
Morgan Stanley	-0.190	0.000	-2.546	0.140
ProLogis	-0.001	0.380	-0.135	0.420
Prudential	0.003	0.130	-0.266	0.030
Wells Fargo	-0.111	0.030	-1.467	0.000

TABLE 30

	Healthcare Sector: ΔCDS_{t-1}			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Aetna	0.001	0.000	-0.147	0.190
Boston Scientific	-0.001	0.000	-0.091	0.450
Tenet	0.000	0.050	-0.170	0.000

TABLE 31

	Industrial Sector: ΔCDS_{t-1}			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Caterpillar	0.002	0.000	-0.196	0.040
Fortune	-0.001	0.030	-0.022	0.750
Goodrich	0.008	0.000	-0.249	0.010
Honeywell	0.005	0.010	-0.274	0.000
Masco	-0.004	0.000	-0.135	0.050
Meadwestvaco	-0.002	0.130	-0.171	0.060
Norfolk	0.007	0.000	-0.313	0.000
Ryder	-0.002	0.000	-0.013	0.900
Textron	-0.002	0.030	-0.229	0.030

TABLE 32

	Oil & Gas ΔCDS_{t-1}			
	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Anadarko	-0.123	0.310	0.002	0.050
Apache	0.006	0.000	-0.021	0.860
Chevron	0.005	0.000	-0.218	0.180
Halliburton	0.003	0.000	-0.190	0.230
Marathon	0.000	0.410	-0.046	0.690

TABLE 33: CONSUMER SECTOR

	Expected Duration Regime 1	Expected Duration Regime 2
Altria	2.7	2.18
Avon	2.42	2.19
Black&Decker	2.71	3.14
CBS	1.6	4.38
Ford	14.91	9.25
Home Depot	2.11	2.45
Interpublic	2.1	5.23
JC Penney	6.43	2.93
Kraft	2.41	2.43
Macy's	3.12	2.68
Nordstrom	1.83	3.53
Safeway	3.06	1.97
Time Warner	2.07	2.66
Walmart	2.82	2.09
Whirlpool	1.91	3.08

TABLE 34: FINANCIAL SECTOR

	Expected Duration Regime 1	Expected Duration Regime 2
AIG	18.3	1.99
American Express	26.32	1.79
Avalon Bay	2.75	2.09
Berkshire Hathaway	2.11	2.55
Bank of America	7.29	3.86
Citigroup	18.57	1.79
Genworth	2.21	2.88
Goldman Sachs	23.03	1.86
J.P. Morgan	7.2	1.32
Kimco	2.55	2.1
sMarsh & McLennan	2.54	2.45
Metlife	1.84	3.37
Morgan Stanley	93.59	5.06
ProLogis	2.52	1.93
Prudential	2.12	3.07
Wells Fargo	7.49	1.73

TABLE 35: HEALTHCARE SECTOR

	Expected Duration Regime 1	Expected Duration Regime 2
Aetna	2.36	2.04
Boston Scientific	2.68	2.07
Tenet	1.55	3.94

TABLE 36: INDUSTRIAL SECTOR

	Expected Duration Regime 1	Expected Duration Regime 2
Caterpillar	1.93	3.39
Fortune	2.02	2.76
Goodrich	2.63	2.75
Honeywell	2.35	2.92
Masco	2.09	3.2
Meadwestvaco	2.07	2.5
Norfolk	2.64	2.82
Ryder	2.24	3.07
Textron	1.83	2.8

TABLE 37: OIL AND GAS SECTOR

	Expected Duration Regime 1	Expected Duration Regime 2
Anadarko	3.41	2.32
Apache	3.07	2.19
Chevron	4.26	1.79
Halliburton	3.03	2.12
Marathon	3.31	1.92

TABLE 38

	LEV			
Sector	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Consumer	-0.001	0.730	-0.296	0.030
Financial	-0.149	0.261	0.025	0.139
Healthcare	0.000	0.460	-0.128	0.030
Oil and Gas	0.000	0.870	-0.076	0.170
Industrial	0.000	0.330	-0.317	0.000

TABLE 39

	RET			
Sector	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Consumer	0.000	0.870	-0.004	0.370
Financial	0.000	0.610	-0.012	0.395
Healthcare	0.000	0.370	-0.011	0.650
Oil and Gas	0.000	0.890	0.012	0.380
Industrial	0.000	0.410	0.006	0.530

TABLE 40

	ΔVIX			
Sector	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Consumer	0.000	0.820	0.016	0.370
Financial	0.000	0.380	0.027	0.345
Healthcare	0.000	0.370	0.017	0.710
Oil and Gas	0.000	0.700	-0.020	0.740
Industrial	0.000	0.470	-0.004	0.630

TABLE 41

	ΔPC_1			
Sector	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Consumer	0.000	0.550	0.145	0.000
Financial	0.049	0.040	0.167	0.005
Healthcare	0.000	0.160	0.193	0.000
Oil and Gas	0.000	0.760	0.000	0.320
Industrial	0.000	0.640	0.131	0.000

[11] Median values

TABLE 42

	ΔCDS_{t-1}			
Sector	Value State 1	Prob. State 1	Value State 2	Prob. State 2
Consumer	0.000	0.140	-0.174	0.070
Financial	-0.018	0.045	-0.633	0.025
Healthcare	0.000	0.017	-0.136	0.213
Oil and Gas	0.003	0.000	-0.046	0.230
Industrial	-0.001	0.000	-0.196	0.040

TABLE 43

Sector	**Expected Duration Regime 1**	**Expected Duration Regime 2**
Consumer	2.420	2.680
Financial	4.975	2.095
Healthcare	2.360	2.070
Oil and Gas	3.310	2.120
Industrial	2.090	2.820

TABLE 44: VARIANCE FROM MARKOV SWITCHING MODEL FOR ALL SECTORS

Variance Consumer Sector		
Company	Regime 1	Regime 2
Altria	0.00000	0.00268
Avon	0.00000	0.00209
Black&Decker	0.00000	0.00253
CDS	0.00000	0.00229
Ford	0.00044	0.00495
Home Depot	0.00000	0.00227
Interpublic	0.00000	0.00161
JC Penney	0.00026	0.00444
Kraft	0.00000	0.00231
Macy's	0.00010	0.00304
Nordstrom	0.00000	0.00260
Safeway	0.00000	0.00303
Time Warner	0.00000	0.00306
Walmart	0.00000	0.00316
Whirlpool	0.00000	0.00304
Average	**0.00005**	**0.00287**

Variance Financial Sector		
Company	Regime 1	Regime 2
AIG	0.00103	0.09405
American Express	0.00148	0.01566
Avalonbay	0.00000	0.00393
Berkshire Hathaway	0.00000	0.00288
Bank of America	0.00070	0.00741
Citigroup	0.00118	0.02000
Genworth	0.00000	0.00763
Goldman	0.00140	0.02330
J.P. Morgan	0.00101	0.01194
Kimco	0.00000	0.00289
Marsh & McLennan	0.00000	0.00195
Metlife	0.00000	0.00562
Morgan Stanley	0.00138	0.05413
ProLogis	0.00000	0.00633
Prudential	0.00000	0.00552
Wells Fargo	0.00096	0.01049
Average	**0.00057**	**0.01711**

Variance Industrial Sector		
Company	Regime 1	Regime 2
Caterpillar	0.00000	0.00334
Fortune	0.00000	0.00183
Goodrich	0.00000	0.00270
Honeywell	0.00000	0.00306
Masco	0.00000	0.00171
Meadwestvaco	0.00000	0.00243
Norfolk	0.00000	0.00309
Ryder	0.00000	0.00221
Textron	0.00000	0.00409
Average	**0.00000**	**0.00272**

Variance Healthcare Sector		
Company	Regime 1	Regime 2
Aetna	0.00000	0.00346
Boston Scientific	0.00000	0.00317
Tenet	0.00000	0.00099
Average	**0.00000**	**0.00254**

Variance Oil & Gas Sector		
Company	Regime 1	Regime 2
Anadarko	0.00562	0.00000
Apache	0.00000	0.00450
Chevron	0.00000	0.00539
Halliburton	0.00000	0.00665
Marathon	0.00000	0.00366
Average	**0.00112**	**0.00404**

TABLE 45: OVERVIEW OF RELATED RESEARCH FINDINGS

Study	CDS Spread Proxy	Sample Period / Frequency	Determinants	Findings
Abid and Naifar (2006)	Starting price Single-Name	15 May 2000 - 15 Mars 2001 / 207 trades	Credit Rating Time to Maturity Risk-free rate Slope of the yield curve Equity Volatility	66 % of variation in CDS spreads
Alexander and Kaeck (2007)	CDS Indices	June 2004 - June 2007 / Daily quotes	Change in Volatility Stock return Interest rate level Slope of the yield curve Lag of CDS	17 % of variation in CDS spreads
Blanco et al. (2005)	Bid/Offer Quotes Single-Name	Jan 2001 - Jun 2002 / Daily quotes	Changes in the spot rate Changes in the slope of the yield curve Equity Returns Changes in implied volatility Changes in the slop of the smirk Stock return	25 % of variation in CDS spreads
Cossin and Hricko (2001)	Bid/Offer Quotes Single-Name	Jan 1998 - Feb 2002 / 392 trades	Credit Rating Interest rates Slope of the yield curve Time to Maturity Stock Price changes Equity Volatility Leverage Market Cap	82 % of variation in CDS spreads
Ericsson et al. (2004)	Bid/Offer Quotes Single-Name	1999 - 2002 / 4813 bid and 5436 offer quotes	Leverage Volatility Risk-free rate Slope of the yield curve Stock return Slope of smirk	60 % of variation in CDS spreads