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DETERMINANTS OF U.S. CORPORATE CREDIT SPREADS

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Abstract

This thesis deals with various issues regarding determinants of US corporate credit spreads. These spreads are estimated as the difference between yields to maturity for corporate bonds and default-free instruments (Treasury bonds) of the same maturity. Corporate credit spreads are considered as measures of default risk. However, the premium required by investors for holding risky rather than risk-free bonds will incorporate a compensation not only for the default risk but also for other factors related to corporate bonds such as market liquidity or tax differential between corporate and Treasury bonds. In this study we firstly examine the relationship between bond ratings and credit spreads given that bond rating changes are expected to carry some informational value for debt investors. The findings indicate that bond ratings generally carry some informational value for corporate bond investors. The Granger causal relationship is more evident for negative watch lists and during periods of uncertainty in financial markets. In line with previous studies, our results suggest that changes in credit spreads are significantly related to interest rate levels, systematic risk factors (Fama and French) factors and equity returns.

Keywords: credit spreads, default risk, bond ratings, bond pricing, panel Granger caUSality, panel data ARCH/GARCH analysis

JEL Classifications: G10, G24, G12, E44

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Chapter One: Introduction

The volatility in bond markets and the advent of credit derivatives have increased researchers' interests in the area of credit risk pricing. Many researchers are trying to develop models that can assist bond investors in exploring factors that drive returns on risky corporate bonds.

Corporate bonds are financial instruments issued by firms in return for access to medium and long-term funding. They can be categorised in different groups depending on their characteristics such as maturity, coupon, collateral, various types of options, etc. Generally, corporate bonds have a longer maturity than 2 years. They can be Used for investment, hedging and speculative purposes. The largest holders of corporate bonds in the US market are insurance companies, followed by private pension funds and commercial banks. Banks often purchase investment corporate bonds for investment purposes in order to benefit from relatively high yields provided by these financial instruments.

While Treasury securities are considered to be default free, corporate bonds are prone to credit risk. "Credit risk can be defined as the possibility that contractual counterparty does not meet its obligations stated in the contract, thereby causing the creditor a financial loss. …A debt contract involving a high amount of credit risk must promise a higher return to the investor than a contract considered less credit risky by market participants." (Amman, 2001:1) The difference in yields to maturity between a corporate bond and a Treasury bond of the same maturity is considered to represent the credit risk borne by corporate bond investors and is referred to as corporate credit spread.

Since credit spreads are considered to capture bonds' default risk, they are expected to depend greatly on bonds' assigned ratings. Corporate bonds are assigned quality ratings by rating agencies. These ratings represent bonds' probability of going into default. Changes in a bond's rating indicate a higher or lower default probability in the future. Investors will be expected to react upon news of bond rating changes leading in turn to changes in corporate credit spreads. Some of the studies on the relationship between bond rating changes and returns on financial assets (Hooper et al (2007), Hothouse and Leftwich (1986), Hand et al (1992), Cantor and Parker (1996) etc.) report significant abnormal bond returns associated with news of downgrades. These findings indicate that bond ratings have some informational value and hence bond rating changes lead changes in returns of financial assets.

On the other side, the unexpected defaults of very highly rated firms (Enron, World.Com, etc.) have put into question the informational value of credit ratings. In order to gain a better understanding on the information that bond ratings convey to the market, some studies (Loffler (2004), Cantor and Mann (2003), etc.) focus on the examination of credit ratings process. Cantor and Mann (2003) argue that in order to achieve the assigned monitoring role in the capital markets, rating agencies try to avoid making rating changes which would later be reversed. Generally, market participants would prefer accurate and stable ratings. However, Cantor and Mann (2003) state that there is a trade-off between rating accuracy and stability. They further argue that the introduction of credit watch lists is intended at easing this tension between ratings accuracy and stability.

Loffler (2004) however notes that the avoidance of rating reversals by delaying rating changes may lead to a loss of information in the market. He further explains that credit ratings are not a reflection of short-term credit risk, but they are rather a reflection of the long-term creditworthiness quality. Hence, the long-term view ratings (known as through-the-cycle ratings) assigned by rating agencies may neglect some information, but they do convey additional information which is not contained in current-conditions ratings. In addition, some other studies (Kou and Varotto (2008), Loffler (2005), etc.) indicate that changes in bond ratings lag changes in credit spreads.

Following this mixed evidence on the relationship between bond ratings and credit spreads one would like to gain a better understanding of the causal relationship between bond ratings and credit spreads. Reisen and Maltzan (1999)'s study examines the causal relationship between sovereign ratings and yield spreads of dollar sovereign bonds. Their findings suggest that changes in sovereign ratings and changes in sovereign bond yields are mutually interdependent. To our knowledge, the causal relationship between ratings and bond yields in the context of corporate bonds is not explored. Hence, one of the objectives of this research is the investigation of Granger causality between bond ratings and corporate credit spreads.

Bond ratings may be one of the factors that explain the variation in corporate spreads. Considering that the aim of this study is the examination of determinants of US corporate credit spreads, the relationship between credit spreads and various market-based factors is examined in the second part of this study. Various academic papers in the area of credit pricing suggest that corporate credit spreads provide compensations that are higher than the premiums for default risk of these bonds. Fisher (1959) suggests that corporate bondholders will require a risk premium which for a rational investor "will depend on the probability that the issuing firm's earnings will be too small to permit it to pay its debts and on the ease with which the bondholder can turn the bond into cash before it matures." Thereby, corporate credit spreads may represent a premium for compensation not only to default risk, but also to liquidity risk and to the differential tax treatment between Treasury and corporate bonds.

The research in the area of credit risk has been characterised by models that try to capture credit spreads by using either stochastic or econometrical techniques. Within stochastic-based models, one can distinguish between structural or firm-value models and reduced-form or intensity-based models. Structural models are based on the option pricing theory (contingent claims analysis) where a firm's value is assumed to follow a stochastic process and it is modelled as a call option with the strike price equal to that of debt's face value. The payoffs to debt-holders are then modelled as a difference between debt's face value and a put option on the firm's value. In these models a firm's default risk is related to firm's gearing level and its underlying assets' value, bond's characteristics and interest rate levels (Merton (1974), Geske (1977), Longstaff and Schwartz (1995), Leland and Toft (1996), etc.). Implementation of structural models fails to provide credit spreads that are similar to those observed in the market. These models ignore default events especially in the case of highly rated firms and are not relevant for privately held firms. Furthermore, they are based in very strong assumptions regarding interest rate and firm's value processes and the timing of a firm's default.

Unlike, structural (firm-value) models, the reduced form models assume that default probability is determined by a jump-intensity process which allows for any bond rating changes. These models use observed credit spreads and calibrated methods to derive jump parameters (Duffie and Singleton (1995), Jarrow and Turnbull (1995), etc). Their main limitation is that they assume similar default processes for every bond within the same rating class when it is well known that bonds in the same rating class have different patterns of credit spreads. Another key limitation of reduced-form models is that they ignore firms' financial fundamentals such as asset value, financial gearing levels, profitability levels, etc.

The difference between observed and estimated credit spreads using both structural and reduced-form approaches has led to what in finance is known as the credit spreads' puzzle. Most of the recent studies are focused on the empirical assessment of various factors and relationships that may explain this puzzle. Due to the availability of data for individual bonds in the last few years, various econometric approaches have been employed in order to examine the factors that affect credit spreads. However, the empirical evidence provided from these approaches so far is inconclusive.

The seminal paper by Collin-Dufresne et al. (2001) utilizes various factors (firm-specific and macroeconomic variables) to explain the behaviour of US credit spreads. Their findings suggest that the variance in changes of credit spreads is mainly explained by a common factor that is independent of the equity returns, credit swaps and other Treasury bonds yields.

Other empirical papers find that corporate credit spreads incorporate a liquidity premium (Chen et al. (2007), Campbell and Taksler (2003), etc.), whereas a study by Elton et al. (2001) indicates that along with default risk and market liquidity another important factor that explains changes in credit spreads is the difference in tax treatment of Treasury and corporate bonds yields. Additionally, the evidence provided by Avromov et al. (2007) indicate that a great proportion of variation in credit spreads changes of high yield bonds is explained by default risk related variables. They further argue that high yield bonds behave more like equity, whereas investment grade bonds more like Treasury securities.

It can be suggested that although existing studies provide an insight to the determinants of credit spreads, there is still an on-going debate on the factors (firm-level or macroeconomic) that may help explain the variation in these spreads. In this study, we examine in detail the relationships between credit spreads and various market-related factors suggested by previous empirical studies. This study will cover a period characterised by various economic events. This will help explore which factors drive credit spreads in difficult (recessionary) and tranquil economic times. In addition, the study aims to investigate whether the same factors drive credit spreads for both investment-grade and speculative bonds.

In the next section we discuss in more detail the aim, objectives and research questions of this thesis and explain how this study will contribute to the existing and on-going research in the area of credit risk.

1.1. Aim, Objectives, Research Questions and the Contribution of the Thesis

This research aims to examine the factors that drive credit spreads of US corporate bonds. To achieve this aim, the following objectives are proposed:

- to provide a literature review on the informational value of credit ratings,

- to undertake a literature review of previous studies in the area of credit risk pricing focusing particularly on the factors that may explain corporate credit spreads,

- to empirically explore the causal relationship between changes in bond ratings and changes in credit spreads,

- to empirically examine factors that may help explain the behaviour of U.S. corporate credit spreads in both recessionary and growth economic periods.

Research Questions

The study addresses two main questions.

Q1: Do changes in bond ratings "Granger cause" changes in credit spreads?

Credit ratings serve not only the purpose of indicating the probability of a borrower failing to honour its financial obligations, but also act as an important factor in multi-factor risk models and empirical analysis of corporate bonds. Assuming that default risk premium explains a large proportion of credit spread and a bond rating captures this default risk as claimed by rating agencies, one expects credit spreads to be closely linked to bond ratings. Furthermore, rating agencies utilise extensive public and private information before announcing a rating. Thus bond ratings may be viewed as mechanisms that can assist issuers in transmitting inside information to capital markets. Investors will react to the new information causing corporate credit spreads to change.

In order to empirically explore this causal relationship, we employ the Granger causality methodology in a panel data context. To our knowledge, this innovative econometric method has not been previously applied in the context of corporate bond ratings. Furthermore, empirical findings of whether bond ratings "Granger cause" credit spreads or the other way around will shed more light on the role of bond ratings and r ating agencies in corporate bond markets. This in turn will have important implications for portfolio managers because their decisions on portfolio reconstructions may be based on bond rating constraints. Managers of some investment portfolios may not be allowed to invest in corporate bonds whose ratings are lower than A. In the case when bond rating changes do not cause any significant changes in credit spreads, then such restrictions on portfolio reconstructions may need to be reviewed. Furthermore, findings of the Granger relationship between credit spreads and bond ratings will shed more light on whether rating agencies favour rating accuracy rather than rating stability.

Applications of Granger causality tests will be employed for four sub-periods in the sampling period. Each sub-period is characterised by important development in the U.S. financial markets. The examination of the causal relationship in these sub-periods will shed more light on role of credit rating agencies in various economic times. Granger test will also be employed for subsamples of rating changes and credit watch lists. This will help understand better the role of watch lists in lessening the conflict between accuracy and stability of ratings.

Q2: Which market-related factors explain US corporate credit spreads' behaviour?

The empirical evidence on the factors that explain credit spreads is mixed. While there are studies suggesting that the variance in credit spreads is explained by variables recommended by structural models (Avromov et al. (2007)), there are also academic papers that support for the impact of non-default related factors (taxes, liquidity factors, etc.) on these spreads (Collin-Dufresne et al. (2001), Elton et al. (2001), Chen et al. (2007), etc.).

In this study we will explore the impact of various factors on changes of U.S. corporate credit spreads over the 2001-2007 period. This period is characterised by intervals of considerable widening and tightening of credit spreads which correspond to some important developments in the U.S. financial markets such as short recession in 2001/2002, financial accounting frauds, unexpected collapse of some US corporations in 2001, difficulties in subprime mortgage market and beginning of a new recession period in 2007. An examination of factors that may influence credit spreads over these distinct macroeconomic time periods will help us examine whether the impact of various factors (firm-specific or common factors) changes with changes in macroeconomic conditions.

Furthermore, in this study we will employ panel data models to explore determinants of credit spreads. One of the benefits of these models is that they allow researchers to observe a number of units (in this case corporate bonds) over a number of periods. Hence, they allow researchers to employ complex models. Additionally, panel data models allow researchers to check for both the heterogeneity over cross-sectional units and the heterogeneity over time for a given unit.

Some studies (Duffee (1998), Joutz and Maxwell (2002), Pedrosa and Roll (1998), etc.) question whether the unexplained variation in credit spreads may be due to the persistence in volatility of credit spreads. Examining daily U.S. credit spreads on corporate bond indices, Pedrosa and Roll (1998) find that “GARCH models reveal some differences among credit spreads across ratings and industry classifications. In most cases the persistence of volatility is rather simple; the conditional volatility on a trading day depends only on the observed squared credit spread on the preceding day. For a few series, however there is evidence of longer-term volatility persistence (p.23).” Furthermore, Dionne et al. (2008) reveal that volatility persistence is strong in corporate bond markets particularly in the face of economic shocks. This is more pronounced in the case of highly rated bonds. They also explain the inconsistent evidence on the impact of systematic factors on credit spreads by this long-term volatility persistence. They further note that this persistence can explain a different impact of systematic factors on credit spreads in recessionary or economic shocks periods.

A very simple graphical presentation of credit spreads' patterns over the 2001-2007 period shows that time series of credit spreads may be characterised by significant time varying variance. We can notice successive fallings and rising episodes of credit spreads over time. In order to account for clustered volatility in credit spreads' time series, an ARCH/GARCH process is suggested. We employ the ARCH/GARCH processes in a panel data context. This innovative methodological approach adds to the originality of this study. To our knowledge ARCH/GARCH processes in panel data are not previously employed at least in the area of credit risk.

Overall, it can be suggested that the research will contribute to the growing literature in the area of credit risk and provide new perspectives on the explanation of credit spreads' behaviour.

1.2. Structure of the Thesis

We begin Chapter 2 by outlining the corporate bond rating process including here an explanation of the factors that will have an impact on bond reclassifications or assignments of watch lists by rating agencies. The chapter then provides a review of previous findings on the relationship between changes in bond ratings and changes in financial asset prices. More specifically we look at the empirical evidence on bond investors' reaction to announcements of rating changes. Next, we switch to a discussion of the recent studies which claim that information from corporate bond markets may be employed to derive bond rating reclassifications. The review of these studies feeds into one of the research hypothesis of this research.

Given that, Chapter 3 moves on to discuss the two most important approaches of credit risk modelling. These are the structural or firm value-based approach and the reduced-form approach. Benefits and limitations of both approaches are discussed in this chapter.

This leads naturally to Chapter 4 which is particularly important for our research as it provides the theoretical basis behind the methodology followed in this thesis. It includes a detailed discussion of the relationships between credit spreads and various financial and economic factors (risk-free term-structure variables, business expectations, corporate bond taxation, bond market liquidity and systematic risk factors). This discussion is based on previous empirical studies in the area of credit risk pricing. Here, we also outline the expected impact of the suggested factors on credit spreads.

Chapter 5 provides a step-by-step procedure on data collection process including the selection criteria used in both bonds and equities' databases. It also provides an explanation of the estimation of variables used in our testing models and an analysis of sample descriptive statistics. A detailed discussion on credit spreads behaviour and corporate bond features during the sampling period of 2001-2007 is also given in this chapter.

Chapter 6 then provides a review of panel data analysis in general. We firstly look at the benefits and limitations of panel data analysis and then provide explanations of the main panel data models.

This leads to Chapter 7 where we introduce the model employed to test for Granger causality and outline various diagnostic checks undertaken to ensure the validity of the model. In this chapter we also provide a detailed discussion of findings on causality relationship between credit spreads and bond ratings.

Chapter 8 firstly provides the model which is employed to analyse the determinants of credit spreads. It then follows with a detailed discussion of modelling issues faced in samples of both investment-grade and speculative bonds. It focuses particularly on the employment of panel GARCH processes to account for clustered volatility in credit spreads and other panel data methods to correct for the presence of cross-sectional dependence in error terms in both samples. The chapter concludes with a discussion of the findings on determinants of US credit spreads.

Finally, Chapter 9, as well as summarising the thesis, suggests possible future ideas which may help develop all the work we have presented in this thesis.

2. Chapter Two: Informational Value of Credit Ratings

"Given the agencies' track record – they (rating agencies) rated Enron investment grade four days before bankruptcy and didn't do much better on Global Crossing, WorldCom and several utilities – it is time for a different approach. Credit ratings pose an interesting paradox. On one hand credit ratings have great market value. Their changes are major news and a downgrade below investment grade can be an issuer's death knell as it was for Enron…On the other hand credit ratings have scant informational value…. Ratings are correlated with actual defaults only because agencies lower their ratings in response to public news." (Partnoy, 2003:52) Recently, there have been further claims that rating agencies are using corporate spreads to decide upon a rating change. This "plays into hand of the hedge funds, who deliberately short the bonds of the companies in the verge of junk status, making the growing corporate downgrade rate a self-fulfilling prophesy." (Tully, 2002: 52)

Based on these two quotations we may argue that investors and market participants are putting into the question the role of credit rating agencies as providers of accurate and reliable ratings. Credit ratings provide opinions of rating agencies on the creditworthiness of a particular issuer or issue. Hence, they are expected to provide some informational value upon which investors will react. In this context one expects credit rating changes to have an impact on financial asset prices. However, various studies argue that rating agencies would be more in favour of stable than accurate ratings and hence tend not to change ratings very frequently if they expect such ratings to be reversed in a short period.

In this chapter, we provide a literature review on the informational value of credit ratings. We start with a description of rating industry set-up which is then followed by an explanation of the rating process. The chapter then provides a comprehensive discussion on the informational value of credit ratings. It concludes with the statement of hypotheses regarding the relationship between changes in bond ratings and changes in credit spreads.

2.1. Credit Rating Industry

The credit rating industry is a global industry in which operate about 150 local and international credit rating agencies (Basel Committee for Banking Supervision, 2000), which rate securities representing at least $30 trillion worth of debt (Langhor and Langhor, 2008). Credit ratings are considered an important component in credit risk analysis and are extensively used by various financial institutions and individual investors. By assigning ratings to debt issuers, rating agencies are given a very important monitoring role in the capital markets.

What is a credit rating? There is not a standardised definition of credit rating. Following the international review of credit rating industry in 2006, various international regulatory bodies provided their definitions of credit ratings.

According to the US Securities and Exchange Commission (2003) “a credit rating reflects a rating agency’s opinion, as of a specific date, of the creditworthiness of a particular company, security, or obligation (p.5)”. The European Commission (2006) notes that credit ratings “assess the likelihood that an issuer will default either on its financial obligations generally (issuer rating) or on a particular debt or fixed income security (instrument rating). (p.1)” whereas the International Organisation of Securities Commissions (2004) suggests that “a “credit rating” is an opinion forecasting the creditworthiness of an entity, a credit commitment, a debt or debt-like security or an issuer of such obligations, expressed using an established and defined ranking system. They are not recommendations to purchase, sell, or hold any security (pp.3)”.

Although these definitions are provided by international regulatory bodies, most of the studies undertaken in the area of credit ratings refer to rating definitions (concepts) provided by the three main credit rating agencies which are Fitch, Moody's and Standard & Poor's. These definitions are given as follows:

- "*Fitch Ratings'* credit ratings provide an opinion on the relative ability of an entity to meet financial commitments, such as interest, preferred dividends, repayment of principal, insurance claims or counterparty obligations." (Fitch Ratings, 2011:6)
- "*Moody's* credit ratings are opinions of the credit quality of individual obligations or of an issuer's general creditworthiness (without respect to individual debt obligations or other specific securities)." (Moody's Investor Services, 2009:1)
- "Standard & Poor's credit ratings are designed primarily to provide relative rankings among issuers and obligations of overall credit worthiness; the ratings are not measures of absolute default probability. Creditworthiness encompasses likelihood of default, and also includes (i) payment priority, (ii) recovery and (iii) credit stability." (Standard and Poor's, 2009: 2)

Despite the wording of these definitions, the common thread is that credit ratings are opinions about whether debt issuers will be likely to default on the payment (timing and amount) of their debt obligations. Reilly and Brown (2003) explain that "bond ratings provide the fundamental analysis for thousands of issues. The rating agencies analyse the issuing organisation and the specific issue to determine the probability of default and inform the market of their analyses through their ratings." Credit ratings rank issuers or debt securities on scale from the least likely to most likely to default. It is important to be noted that while the same ratings may be assigned to bonds of various issuers, this does not imply that these bonds are of an identical quality. Credit ratings do not represent a unique default probability.

Credit rating agencies have assigned ratings for a period of more than 100 years. "John Moody, in 1909, was the first to issue publicly available bond ratings. Poor's Publishing was second in the business in 1916; Standard Statistics followed in 1922. (The two companies merged in 1941 to form S&P. This was later absorbed by McGraw-Hill.) In 1924, Fitch Publishing made its entrance into the industry." (White, 2007: 48) These were the only rating agencies before 1930s trying to sell their rating manuals to debt investors. As Partnoy (2006) notes the early rating agencies made money by charging subscription fees to investors but they did not charge debt issuers.

The regulatory changes in financial markets in late 1930s and 1940s required banks and insurance firms to hold portfolios of only investment-grade rated bonds. Hence, the bargaining powers in the rating industry changed. The issuing firms were hence forced in having their debt rated, so their bonds could be eligible for investment portfolios held by banks and banks and insurance firms. However, Partnoy (2006) finds that credit rating industry remained stagnant till early 1970s due to the lack of informational content of credit ratings.

Two major changes occurred in the 1970s. The first change was related to the introduction of SEC regulation regarding broker-dealers minimum capital requirement being related to the quality of bonds they held in their portfolios. White (2007) further clarifies that SEC decided to introduce a new regulatory category according to which broker-dealers' capital requirements would be based on valid credit ratings provided by "nationally recognized statistical rating organizations" (NRSROS). The U.S. Securities and Exchange Commissions would designate NRSRO status to rating organisations. Only the three original rating agencies were designated NRSRO status. In the same period, SEC and other administrative institutions introduced other regulatory requirements which depended on NRSRO ratings. This led to a change in the business model in rating industry. In particular, the business model shifted from an "investors pay" model to an "issuers pay" model. Credit rating agencies started charging bond issuers for ratings based on the size and complexity of their issues.

As more administrative regulatory requirements started to depend on NRSRO ratings, the business of rating agencies was expected to flourish. Partnoy (2006) argues that this was not the case till late in the 1990s when the business and profit margins of the three original rating agencies grew dramatically. He further implies that the growth in their business was related to their NRSRO status and barriers of entry faced by smaller rating organisations. However, Enron's failure and other corporate scandals (WorldCom, etc.) in 2001 brought into the surface the issue of potential conflicts of interests between recognised rating agencies and debt issuers which somehow might have felt threatened with lower ratings if they did not pay the required rating fees or did not agree to purchase ancillary (consulting) business from NRSROs. The U.S. Securities Exchange Commission undertook a review of the criteria required for evaluation and designation of NRSROs status and the importance of rating agencies' activities in financial markets in 2003. This led to the introduction of the Credit Rating Agency Reform Act legislation in 2006 (White 2007). The main aim of this law was the improvement of ratings quality in a more transparent, accountable and competitive environment so that rating agencies could act in the public interest. "In response to the legislation, the SEC designated three new NRSROs in 2007 (Japan Credit Rating Agency; Rating and Information, Inc. [of Japan]; and Egan-Jones) and another two NRSROs in 2008 (Lace Financial, and Realpoint). The total number of NRSROs is currently ten." (White, 2010:12).

Credit ratings cover a wide spectrum of corporations, governments, financial institutions, insurance firms, banks, various public finance entities and the debt securities they issue. They can be grouped according to either the type of rated issuer or the type of issued instrument. Under the first category, credit ratings can be further classified as either issuer ratings or sovereign ratings. According to Standard and Poor's (2009), "issuer credit rating addresses an issuer's overall capacity and willingness to meet its financial obligations. More specifically, an issuer rating usually refers to the issuer's ability and willingness to meet senior, unsecured obligations (pp.7)." Issuer ratings can be further classified according to the industry in which issuers operate. The largest group of issuers is represented by industrials and corporates, followed by financial institutions which are largely represented by banks.

Governments also fall in the category of issuers as they issue various debt securities. Governments usually seek the assignment of a credit rating known as sovereign rating. These ratings help governments - and corporations domiciled within their borders – gain access to the international capital markets. Institutional investors who are more likely to invest in international debt securities will not consider such investments unless they have an adequate rating validated by reliable rating agencies. Without the assignment of sovereign ratings, emerging markets governments would have found difficult to tap into the international capital markets due to the issue of information asymmetries between emerging markets governments and potential investors. The entry of a government into international capital markets is usually followed by the entry of its country's top corporations, banks and financial institutions in these markets. Hence, sovereign ratings are important not only for the public sector, but also for the private sector.

Langhor and Langhor (2008) explain that "one of the reasons that such sovereign ratings are so important to the private sector is that a rating agency will rarely assign a higher rating on the foreign currency debt of a company than the "country ceiling", which is directly linked to the sovereign rating and is either equal to or notched upward from the sovereign rating. The "country ceiling" makes it very hard for a company – no matter how creditworthy – to obtain low-cost funding if the political environment in which it operates is deemed to be volatile and high risk by the rating agencies…(pp. 135)." The importance of sovereign ratings for private sector and the public sector governance reform in developing countries has led to an expansion in demand for these ratings.

The second category (issued instrument) includes ratings given to different obligations of issuers. According to Standard and Poor's (2009) "an issue rating relates to a specific financial obligation, a specific class of financial obligations, or a specific financial program (including ratings on medium-term note programs and commercial paper programs). The rating on a specific issue may reflect positive or negative adjustments relative to the issuer's rating for (i) the presence of collateral, (ii) explicit subordination, or (iii) any other factors that affect the payment priority, expected recovery, or credit stability of the specific issue (pp.7)". Among various debt-obligation ratings, the ones that have attracted more interest in the financial markets due to the recent development in these markets are bond ratings and structured finance ratings.

Bond ratings are ratings assigned to bond instruments issued by a wide spectrum of issuers (corporations, financial institutions, banks, insurance firms, local authorities, governments, etc.) operating in multiple currencies, sectors and borders. Langhor and Langhor (2008) note that due to the expansion in the supply of bonds as financing instruments, credit rating agencies differentiate between instruments raised for the domestic market versus those targeted for international market, and those issued in the currency of the targeted market versus those issued in another currency of the targeted market.

Structured finance ratings are different to and more complex than bond ratings. Fender and Mitchell (2005) note that "structured finance instruments can be defined through three distinct characteristics: (1) *pooling of assets* (either cash-based or synthetically created); (2) *delinking* of the credit risk of the collateral asset pool from the credit risk of the originator, usually through the transfer of the underlying assets to a finite-lived, standalone special purpose vehicle (SPV); and (3) *tranching of liabilities* that are backed by the asset pool. While the first two characteristics are also present with classical pass-through securitisations, the tranching of liabilities sets structured finance products apart. They also cover the structured finance securities which are financial securities backed by receivable accounts or other financial assets…. A key aspect of the tranching process is the ability to create one or more classes of securities whose rating is higher than the average rating of the underlying collateral asset pool or to generate rated securities from a pool of unrated assets (pp.69)".

Assignment of credit ratings to these instruments will be based on the mapping of cash flows to different tranches. This on the other hand requires the estimation of a loss distribution on the asset portfolio. If the asset portfolio is represented by a number of heterogeneous assets, then the estimations of loss distribution for each of the assets and the losses on correlated cash flows of these assets will be required. Hence, credit rating agencies "rate different tranches, assess third parties involved in the transaction, and ensure the legal soundness of the structure, including the proper de-linking of the default risk of the asset pool from the default of the originator."(Langhor and Langhor, 2008: pp.141) Credit rating agencies play an important role in removing any informational asymmetries related to structured finance instruments, since there is no detailed public information regarding the assets pool. This explains the increased investors' interest in structured finance ratings in the recent years.

What does the rating process involve? It usually begins with the request of a bond issuer or when such request is not presented the rating agency may contact the issuer once the bond is registered according to SEC regulations. The main factors that may influence credit ratings (although credit rating agencies do not reveal the exact factors) usually include "the amount of earnings compared to the interest payments, the variability of earnings, the amount of debt in the capital structure, the net worth, and the amount of short-term assets compared to short-term liabilities." [1] After a careful assessment of issuer's performance based on both public (financial accounts) and inside information (such as technological changes, regulatory actions, etc.) the rating agency assigns a rating to the issue. Once the assigned rating is announced to the public, the issue is added to the surveillance system.

Credit ratings assigned to either issuers or specific issues represent issuers' ability to honour its overall or specific outstanding debt obligations. They range from the highest AAA[2] indicating a

[1] Elton et al (2007) "Modern Portfolio Theory and Investment Analysis", Seventh Edition, John Wiley and Sons Inc. (pp. 526 – 527)
[2] In this thesis, only S&P ratings will be employed.

great ability of the issuer to honour all its debt obligations to the lowest D indicating that issuer has already defaulted in its payment obligation on either coupons or bond's face value. (Appendix. 1) The main S&P rating classes are AAA, AA, A, BBB, BB, B, CCC and D. Ratings can be further differentiated with a plus or minus sign within one of these broad categories to indicate whether the rating is at the higher or lower end of the respective category. For example, AA-, AA+, BBB+, BBB-, BB+, BB-, B+ and B-, CCC+, and CCC-. Credit rating of BBB- acts as a cut-off point between investment-grade and non-investment or speculative bonds. Bonds with ratings higher than BBB- will be expected to have a lower default probability and they are known as investment grade bonds. In contrast, bonds with ratings lower than BBB- will be characterised by higher default risk making investors require a higher return premium for the credit risk they undertake. These bonds are known as non-investment or speculative grade bonds. Speculative bonds which were assigned a rating higher than BBB- when firstly issued are known as fallen angels.

A firm's changing economic conditions may require a reconsideration of its creditworthiness quality. Its debt may be either downgraded or upgraded by the rating agency. An upgrade indicates less expensive financing and higher shareholders value whereas a downgrade on the contrary may indicate higher financing costs and lower shareholders value. According to Standard and Poor's procedures[3], regular meetings with management of the rated issuers are planned on a routine basis usually once a year. The objective of these meetings is for the analysts to get information about any potential changes in the issuer's plans and discuss any new developments or potential problems. Following from these meetings, analysts can suggest whether a particular rating should require further consideration. This may lead to an issuer/issue being put in a watch list.

[3] "General description of the credit rating process", Standard and Poor's, 2007, http://www2.standardandpoors.com/spf/pdf/fixedincome/general_description_creditrating_process.06.26.07pdf.pdf

“A “credit watch” or “rating review” notice is issued if there is reason to believe that the review may lead to a credit rating change.” (Crouchy et al, 2001: 52) There are three categories of Watchlists: watch positive, watch negative and watch developing. The “positive” sign implies a possible upgrade, a “negative” sign implies a possible downgrade whereas “developing” means that a bond may be upgraded, downgraded or not changed in the near future. “Credit Watch” list is not intended to include all ratings under review and rating changes may happen without ratings being firstly put in the watch list.

Credit rating assignments or their changes are expected to be of great importance to their users. Kliger and Sarig (2000) argue that firms choose to pay for ratings either because they hope to get a better rating or because they want to make use of the assigned rating to provide inside information to the public without disclosing it in details. “Publicly revealing inside information might benefit competitors or subject insiders to lawsuits should the projects not materialize, whereas rating agencies can incorporate privately disclosed information into the ratings that they assign without fully revealing it. Indeed, during the rating process, corporations provide raters with detailed inside information (e.g., five year forecasts and pro-forma statements, internal reports).” (Kliger and Sarig, 2000: 2879). Hence, credit ratings help to reduce any informational asymmetries between debt issuers and investors.

When referring to investors, Duff and Eining (2009a) further explains that credit ratings are particularly important for small investors as these ratings provide small investors with information required when competing with professional investors. Duff and Eining (2009a) identify two other users of credit ratings: financial institutions whose investment policies prohibit investments in speculative bonds and other interested parties who use ratings in decision making such as investments in swaps, joint ventures, etc.

In a survey of UK representatives from each of these four groups, Duff and Eining (2009) try to identify the main qualities these groups value when considering a credit rating. They find that the four stakeholder groups perceive credit ratings quality to depend on the rating agency's reputation, its rating methodologies, its independent credit rating evaluations and the agency's internal operation processes. Furthermore, Duff and Eining (2009) do not report any statistically significant difference between "technical qualities" and "relationship qualities" required by rating user groups. The only exception was the issuers' group who value some of the relationship qualities (trust, issuer orientation and service quality) higher than the other market participants. These findings indicate that rating agencies have their work cut out when it comes to gaining rating users' trust.

This section provided an overview of the credit rating industry including a detailed explanation of credit ratings and rating process. It also discussed the main users of these ratings and the issues that the credit rating industry has faced over the years. Next section will present a literature review on the informational value of credit ratings.

2.2. Informational value of bond ratings

As explained in the previous section "rating agencies are important institutions which mitigate problems of asymmetric information between participants of the capital market. Lenders consider a firm's rating to not only decide on credit approval, but also to use for pricing, monitoring and risk provision purposes." (Norden and Weber, 2004: 2813). Rating agencies, on the other side, argue that ratings do not comment as to the market price of bonds, but they do provide some information needed by investors to make their investment decisions. Considering that this information is above and beyond public data provided by annual financial statements, one expects credit rating announcements to have some informational value and consequently some impact on credit spreads.

However, the evidence from both equity and corporate bond markets in the recent years depicts another picture. Changes in credit ratings are associated with low abnormal returns in both equity and bond markets. Furthermore, rating agencies have been recently criticised for their slowness in announcing rating changes. Consequently the important informational role of bond ratings for investment community is questioned.

Langhor and Langhor (2008) argue that “business community, regulators, legislators, academics and journalists occasionally have unrealistic expectations of what the ratings actually mean (pp. 78)”. They further claim that ratings “are not probabilities, ..(they) maintain a time perspective on credit risk for at least as long a period as the maturity of the instrument, …(they) are descriptive, not prescriptive of a debt situation, … (they) measure credit risk, they do not price it, … (they) are credit ratings, not equity ratings (pp.78).” Following Langhor and Langhor (2008)’s argument we aim to provide a review on existing empirical findings regarding the information that ratings provide for their users.

Fama (1970) argues that a market in which prices always fully reflect available information is called efficient. He further suggests that one can distinguish among three forms of market efficiency. A market in which asset prices reflect historical information is known as being weakly efficient. A market where asset prices adjust to new information made publicly available is known as semi-strongly efficient. A market where asset prices reflect both public and private information is known as strongly efficient. In the case of an extremely efficient market where all information is reflected in the asset prices, announcements of bond rating agencies will not provide new information to investors and consequently will not have any effect on asset prices. However, in a market where investors are oblivious to firms’ financial changing conditions, these announcements will introduce new information on the basis of which investors will react in a way that will have an impact on asset prices. The correction in prices is expected to last till some new information arrives in the market.

What *new* information will a bond rating change (downgrade or upgrade) bring to the market? West (1973) questions whether bond ratings may act as surrogate variables that represent factors for which public information is not available such as the legal terms and other constraints related to particular issues. He finds bond ratings to have a systematic impact on bond yields even after controlling for firm-specific factors.

Pinches and Singleton (1978) argue that rating agencies follow a dichotomous model in reassessing firms' bond ratings. More specifically, agencies may decide on a rating change following either changes in firm's financial and operating performance or specific firm-related events. Capital markets may reflect firms' performances long before rating agencies confirm rating changes for these firms. On the other side, a firm-related event may force the rating agency to review firm's rating within a very short period of time. Thus there will be fewer expectations about a change in ratings reflected in capital markets when rating changes are related to specific firm events. Pinches and Singleton (1978) reveal little support for the hypothesis of informational content in bond rating changes because they argue that both downgrades and upgrades are anticipated in the equity market.

Contrary to this study, Ederington et al. (1984) claim that bond ratings may have some informational value for three main reasons. Firstly, proper evaluation of public information may be costlier for individual investors than for rating agencies. That is why the information transmitted by rating reclassifications may have some value for investors. Secondly, rating agencies are provided with specific sensitive information which firms may not be prepared to share with their competitors. As such, rating changes may convey important information to investors without going into details. Finally, the fact that both bond issuers and investors are prepared to pay high fees for bond rating services shows that such ratings may have some important information for investors.

Covitz and Harrison (2003) explain that "bond rating agencies have an obvious conflict of interest. They have a financial incentive to accommodate the preferences of bond issuers because they are selected and paid by the issuers ("the conflict of interest hypothesis"). This incentive conflicts with agencies' stated goal of supplying independent and objective credit-risk analysis to investors ("reputation hypothesis")" (Covitz and Harrison, 2003:1). Contrary to their expectations, Covitz and Harrison (2003) find substantive evidence in support of reputation hypothesis suggesting that rating agencies undertake timely actions favouring investors not issuers' interests.

As it was previously explained, rating agencies have been delegated an important monitoring role in capital markets. Cantor and Mann (2003) argue that in order to achieve this goal rating agencies try to avoid making rating changes which have to be later reversed. Generally, market participants would prefer accurate and stable ratings. However, there is a trade-off between ratings accuracy and stability. As Cantor and Mann (2007) suggest market participants (both investors and issuers) would not necessarily prefer "ratings that track market-based measures of credit risk. Rather, ratings should reflect independent analytical judgments that provide counterpoint to often volatile market-based assessments short-term market-measures of credit risk. (pp.60)"

They further argue that short-term accuracy of ratings may be achieved at the expense of their stability. Short-term accurate ratings may lead to frequent reconstructions of bond portfolios which in turn will incur high transaction costs in bond markets. Furthermore, debt issuers and financial regulators will favour ratings stability, because as Cantor and Mann (2007) point out a rating change (upgrade or downgrade) over a short-term may lead to substantive changes in firms operational activities. Such changes cannot be easily reversed. Hence, these authors argue that all market participants may favour at some degree ratings stability against ratings accuracy.

"Stability in ratings" objective may explain at some degree agencies' reluctance to frequently downgrade or upgrade firms as they want to avoid any potential loss to their reputation. This avoidance policy has its own consequences because as Lőffler (2005) suggests it "can reduce the informational content of ratings by more than a rating system that reviews credit quality only twice per year". Noting that credit ratings do not reflect short-term default risk, but rather consider firm's performance through the cycle, Lőffler (2004) questions whether credit rating peculiarities reflect information inefficiencies or whether they are inherited in agencies' rating systems. His findings suggest that agencies' "through-the-cycle" ratings and current-conditions ratings cannot be used interchangeably. Despite the fact that both the avoidance of rating reversals and the assignment of "through-the-cycle" ratings may lead to ratings' stability, Lőffler (2004) argues that there is a difference between these two rating policies. He explains that "avoiding rating reversals by suppressing rating changes works like a filter that leads to a loss of information. Through-the-cycle ratings, too, neglect information, but only in order to convey other information not contained in current-condition ratings."

An empirical study undertaken by HolthaUSen and Leftwich (1986) reports negative abnormal returns associated with downgrade announcements. News of a bond downgrading may indicate weakening financial prospects for the firm which in turn results in negative reaction by stockholders. However, Goh and Ederington (1993) reveal that a rating downgrade may not necessarily be bad news for stockholders. They find that only downgrades following news of deteriorating financial performances provide new negative information for shareholders, whereas downgrades associated with changes in a firm's leverage ratio do not provide significant negative reaction in equity markets. On the other hand the equity market also seems to perceive news of bond upgrades as not bringing new information to the market. While reporting significant negative abnormal returns for downgrade announcements, Hand et al. (1992) find little evidence of reaction to bond upgrade announcements.

Considering that stockholders may anticipate bond rating changes, some researchers examine the informational value of "credit watch" lists to find whether such lists may explain low reactions to rating changes. Cantor and Mann (2004) argue that designation of rating outlook/watch lists eases the conflict between accuracy and stability of ratings. Alssaka and ap Gwilam (2010) note that news of credit watch acknowledges changes in issuer's credit quality. This may explain why a credit watch rather than a reclassification (upgrade or downgrade) is announced.

Followill and Martell (1997) obtain significant excess stock returns to news of reviews[4] announcements for downgrades, but find no support for market reaction to actual bond downgrades that follow review announcements. Unlike the previous study, Hand et al. (1992) find little evidence of stock market reaction to either indicated upgrades or indicated downgrades. However, when the sample of non-contaminated news of "watch" additions are partitioned into "expected" and "unexpected" news, they report significant market reaction for the unexpected news.

Wansley et al. (1992) find that market reaction to rating announcements does not depend on whether bonds had been previously put in a CreditWatch lists. Similarly, Steiner and Heinke (2001) stipulate that the magnitude of market reaction to rating reclassifications is not affected by whether the bond had been previously either reclassified by another rating agency or put on a "watch" list. However, they find significant abnormal returns around news of negative "watch" lists but no reaction around news of positive "watch" lists. Furthermore, their findings indicate that previous insertions of bonds in a negative "watch" list do not have an impact on market reaction to actual downgrade reclassifications. Norden and Webber (2004) report significant

[4] In some papers terms of "reviews" and "watch lists" are U.S.ed interchangeably. Moody's puts ratings under review in watch lists whereas S&P refers to these lists as "credit watch" lists.

reaction in both equity and CDS markets for rating reviews but not for the actual rating changes. Kaminsky and Schmukler (2002) findings indicate that rating and outlook changes for sovereign ratings affect both bond and stock markets. They further reveal that outlook changes are at least as important as actual rating change and that the impact of both ratings and outlook changes is more pronounced in crisis time.

Although the general view on the introduction of “watch” lists is that they were introduced by rating agencies to avoid rating reversals, Boot et al. (2006) argue that watch lists despite disseminating more accurate information to the market assist rating agencies to play a monitoring role. They argue that “the credit watch allows for an implicit contract between the firm and the credit rating agency where the former implicitly promises to undertake specific actions – recovery effort in our formulation – to mitigate the possible deterioration of its credit standing (and rating)” (pp.82). Hirsch and Bannier (2007) examine whether the introduction of “watch” lists has contributed to the informational value of bond rating changes. They do not find any significant evidence of abnormal returns in relation to upgrade news, but report “positive” reaction in equity markets to downgrade announcements preceded by watch news. Such evidence provides strong support for the hypothesis of “watch lists” being used as implicit contracts between rating agencies and rated firms. However, this finding refers to negative watch lists only because as Boot et al (2006) argue rating agencies do not have any incentive to enforce a credit watch when firms tend to and are expected to do well in the future.

While the discussion so far focuses on the informational value of bond rating news mainly in equity markets, the empirical evidence provided by bond markets seems to resemble to that of equity markets. The earliest study undertaken by Grier and Katz (1976) suggests a gradual and continuing adjustment of industrial and utilities bond prices following news of reclassifications in bond ratings. They further find that there is some anticipation of a decrease in bond ratings for industrial bonds but not for public utility bonds. Further evidence provided by Hite and Warga

(1997) indicates that bond investors react more to news of rating downgrades from investment to non-investment grade classifications than to news of rating downgrades within classes of investment grade ratings.

Steiner and Heinke (2001) also report similar findings but for news of downgraded Eurobonds. They attribute this dissimilar reaction to downgrade announcements from investment-grade to speculative bonds to the institutional regulations (or as they argue the price-pressure hypothesis) rather than to informational content of bond ratings (as suggested by the market efficiency hypothesis). Their main argument is that most of the financial institutions are required to invest in bonds that have achieved at least a certain rating. It is well known that many brokerage firms put together pools of bonds of various ratings and then issue shares in these pools. These pools are normally restricted to bonds of rating A or higher. Consequently, downgrades of these bonds will require institutional bond selling whereas an upgrade may not necessarily stimulate any trading activities. This in turn may explain not only higher abnormal returns for downgrades from investment to non-investment grade ratings but also the insignificant reaction by bond investors to upgrade news especially when such upgrades occur within the investment grade classifications. However, upgrades from speculative to investment-grade classification may be followed by new portfolio compositions thus stimulating the market trading for these bonds. Hite and Warga (1997) provide some empirical support for this hypothesis as they report some positive reaction to upgrade rating movements from non-investment to investment classes.

Generally, the empirical support for a significant (statistically and economically) bond market reaction to upgrade news is limited. This may be partly due to some methodological issues related to the examination of market reaction to such news. Various studies which investigate the informational content of bond ratings news report small samples of upgrade announcements. Ederington and Goh (1998) claim that rating agencies allocate more resources in detecting credit quality deteriorations than improvements, hence leading to a smaller number of upgrade than downgrade announcements. Blume et al. (1998) further argue that the relatively small number of upgrade announcements may be due to a decline in the US credit quality which may be partly explained by stringent standards followed by agencies in evaluation of credit quality. Small sample sizes for announcements of bond upgrades may cause low test statistic values which in turn suggest statistically insignificant market reaction for upgrade reclassifications.

Another issue to consider when looking at abnormal returns particularly in the corporate bond market is the illiquidity that characterises this market when compared to government bonds market. In their study, Wansley et al (1992) employ institutional bond prices instead of quotes of infrequently traded listed bonds to examine reaction of corporate bond investors to news of bond rating changes. Similar to previous studies, their findings indicate no significant reaction to upgrade announcements and significant negative abnormal bond returns for downgrade announcements in the period just before and after these announcements. Hence, their results suggest that illiquidity in corporate bond markets does not necessarily affect market reaction to bond rating reclassifications.

Consistently with this study, Kliger and Sarig (2000) also find that lack of market liquidity does not have a significant impact on abnormal returns related to news of rating changes. However, Daniel and Jensen (2005)'s findings of a faster reflection of news in credit default swaps (CDS) prices rather than corporate bond prices indicate that market liquidity should also be considered when market reaction of bond investors is examined.

It should be pointed out that studies mentioned so far employ event study methodologies to examine the bond market reaction to rating change announcements. One of the issues with event studies as noted by Kliger and Sarig (2000) is that it is not clear whether abnormal returns found in these studies represent the information value of rating reclassifications or that of other economic events considering that such reclassifications may be triggered by various economic events. In order to capture the impact of "uncontaminated" rating news, they examine Moody's announcements of rating changes for all issues from coarser to finer ratings. These announcements are not related to any reclassifications triggered by changes in issuer's idiosyncratic risk, but relate to changes in ratings when Moody's considered refining its ratings. Hence, market reaction to these announcements reveals a "pure" impact of news about rating changes. Kliger and Sarig (2000) reveal that bond investors react negatively to news of these downward adjustments. These findings suggest that corporate bond markets are generally sensitive to rating classification news.

So far we have provided a review of existing studies which have employed the event study methodology to examine the informal content of bond rating news. However, there are some studies which employ econometrical approaches to investigate the role of bond ratings in explaining variations in bond yields. Liu and Thakor (1984) find that ratings jointly with three other economic variables (total net direct debt, per capital debt and unemployment rate) have a significant impact on credit spreads of state bonds. Ederington et al. (1984) also provide evidence on the presence of this relationship for corporate bonds. Their findings indicate that "market yields also vary with rating independently of the financial accounting variables." (Ederington et al., 1984: 23)

In a more recent study undertaken by Campbell and Taksler (2003), bond ratings are found to explain corporate credit spreads better than accounting data. Hence, bond ratings are assumed to incorporate information that is not included in firms' financial reports. While they find that firm's equity volatility and bond rating each account for one third of the variation in credit spreads, they argue that equity volatility "can reflect continuous information that distinguishes bonds with the same credit rating, as well as recent information that may not yet be reflected in a bond's credit rating." (Campbell and Taksler, 2003: 2334) These studies generally indicate that bond ratings may help explain a proportion of bond yields, but there are other financial factors which add to the explanatory power of these yields.

Loffler (2005)'s findings indicate that bond ratings lag changes in default risk when this risk is estimated based on Merton's option approach employing data on equity returns, financial leverage and interest rates[5]. Consistently with this study, Anginer and Yildizhan (2008) report that credit spreads explain time to default better than bond ratings. Their findings of considerable variation in credit spreads within the same rating group suggest that bond ratings may not be a very good proxy of default risk. While Lőffler (2005) employs the structural approach to derive default probabilities, other authors such as Breger et al. (2003) and Kou and Varotto (2008) suggest that ratings derived from corporate bond market data provide better information than agencies' bond ratings. Breger et al. (2003) argue that their market-implied ratings help explain changes in corporate credit spreads better than agencies' bond ratings. Similar findings are also reported by Kou and Varotto (2008). They show that market-implied ratings "(a) … can predict agency ratings up to six months before the announcement date; (b) that such predictions are statistically significant for both downgrades and upgrades; this is surprising given that recent studies commonly find no or mild bond spread anticipation of rating upgrades; ….. (Kou and Varotto, 2008: 504)". Hence, the recent empirical evidence seem to suggest that market information may provide more reliable information on a firm's default risk than ratings assigned by agencies.

In summary, there are two main views regarding the relationship between asset prices and rating changes. The first view is that bond rating changes have an informational value and thus bond reclassifications provide new information for investors (shareholders and bondholders). The existing empirical studies report some significant abnormal returns associated mainly with announcements of bond downgrades. However, most of these studies find market price

[5] This model is discU.S.sed in more detail in Chapter 3 of this thesis.

adjustments to be financially weak and to start before the rating announcement. The introduction of credit watches has increased the informational value of bond ratings by easing the conflict between ratings accuracy and stability. These credit watches can either help agencies to transmit the information gradually while they re-consider their “through-the-cycle” ratings or they can serve as monitoring mechanisms to give time to firms to improve the quality of their creditworthiness.

Despite the introduction of credit watches, the literature review indicates that there is another viewpoint regarding the relationship between bond rating changes and financial asset returns. This is that due to rating agencies’ concern on potential rating reversals in short-term, changes in bond ratings will lag changes in financial asset returns. Recent studies have found that market-implied measures of default risk lead changes in bond ratings. Given the mixed evidence on the relationship between bond ratings and credit spreads one of the issues that need to be further examined is whether bond ratings lead or lag credit spreads. The following hypothesis will be tested:

H1: Changes in bond ratings “Granger cause” changes in corporate credit spreads.

Chapter Three: Corporate Bond Pricing Models

So far we discussed the relationship between bond ratings and credit spreads assuming that bond ratings provide investors with required information on firm's default probability. While approaches used by rating agencies generally estimate default probabilities based on firm's financial ratios, there are other credit pricing approaches which employ data on firms' assets value and their capital structure, interest rates and asset recovery rates (in case of default) or even bond prices data to estimate default probabilities or predict corporate spreads.

In this chapter we provide a general discussion on the elements employed by these approaches to then explain in more detail similarities and differences between structural (firm-value based) and reduced-form (intensity-based) modes of bond pricing. The objective of this chapter is to provide only an intuitive introduction of the main approaches (and some of the models) used in credit risk pricing. This introduction will help identify factors that are expected to affect the behaviour of credit spreads. The relationship of credit spreads with these factors will then be discussed in detail in chapter four. This chapter starts with an introduction of the common elements considered in credit risk pricing. It then follows with an explanation of both structural and reduced-form approaches employed in credit risk price models.

Corporate bond pricing models differ from each other on how they model three main elements that are considered in almost all models. These are: (1) interest rate processes, (2) default risk processes[6] and (3) asset recovery processes. Kao (2000) provides an explanatory summary of these three processes. He explains that evolvement of interest rates over time (the first element) is captured by Cox-Ingersoll-Ross in a stochastic process which has three main elements- the average interest rate, a factor determining the reverting speed of interest rate to its mean and lastly a drift term which depends on volatility and level of interest rate. This process is known as a

[6] Some models consider not only default risk processes but also ratings transition processes.

stochastic diffusion process. If a jump component is added to this process, then the process will be referred to as the jump diffusion process. This jump component may be modelled as constant, deriving from a probability distribution or from a set of predetermined state variables.

Credit risk literature suggests that default risk processes (the second element of credit pricing models) may also be modelled as diffusion or jump diffusion processes or in some models as a deterministic process. However, a very important point to be considered in default process modelling is how and when default is triggered. Kao (2000) explains that "default trigger is described by one of the following: (i) the relationship between firm value and book value of debt; in this approach how firm (or asset) value evolves over time must be defined; (ii) an endogenously or exogenously defined boundary; or (iii) the hitting time of a jump process with an intensity measure. (pp. 57)"

The third element of credit pricing models, the asset recovery process, is as important as the default process. Recovery rate (in case of default) represents a fraction of firm's debt value that is recovered once the firm has defaulted. It may be estimated as a fraction of debt's face of market value or as a fraction of the value of a default-free bond with same maturity and face value as the defaulted one. Knowing both probability of default and recovery rate helps an investor to estimate potential credit losses in case of issuer's bankruptcy but the estimation of recovery processes in particular has its own difficulties due to some complexities in the bankruptcy system.

Kao (2000) states that firms may not necessarily be liquidated when declared bankrupt but instead are restructured, so it may be difficult to estimate the recovery rate in such cases. Sometimes, restructuring may take place even when firms are not firstly declared bankrupt. Furthermore, recovery rate estimations are complicated in cases when "absolute priority rule"[7] is violated. Despite these challenges, researchers have tried to incorporate asset recovery processes

[7] "Absolute priory rule" implies that in case of firm's being liquidated senior bonds have priority in payback.

in pricing models by assuming these processes to be either deterministic or stochastic. However, implementations of models with stochastic recovery processes are more limited due to lack of data availability for recovery rates.

Kao (2000) further notes that a very important issue in bond pricing is the correlation between the three discussed elements of interest rate, default and asset recovery. This adds more to the intricacy of bond pricing models as inferences on such correlations may not be very realistic due to either limited availability of data in drawing such inferences or the way in which each process is modelled. Although bond pricing models can be viewed as a combination of interest rate, default and recovery processes, they are generally classified as either structural (firm-value) or reduced-form models. This categorisation is based on the type of data employed by models.

The work on bond pricing started from Black and Scholes (1973) who demonstrate that corporate liabilities can be considered as combinations of option contracts. Merton (1974) refines this concept further and develops a theoretical framework known as contingent claims analysis (CCA). In this framework, the default risk is contingent upon the firm's operational cash flows or its assets value. However, Merton's model is based on various strong assumptions whose relaxations led to a strand of models which in finance are referred to as structural models. On the contrary to structural models, reduced-form models specify credit event as a surprising event and relate it to bonds' prices rather than to firm's asset value.

3.1. Structural (Firm-Value) based models

Structural models are based on option pricing theory. Black and Scholes (1973) argue that both common stock and bonds may be viewed as options. If, for example, a firm is funded by outstanding discounted zero-coupon bonds and common stock (with dividend payments as residuals of bonds payoffs) and its only assets are the shares of common stock of a second firm, Black and Scholes (1973) suggest that at bonds' maturity time the firm will use the proceeds from the sale of second firm shares to pay off debt and distribute dividends to its common shareholders. Hence, they further argue that under these conditions, bondholders effectively own the firm's assets whereas shareholders have been provided with an option of purchasing these assets back.

Following from this explanation, Merton (1974) develops an intuitive framework in pricing zero coupon risky corporate bonds. He suggests that if a firm has only equity and a zero coupon risky bond (which is assumed to be the only source of debt), at the time of debt maturity (T), shareholders will receive a maximum payment between literally nothing (when the value of assets is lower than value of debt at maturity point) and the surplus of the firm's asset value (V_T) over the debt face value (D_T) at maturity. Thus their payoffs will be:

$$E_T = \text{Max}\ [0, V_T - D_T] \qquad \text{[Equation 3.1]}$$

These payoffs resemble to the payoffs from a European call option with the underlying asset being the firm value (V), the exercise price equal to the face value of the bond (D) and expiry date equal to maturity date of the zero coupon bond (T). Assuming that firm's asset value (Vt) at any time t follows a geometric Brownian motion with volatility σ and applying Black-Scholes (1973) formula for a call option, the value of payoffs to shareholders (E) at any time *t* will be a function of the following variables:

$$E_t = c(V_t, D_T, \sigma, r, T\text{-}t) \qquad \text{[Equation 3.2]}$$

where *c* represents Black-Scholes formula for the value of a call option contract[8] and *r* represents the risk-free rate.

Similarly, bondholders will be entitled to a minimum value between market firm's value (V_T) and bond's face value (D_T). Hence, bondholders will receive:

D_T= Min [V_T, D_T] = D_T – max [D_T – V_T, 0]. [Equation 3.3]

As Merton (1974) suggests the value of zero-coupon risky bond at maturity will be equal to the difference between the face value of default-free bond and a European put option written on firm's asset value with strike price equal to bond's face value and exercise date equal to bond's maturity date. Employing the well-known Black-Scholes formula for the price of a European put option, the value of the zero-coupon risky bond at any time *t* will be given as:

$D_t = D_t e^{-rt} - p(V_t, D_T, \sigma, r, T\text{-}t)$ [Equation 3.4]

where *p* represents Black-Scholes formula for the value of a put option contract[9].

Merton (1974) then estimates what he refers to as "the risk premium" as a difference between the yield-to-maturity on the risky debt, provided that the firm does not default, and the risk free rate. He further suggests that this risk premium "is a function of only two variables: (1) the variance (or volatility) of the firm's operations, and (2) the ratio of the present value (at the riskless rate) of the promised payment to the current value of the firm. (pp. 454)" Hence, the information required to derive credit spreads based on Merton's model include the volatility of

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[8] Black-Scholes formula for the value of a call option is given as C = $s\phi(d_1) - xe^{-rt}\phi(d_2)$ where $d_1 = \dfrac{\log(s/x) + (r + \sigma^2/2)/t}{\sigma\sqrt{t}}$ and $d_2 = d_1 - \sigma\sqrt{t}$. S is the price of underlying asset, x is option contract's strike price, ϕ represents the standard normal cumulative distribution function, r is the risk-free rate, σ is the implied volatility for the underlying asset and t is the time left till the expiration of option contract.

[9] Black-Scholes formula for the value of a put option contract is given as P = $xe^{-rt}\phi(-d_2) - s\phi(-d_1)$

firm's asset value, its debt to equity or leverage ratio, risk-free rates and bond's maturity date. However, Merton (1974)'s theoretical model is based on very strict assumptions such as:

- "the capital structure is simplistic: equity plus one issue of zero coupon debt,
- the value of the firm is assumed to be perfectly observable,
- the value of the firm follows a lognormal diffusion process. With this type of process, a sudden surprise (a jump) leading to an unexpected default cannot be captured. Default has to be reached gradually, "not with a bang, but with a whisper" as Duffie and Lando (2001) put it,
- default can only occur at the debt maturity,
- riskless interest rates are constant through time and maturity,
- the model does not allow for debt renegotiation between equity and debt holders,
- there is no liquidity adjustment". (De Servigny and Renault, 2001: 67)

Relaxation of some of these assumptions has led to the development of structural (firm-value based) models. Black and Cox (1976) extend Merton's model by allowing default to happen before the maturity of the bonds. They also extend the model for bonds with safety covenants related to firm's bankruptcy. However, similar to Merton's model, Black and Cox (1976)'s model is based on the strong assumption of constant instantaneous interest rates.

Noting that zero-coupon bond model represents only a special case of models used for risky coupon bonds, Geske (1977) derives a pricing model which caters for risky bonds with coupon. Based on his model, on coupon dates shareholders decide whether to pay off the coupon or not. Hence, shareholders have a compound option. If shareholders decide not to service any of the coupons, default occurs and bondholders receive the firm. Hence, the default boundary in Geske's model is endogenous.

Longstaff and Schwartz (1995) suggest that both default and interest rate risk should be incorporated in bond pricing models. They develop previous models by incorporating stochastic interest rates and allowing the firm to default the moment that its assets value reaches a default threshold even before debt maturity. The implication of the latest assumption is that the model allows for simultaneous default on all of firm's debt obligations. They find that variations in default risk over time are accompanied by variations in credit spreads.

While Longstaff and Schwartz (1995) treat default boundary as exogenous, Leland and Toft (1996) develop the structural models by assuming endogenous default boundary. They attempt to express credit spreads and bankruptcy probabilities as functions of flow ratios. Their analysis indicate how these flow ratios should interact with one another and with exogenous parameters, such as debt maturity, default-free interest rate, current asset value, risk, etc. to determine credit spreads and bankruptcy probabilities. They have predicted higher spreads on most of bonds, particularly on the ones with high coupons.

Furthermore, Collin-Dufresne and Goldstein (2001) propose a structural model with stochastic interest rates and mean-reverting leverage ratios assuming that firms do change their outstanding debt levels according to changes in firm's values thereby increasing the risk of default and lowering the recovery rate in case of default. Their model predicts a negative relation between spreads and firms' leverage reporting higher spreads for low leverage firms. They also find that the predicted spreads are not very sensitive to changes in firms' values.

The empirical evidence provided by application of structural models is mixed. Jones et al. (1984) find that default spreads based on Merton model are lower than the observed credit spreads, although they provide some limited support for this approach for non-investment grade bonds. On a more optimistic note, Sarig and Warga (1989) find similar patterns between observed term structures for US credit spreads and those predicted using Merton-based models for highly leveraged firms. However, more recent studies such as Huang and Huang (2003) demonstrate that bond yields generated by structural models are too high to match the observed data.

Eom et al. (2004) undertake an empirical study to compare the performance of various structural models in providing accurate credit spreads. Their analyses are based on cross-sectional data of US corporate bonds. Interestingly, none of the considered models provided similar results to those observed in the market. They find that while Merton (1973) and Geske (1997) models provide credit spreads that are lower than the observed ones, credit spreads based on Longstaff and Schwartz (1995) and Leland and Toft (1996) models are higher than the observed spreads. Furthermore, they reveal that structural models “tend to severely overstate the credit risk of firms with high leverage or volatility and yet suffer from an under-prediction problem with safer bonds”.

The under or over prediction of credit spreads based on structural models is arguably their main shortcoming. The main difficulty in the application of structural approaches originates from estimation of one of the key parameters in these models such as volatility of firm’s assets value. De Servigny and Renault (2001) note that several methods are suggested to calculate this parameter but they do not provide robust estimators. Hence, estimation of the historical volatility of firm’s assets value (as one of the suggested approaches) is generally based on the use of low frequency data provided by annual balance sheet, whereas estimation of implied volatility although provides accurate prices of equity relies on very strong assumption that equity pricing model is correctly specified.

Another shortcoming of these models comes from the complex capital structures employed by firms. De Servigny and Renault (2001) explain that “structural models can at most cope with a simple capital structure with senior and junior debt and equity. A realistic capital structure may include five bond issues, some bank debt, trade credit, convertibles, preferred shares, etc. It therefore becomes necessary to aggregate the various instruments into a limited number of claims such as long-term and short-term debt and equity. These approximations no doubt impact on the accuracy of the pricing model. They can also be costly in terms of processing time (p.326)". While information from equity market is incorporated in the structural models, the underlying information from bond markets is ignored. This is an additional shortcoming of these models.

The earlier structural models tend to price only default risk and ignore other factors (liquidity, taxation, etc.) that may have an impact on bonds' yields[10]. Consequently, these models tend to misprice investment-grade bonds in which a large proportion of credit spreads is attributable to other factors than default risk.

A further limitation of structural models is that they cannot be used to predict default event for highly rated firms which can default unexpectedly. This drawback comes from the assumption that a firm's value follows a continuous process in the form of a geometric Brownian motion. As Schmid (2004) explains "if we model the firm value process only with a continuous diffusion the probability of a firm to default in the next instance is zero. Hence, firms would never default unexpectedly (p.58)".

Finally, since structural models require a considerable amount of complex information and follow the option pricing approach, they are considered by academics and practitioners to be computationally burdensome.

3.2. Reduced-form (intensity-based) models

Structural models generally assume that financial modellers are as well informed on firms' assets and liabilities as managers who run these firms. Jarrow and Protter (2004) argue that unlike structural models, the reduced-form approaches assume that modellers possess the same

[10] Please refer to our previoU.S. discU.S.sion on assumptions of Merton model.

imperfect knowledge on firms' financial performance as the other market participants. As such, these approaches rely only on observable market information to draw any inferences on firm's time to default.

The observed yields on a risky bond can be decomposed in a risk-free return and a risk premium. Reduced-form models are based on this decomposition to find default probabilities and recovery rates of risky bonds. Default event in these models is treated as an unpredictable event involving a sudden loss in market value. Bond yields employed to derive default probabilities are assumed to follow Poisson processes characterised by jumps that are captured by large discrete rather than small continuous movements.

Choudhry (2004) note that in reduced form models "complete and arbitrage free credit market conditions are assumed, recovery rate is an input in the pricing model, use of credit spread data to estimate the risk neutral probabilities, use of transition probabilities from credit agencies can be accommodated in some of these models (the formation of the risk-neutral transition matrix from the historical transition matrix is a key step), default can take place randomly over time and the default probability can be determined using the risk-neutral transition matrix. (p.68)"

Reduced-form models can be classified into hazard rate models and transition matrix models. While in hazard rate models (Jarrow and Turner (1995), Duffie and Singleton (1995)) default is modelled as a surprise in a default process which is not related to any asset value process, in transition matrix models (Jarrow et al. (1997)) the bond is assumed to go through various bond rating states before it defaults. Transition matrix models are more comprehensive than hazard rate models because they account not only for possible downgrades but also for possible upgrades prior to a bond's default. Jarrow et al (1997) use historical bond ratings provided by rating agencies to derive rating transition matrices. These matrices provide the information on cumulative default probability over time for a given bond. Since these models focus on the default and/or recovery process and they can be adopted to allow for credit rating changes. Hence, reduced form models allow default risk to be an important factor in the pricing of corporate bonds.

The major shortcoming of reduced-form models is that they rely on the use of noisy bond market data. Hence, in these models it is difficult to link default and recovery value to the fundamental characteristics of bonds and their issuers making these models harder to interpret from an economic standpoint. Furthermore, credit spreads may result from default risk but they also may be due to liquidity premium or taxes. Another limitation of these approaches is that they assume the same default process for every bond within the same rating class, whereas in practice different bonds within the same rating class have different credit spreads.

The discussion so far suggests that both structural and reduced-form approaches have their own benefits and limitations particularly related to their implementations. However, financial institutions are required by the Bank of International Settlements either to develop their in-house credit risk models or to employ one of three models (KMV, Credit Risk Metrics and Credit Risk+) available in the market. While KMV's model follows a structural approach, JP Morgan's Credit Metrics and Credit Suisse' Credit Risk+ both follow a reduced-form approach. However, Credit Metrics is a transition matrix based model whereas Credit Risk+ is a hazard rate model.

Difficulties in implementation of both structural and reduced-form models and the recent availability of larger databases on corporate bonds' individual data, have led to researcher employing more econometrical approaches to investigate the relationships between credit spreads and various economic (macro or firm specific) factors which may lead to changes in credit spreads. The following discussion provides a review of existing literature on links between credit spreads and some of the factors identified in credit pricing model. .

Chapter Four: Relationships between Credit spreads and Various Financial and Economic Factors

This chapter provides a review of empirical studies which consider the impact of various factors (financial and economic) on corporate credit spreads. Structural theoretical models discussed in the previous section suggest that the default risk of a firm will depend on changes in interest rates and changes in a firms' value of assets. However credit spreads provide compensations not only for the default risk faced by corporate bond investors, but also for tax differentials between corporate and Treasury bonds and market illiquidity risk borne by these investors. Hence, corporate credit spreads are expected to be affected by various common factors. This chapter starts with a discussion of previous empirical findings on the relationship between interest-rate variables derived from risk-free term structure and credit spreads. Next, it follows on with a discussion about the impact of taxation, corporate bond market liquidity and systematic risk factors on credit spreads. Finally, it provides a summary of previous findings on these relationships and states the expected relationships to be tested in this thesis.

4.1. Credit spreads and interest rates

The finance theory suggests that variations in the risk-free term structure have a significant impact on corporate credit spreads. Litterman and Scheinkman (1991) suggest that "most of the variation in returns on all fixed-income securities can be explained in terms of three "factors", or attributes of the yield curve", which they refer to as the level, the steepness and the curvature of the yield curve. However, their findings indicate that changes in the first two factors (level and slope of the yield curve) explain a high proportion of the changes in returns on zero coupon Treasury securities for all maturities.

Various papers investigating the behaviour of credit spreads have looked at the impact of the level and slope of risk-free term structure on these spreads. An increase in risk-free interest rates will lead to lower bond prices. Changes in the shape of the risk-free term structure will affect not only the prices of corporate bonds, but also investors' perception about firm's default risk. Earlier studies document a complex relationship between interest rates and credit spreads. This section provides a review of these studies looking respectively at the impact of both the level and the slope of risk-free term structure on credit spreads. While interest-rate factors are expected to affect firm's default probability and hence corporate credit spreads, a firm's expected recovery is also expected to have some impact on corporate credit spreads. Collin-Dufresne et al. (2001) suggest that even in cases when a firm's default probability remains constant, changes in credit spreads of its corporate bonds may be affected by its expected recovery rate. A firm's recovery on the other side is closely related to the overall business climate. A discussion on the impact of business cycles on changes of credit spreads is also provided in this section.

4.1.1. Credit spreads and the level of risk-free interest rates

Structural models of credit pricing argue that risk free interest rates are inversely related to credit spreads. In these models, interest rate is employed to estimate the present value of expected cash flows from the put option on the firm's asset value. An increase in the interest rate is expected to reduce the present value of these cash flows and consequently the value of the put option. This in turn is expected to lower credit spreads.

Longstaff and Schwartz (1995) attribute the magnitude of relationship between level of riskless interest rates and credit spreads to the strength of the correlation between firm's equity returns and changes in riskless interest rates. The higher the correlation, the stronger the effect of interest rate levels on credit spreads. They find a negative relationship between credit spreads and the level of interest rates. Similar to Longstaff and Schwartz (1995), Duffee (1998) documents a weak statistically significant negative. However, he finds the magnitude of this relationship to be closely linked to bond's credit quality. His findings indicate a weak relation between changes in 3-month Treasury rates and changes in credit spreads of investment grade bonds, but higher relations for lower rated bonds. Alesandrini (1999) also reports a negative relationship between credit spreads and the level of interest rates especially for Aaa and Baa Moody's indices but he further suggests that the variance in credit spreads is largely explained by changes in long-term risk free rates.

Other studies (Kao (2000), Brown (2001), Huang and Kong (2003), etc.) provide additional supporting evidence on the negative relationship between interest rate levels and credit spreads of bond indices. Consistent evidence on this negative relationship is also provided for samples of individual corporate bonds (Collin-Dufresne et al. (2001), Campbell and Taskler (2001), Avramov et al. (2007), etc.). While Collin-Dufresne et al. (2001) find credit spreads to be more sensitive to interest rate levels for lower credit qualities, Papageorgiou and Skinner (2006) argue that such relationship is fairly constant across rating categories.

Generally, previous studies provide coherent evidence on the negative impact of level of risk free rates on credit spreads. Morris et al. (1998) criticise previous studies for focusing only in the short-term relation between these two variables. Employing the co-integration[11] method which they argue is a better suited statistical technique to capture this complex relationship, they find that "in the short-run, a rise in Treasury rates is associated with a decline in credit spreads. In the long-run, however, a rise in Treasury rates will increase credit spreads." A possible explanation for changes in this relationship in time may be that a rise in interest rates is not immediately followed by an increase in credit spreads, but in long-term this rise in interest rates may slow firm' growth

[11] Cointegration is suggested becaU.S.e the relationship between term structure variables and credit spreads is stationary even when series of these variables are nonstationary.

leading to higher default risk and consequently higher credit spreads. While Morris et al. (1998)'s study examines investment grade bonds Joutz and Maxwell (2002) extend their research to non-investment grade bonds. Reiterating the important role in use of co-integration method in examination of relationships between interest rates and credit spreads, they report negative significant effect on credit spreads in short-run but positive in long-run even for non-investment grade bonds.

In summary, empirical evidence of the relationship between level of risk-free interest rates and credit spreads is mixed. While many studies argue that this relationship is statistically negatively significant, there are a few studies which suggest that the negative relationship is valid in short-term, but positive in long-term.

4.1.2. Credit spreads and the slope of risk free term structure

While structural models discussed so far suggest that credit spreads depend on short-term interest rates, the dynamics of these interest rate processes depend on other factors. Generally it is reasonable to expect that the longer a bond's maturity date the greater the interest rate the borrower has to offer as a compensation for the longer period the lender is parted from his money. The relationship among interest rates at different maturities is referred to as the term structure of interest rates, whereas the graphical presentation of this relationship is known as the yield curve. The yield curve can be upward sloping, flat or downward sloping. An upward-sloping yield curve implies an increase in expected short-term interest rates. A downward-sloping yield curve suggests that long-term bonds are having lower yields than short-term bonds implying that future interest rates are expected to decline.

The term structure of interest rates at any time is a function of investor's expectations regarding the movement in interest rates over time and their attitudes towards risk. According to the expectation hypothesis, the slope of the yield curve is an optimal indicator of expected short-term interest rates. The slope of the yield curve is normally expressed as the difference between long-term and short-term bond yields. As such, a fall in the slope of yield curve will increase the price of the put option in Merton's model and thus increase firm's default risk.

Furthermore, Estrella and Mishkin (1996) state that the slope of the yield curve is a very good predictor of US future economic activity and likelihood of recessions in this economy. In different time periods these slopes may narrow or widen indicating periods of respectively low or high volatility in interest rates markets. When the yield slope takes negative values, there is an indication for an expected economic downturn which in turn may decrease a firm's growth rate and increase its default probability. Hence, theoretically one can expect an inverse relation between the yield curve slope and credit spreads. On the other hand, a decrease in expected future interest rates as implied by an inverse yield curve may increase the number of projects with positive net present value (NPV) available to the company leading to higher firm value and in turn to lower credit spreads.

Various studies in this area have used various maturities of Treasury indices in an effort to capture the measure of slope of risk free term structure. Duffee (1998) reports negative relation between credit spreads of investment grade bonds and the slope of the yield curve when the slope is measured as the difference between three-month Treasury bill and 30-year constant maturity Treasury bonds. He further suggests that this relationship is stronger for long-term than for short and medium term bonds and it changes as the credit quality falls across various maturities. Following studies in this area provide inconsistent evidence on the relationship between the slope of risk free term structure and credit spreads. Collin-Dufresne et al. (2001) do not find strong supporting evidence on this relationship. However, Papageorgiou and Skinner (2006) lend support for the negative impact of Treasury term structure slope to credit spreads and find this impact to be consistent across rating classes.

Instead of employing only one proxy for the slope of risk-free term structure, Avromov et al. (2007) use three measures of this slope to capture different segments of the term structure. Their results are mixed. They find a positive strong relation between changes in credit spreads and changes in the slope when the term structure slope is measured as the difference between 30 and 2 year Treasury yields. Avromov et al. (2007) argue that changes in the long-term slope will reduce expected NPVs of projects thus contributing to lower firm values and higher credit spreads. However, when the slope represents the short-end of the term structure (difference between 5 and 2-year Treasury yields), they report a negative relation between credit spreads and the slope measures. An increasing slope in the short-term may suggest an improving economy and hence lower default probabilities and credit spreads.

Morris et al (1998)'s findings on the relation between credit spreads and term structure slope is mixed. Joutz and Maxwell (2002) find a more complex relationship between credit spreads and the slope of risk-free term structure. They further argue that this is due to the maturity of the bond indices considered. Their findings indicate a significant negative impact for intermediate and long term bonds in the long run, but only for intermediate bonds in the short run.

In addition, a few recent studies (Bakshi et al. (2006)) reveal that interest rate risk has a first-order impact in movements of investment grade bond yields. They further find that for low grade bonds the relation between credit spreads and term structure variables is significantly stronger mainly for investment grade bonds. This may suggest that interest rate risk may explain the behaviour of investment-grade bonds which as it has been found behave more like Treasury securities.

4.2. Credit spreads and business cycles

Understanding what drives changes in interest rates is necessary for an investor who hopes to maximise returns from investing in bonds. Interest rates tend to move with business cycles. They are high when the economy is close to full employment and low when the economy experiences recessions and high levels of unemployment. Bond prices on other hand will move in the opposite direction. They will be declining when the economy is booming and inflation is accelerating and increasing during recessions. Moreover, investors' appetite for risk may change with stages of business cycles causing spreads to vary accordingly within a business cycle.

Changing macroeconomic conditions will influence also two other stochastic determinants of credit spreads such as default risk and expected recovery rate in case of default. Intuitively, one can expect firms to face higher default risk during business cycle contractions and lower rates of default during economic expansions. Furthermore, recovery rate is expected to be higher during expansion than during recession periods. Thus the magnitude of credit spreads is expected to depend on stages of the business cycle.

Credit spreads of high-yield bonds are expected especially sensitive to these cycles as in recession firms will find it more difficult to generate the necessary cash flows. In recessionary periods, investors also tend to become more risk-averse and invest in lower risk securities or prefer to hold more liquid securities. Hence, the relationship between variables capturing business cycles and credit spreads is expected to be stronger for more liquid and marketable securities.

Various studies provide empirical evidence in support of variation in credit spreads according to stages of business cycles (Alessandrini (1999), Huang and Kong (2003)). Alessandrini (1999) also looks at the impact of business cycle on variations in credit spreads and reports a clear business cycle effect when looking at the sensitivities in both recessionary and expansionary periods. He further suggests that generally credit spreads react more to recessionary periods and that this reaction is more pronounced for lower rated than high-rated bonds.

Measures of equity market returns have been suggested by previous research as good proxies of business climate. Collin-Dufresne et al. (2001) find negative significant coefficients for S&P500 returns across all groups of bonds. Avromov et al. (2007) find equity market returns to be ranked second after risk free interest rates in the list of common factors that explain changes in credit spreads. Their findings provide further support to the existence of this relationship for the US credit spreads especially in volatile periods such as that of 2002-2003. Hence, overall we can conclude that business cycles are expected to have an impact on credit spreads.

4.3. Credit spreads and taxation

Earlier studies argue that one of the factors that may help explain credit spreads is the tax differential treatment of returns between Treasury and corporate bonds. The US tax system on proceeds from bond investments is very complex. As Constantinides and Ingersoll (1984) explain the coupon income for individual investors is taxed at the marginal tax rate, whereas the realized gains/losses from bond trading are treated as capital gains. The taxation of capital gains for these investors is much more complex as the gains/losses are categorised in short and long term for tax purposes. For banks, financial institutions, and bond dealers, bond coupons and all realized capital gains/losses are treated as ordinary income.

It is well known that the main participants in the bond markets are institutional investors due to the high minimum denominations of most issues and the complexity of bond markets. Rielly and Brown (2003) suggest that these "institutions tend to favour different sectors of the bond markets based on two factors: (1) the tax code applicable to the institution and (2) the nature of the institution's liabilities…. Pension funds are virtually tax free institutions with long term commitments, so they prefer high-yielding, long-term government or corporate bonds."

In the US, interest income earned on corporate bonds is taxed at federal, state and local level, whereas interest income from Treasury bonds is exempted from state and local taxes. On this basis, corporate bond investors are expected to require higher yield returns that will compensate them for differences in taxes. Marginal tax rates on corporate bonds vary from 5% to 10% across states. Estimating corporate spreads using various effective tax rates (4.875%, 4% and 6.7%), Elton et al (2001) find that taxes are an important element that can help explain corporate spreads. Driessen (2005) however suggests that the optimal effective tax rate for investment grade bonds data is 3% instead of 4.875% employed by Elton et al. (2001) study. He argues that a lower effective tax rate may indicate a relatively higher impact of taxes for investment grade bonds which are generally characterised by low credit spreads. While these two studies follow a reduced-form approach to estimate credit spreads, Delianedis and Geske (2001) employ a structural approach to estimate such spreads and analyse the impact of tax differentials on these spreads. Similar to the previous two studies, their findings suggest that taxes may help explain variation in credit spreads.

Considering that the tax differential treatment between treasury and government bonds relies only on the coupon payments, one may expect corporate bond investors to have a preference towards lower coupon bonds. Sharpe et al. (1995) suggest that taxation can affect bond prices and yields in another way. They explain that the returns for an investor purchasing a low coupon bond at a discount value will be in two forms: (i) coupon payments and (ii) gains from possible appreciation in bond value. Taxes on the latter return may be deferred until the bond either is sold or matures if the bond is sold at par. Hence, these bonds will have a tax advantage due to this deferral resulting in slightly lower before tax-yields than high coupon bonds (assuming that the other factors do not change).

Various studies have employed coupon rate as an explanatory variable to account for the tax differential treatment. As Longstaff et al. (2005) suggest the rationale for using coupon rate as a proxy is that "an investor with a marginal tax rate of τ would need to receive a pre-tax coupon of $c/(1 - \tau)$ to have an after-tax coupon of c. Thus, the mark-up in the coupon to compensate for the additional state and local taxes incurred by corporate bonds should be roughly proportional to the coupon rate of the bonds". Their findings however indicate that the tax effect on spreads is quite weak. Chen et al. (2007) study also provides similar evidence. Considering that the main participants in the corporate bond markets are tax-exempt investors such as pension and retirement funds, the evidence provided by these studies is not surprising. However, as Chen et al. (2007) note the weak significant tax impact on credit spreads may be due to the illiquidity of high coupon bonds.

Christensen (2008) argues that another argument against a considerable impact of taxes on credit spreads is that there have not been so many changes in the US tax system to instigate the observed yield changes in corporate bond markets. However, Liu et al. (2007) state that there have been some major shifts in the US tax policy especially in May 2003. "The tax bill passed on May 23, 2003 accelerates the tax reduction scheduled for 2004–2006 by the Economic Growth and Tax Relief Reconciliation Act of 2001. Both income and capital gains tax rates are reduced." (Liu et al. 2007: 600). A tax reduction could have led at a higher demand for corporate bonds and consequently to lower credit spreads.

Despite their remarks on more recent changes in the US tax system, Liu et al. (2007)'s study employs data return data on Treasury and corporate bonds for the period up to 1996. They find that marginal investor's income tax rates are significantly incorporated in corporate bond prices especially after 1986. Examining investment grade bonds, they further argue that the proportion of credit spreads captured by taxes is high for higher-rating bonds with shorter maturity. Nevertheless, their findings may not hold for lower quality bonds. As Liu et al. (2006) argue although personal taxes are important, liquidity risk should also be taken into account when corporate bond spreads are investigated. This is especially important when lower quality bonds are concerned as they tend to be more illiquid than the high quality bonds.

To sum it up, there are only a few studies that examine the relation between tax differential treatment between Treasury and corporate bonds and corporate credit spreads. Overall, the empirical evidence indicates the presence of a very weak impact of this factor on credit spreads. This relationship is found to be stronger for investment grade bonds. However, the impact of tax differential is not clear for low quality bonds since they tend to be less liquid than investment-grade bonds.

4.4. Credit spreads and bond market liquidity

So far the relationship between credit spreads and various factors suggested by structural approaches is discussed. Structural models assume perfect and complete capital markets in which the trading takes place continuously. It is well known that corporate bond markets are characterised by thin rather than frequent trading implying that these markets are fairly illiquid. "A narrow spread of between one-quarter to one-half of 1 percent may indicate a liquid market, while a spread of 2 percent or 3 percent may indicate poor liquidity for a bond. Even for major issues, news of credit problems may cause temporary liquidity problems."[12] Corporate bond holders are expected to require a premium for illiquid issues. The less liquid the bonds, the higher the required yields and hence the higher the credit spreads for these bonds. In this section we provide a literature review about the impact of market liquidity on credit spreads.

Various textbooks suggest that a liquid asset is one that can be converted into cash quickly without loss. Market liquidity has two aspects: marketability and well-behaved price. Even if an

[12] "Trading and Capital Markets Activities"
http://www.federalreserve.gov/boarddocs/supmanual/trading/200704/0704trading.pdf

asset is marketable (quickly sold at low transaction costs), it is not liquid if selling it immediately rather than waiting to sell generates a loss. This may be the case for an asset which is traded in a thin market. In such markets prices may be depressed generating in this way losses for investors. Thus, the yield on a liquid asset, other things being equal, will be lower than the yield on an illiquid asset.

Generally liquidity is considered to be associated with trading, so an examination of liquidity will require trading information. This becomes difficult especially for thinly traded securities such as corporate bonds. These bonds are characterised by limited availability of trading data. Chacko (2006) reports that "while the median stock trades once every few minutes, the median US corporate bond trades approximately once every two months. (pp.4)" Thin trading in corporate bond markets raises the question of variables that can adequately capture liquidity differences across bonds. So far, previous studies have suggested several liquidity proxies. This in turn has provided mixed results on the impact of liquidity on corporate credit spreads.

"The principal basis for grading the marketability of a security is the size of the spread between dealers' bid and offer prices… The principal determinant of the size of the spread is the volume of trading in an issue (i.e., the "thickness" of the market). This stems from the fact that a high frequency of arrival of new orders reduces the market maker's cost of holding inventories and mitigates the risk of unfavourable price movements while inventories are being held. The number of dealers moreover is more or less proportionate to the volume of trading. If there is a lot of business in a bond issue, a lot of dealers seek the business. A large volume of trading and a large number of dealers make a highly competitive market where bid-ask spreads are pressed down." (Fabozzi and Modigliani 1992: 483)

Fisher (1959) employs bonds' trading volume and the market value of all publicly traded bonds as liquidity proxies. His findings suggest that corporate bond yields compensate for both default and marketability risk. Sarig and Warga (1989) argue that a bond's liquidity is also related to some of its characteristics. They suggest that once bonds satisfy the objectives of investors' portfolios, they are taken out of circulation for a long period of time. The longer they are absorbed in these portfolios, the more illiquid they become especially as their maturity date approaches. That is why they argue that a bond's age may be a good proxy for its marketability. They suggest that two other liquidity proxies may be bid/ask trading spread and the amount of an issue outstanding. Sarig and Warga (1989) also claim that to reduce noise and avoid selection bias researchers should employ data filters based on these proxies. However, they agree that the use of these filters may not be possible due to the limited availability of trading data.

Empirical evidence on the impact of liquidity proxies on corporate spreads varies. Craber and Turner (1995) do not find any supporting evidence on the link between a bond's issue size and its market liquidity. They explore the yields between corporate bonds and medium term notes issued by the same firm only to find that these yields are very similar. Given that the main difference between these two issues lies on their issue sizes, Craber and Turner (1995) argue that issue size is not a significant determinant of a bond's liquidity.

Elton et al. (2001) find that two indirect measures of liquidity such as the value of outstanding bonds and the proportion of months that a bond is matrix-priced do not help explain the variation in credit spreads. However, they note that new bond issues (including seasoned issues) are more liquid than bonds closer to maturity. A following study by Driessen (2005) also finds that the liquidity difference between newly issued and old bonds is an important determinant of credit spreads. Both these studies imply that liquidity plays an important role in variations of credit spreads. On the contrary, Ericsson and Renault (2002) do not find any liquidity differences on newly issued bonds and more mature bonds. However, they report a decreasing term structure for liquidity premium and similar to previous studies acknowledge the link between credit and liquidity risk.

Employing various proxies for bond liquidity Longstaff et al. (2005) report negative coefficients for proxies of issue size and bond's age but positive coefficients for proxies of bid/ask spread and time to maturity. They do not find any industry effect in the liquidity of corporate bonds, but report the presence of small "flight to quality" premium in credit spreads of higher rated bonds. Most importantly, they conclude that the non-default component of credit spreads can be attributed more to bonds' illiquidity than tax differential factors.

Contrary to Longstaff et al. (2005), Chen et al. (2007) do not find supporting evidence for the impact of issue size on credit spreads. They further argue that the limited sample employed by Longstaff et al. (2005) questions the generalization of their results. In addition to two previously used proxies (bid/ask spread and percentage of zero returns), Chen et al. (2007) also incorporate a new measure which takes into consideration the fact that the marginal trader will consider trading only when the gains from the informational content are higher than the trading costs. Their empirical findings indicate a positive significant relationship between changes in each suggested liquidity measure and changes in credit spreads. However, they reveal that the magnitude of these relationships differs with the proxies used for liquidity and across credit quality and maturity of bonds. They also provide a strong evidence of the impact of bond volatility in explaining bond liquidity.

Due to limited availability of trading data, some studies use aggregate variables to capture the liquidity factor in credit spreads. Collin-Dufresne et al. (2001) employ the difference between on and off-the run Treasury yields and the difference between 10-year swap yields and Treasury yields to proxy for market liquidity. Their findings indicate a statistical significant impact of these two factors on changes in credit spreads. Avromov et al. (2007) employ a dummy variable representing FED's expansionary and contractionary policies. If an expansionary (contractionary) policy is followed by either reducing (raising) fed funds rate or discount rate, or by purchasing (selling) Treasury securities in the open market, then an increased (decreased) activity in the corporate bond market is expected. This in turn will lead to narrower (wider) credit spreads. Avromov et al. (2007) do not report strong supporting evidence for this association. However, De Jong and Driessen (2006) find that liquidity risk in equity and Treasury bond markets has an impact on returns in corporate bond markets. Furthermore, they argue that both U.S. and European corporate bonds are exposed to liquidity shocks which may explain the expected bond returns.

So far the empirical evidence about the impact of liquidity factors on credit spreads is mixed. It depends on the proxies employed to capture this liquidity. Houweling et al. (2005) questions the reliability of liquidity proxies employed by various studies. They find that none of the nine suggested proxies (issued amount, whether they are listed, age, on/off the run yield differences, missing prices, yield volatility, number of contributors and yield dispersion) has a superior explanatory power for variation in credit spreads. This finding provides at some extent the summarising point for this section. However, an important point to be made here is also that studies on credit spreads consistently report the presence of some liquidity premium in corporate credit spreads.

4.5. Credit spreads and Fama-French systematic risk factors

Modern portfolio theory argues that investment risk can be decomposed into unsystematic (fundamental) risk and systematic (market) risk. As Fabozzi (2002) explains that "unsystematic risk… is the risk that is unique to a company, such as a strike, the outcome of unfavourable litigation, or a natural catastrophe. … Systematic risk is that which results from general and market and economic conditions that cannot be diversified away (p. 21)." In case of corporate bonds, the unsystematic risk is represented by bond's default risk. In addition to this risk, these bond returns will be affected by systematic risk. Components that will contribute to bonds' systematic risk are those factors that have an impact on yields of many individual bonds. In this section we provide a review of existing empirical findings on the relationship between credit spreads and systematic risk factors.

Pedrosa and Roll (1998) argue that investors reassess default probability of all bonds once their beliefs and perceptions for the future outlook of the economy change. Hence, as they suggest even interest rate hedged and well-diversified positions of corporate bond dealers still face some systematic risk as yield spreads of these bonds move together. Elton et al (2001) argue that the presence of systematic factors influence in credit spreads can be explained either by the link between expected default losses and stock prices or by the changes over time of required returns from investors in both stock and bond markets.

Studies examining changes in credit spreads focus on the impact of equity systematic risk factors on these spreads. Such effects are captured by including in regression models Fama and French's systematic risk factors of SMB and HML. While SMB factor represents the difference in returns between a portfolio of small stocks and a portfolio of large stocks, the other factor (HML) measures the difference in returns between a portfolio of high book-to-market stocks and a portfolio of low book –to-market stocks. They argue that that SMB returns represent the premium required by investors for small market capitalisation firms relative to big market capitalisation firms. HML returns represent the return premiums expected from firms with high book-to-market ratio relative to firms with low book-to-market ratio.

Inclusion of these variables in statistical models stems from Fama and French's (1993) study in which by assuming the integration between equity and bond markets, they empirically investigate whether there are any factors that may explain returns in stocks and corporate bonds. Fama and French (1993) find that "the stochastic links between the bond and stock markets do, however seem to come largely from the term-structure factors. Used alone, the excess market returns and the mimicking returns for the size and book-to-market equity factors seem to capture common variation in bond returns. But when the two term structure factors are included in the bond regressions, the explanatory power of the stock market factors disappears for all but the low-grade bonds. (pp. 6)".

Collin-Dufresne et al (2001) report statistically significant impact of SMB factor on credit spreads. However, they find this impact to be economically weak and changing from negative to positive as the leverage ratio increases. While Joutz et al (2001) also document the significance of Fama and French risk factors for credit spreads of investment grade bonds, Huang and Kong (2003) find HML factor to account for a significant proportion of spread changes for low quality bonds. Avramov et al (2008) report a significant negative association between Fama-French systematic factors and changes in credit spreads, but they find that this association does not get stronger for higher levels of credit risk.

Elton et al. (2001) also examine the relationship between Fama and French factors and credit spreads but unlike the previous studies they focus on the impact that these factors have on the residuals of credit spreads that are not explained by expected default losses or taxes. Their results suggest a positive relationship of these factors on credit spreads. They further find that the relationship gets stronger for longer maturities and lower bond quality.

However, King and Khang (2005) claim that these results are biased because Elton et al. study does not account for relevant variables proposed by structural models. They argue that after controlling for such variables, systematic risk factors have only limited explanatory power for credit spreads. They conclude that credit spreads are predominantly driven by default–based variables, such as leverage ratios and equity return volatility.[13] Similar to this study, Bakshi et al. (2006) find no supporting evidence for the impact of systematic factors on bond yields. Hence, we

[13] King and Khang (2005) find

can suggest that the empirical evidence on the impact of Fama-French systematic factors on credit spreads is inconclusive.

4.6. Summary of the chapter

Most theoretical models in the area of credit risk are based on the assumption that credit spreads are attributable to default risk. However, most of these models cannot explain a large proportion of observed credit spreads. While they find significant impact of various market-driven and macroeconomic factors on credit spread changes, Collin-Dufresne et al. (2001) conclude that changes in credit spreads are better explained by a common factor in the corporate bond market that is independent of equity, swaps and Treasury markets. They recommend that in examining factors driving credit spread changes one should focus on the analysis of demand/supply segmentation of bond markets. Following studies (Elton et al (2001), Delianedis and Geske (2002)) suggest that tax treatment, liquidity and market risk factors explain most of the variation in credit spreads.

More recent studies (Huang and Kong (2003), King and Khang (2005), Bakshi et al (2006), etc.) indicate that credit spreads of low grade bonds are greatly explained by default risk related factors. Furthermore, Avromov et al. (2007) suggest that credit spreads of high quality bonds behave more like yields of Treasury securities, whereas spreads of low grade bonds behave more like returns of equity.

Other studies (Longstaff and Schwartz (2005), Chen et al (2007)) suggest that non-credit risk related factors such as bonds' market illiquidity may explain credit spreads for high quality bonds. Bakshi et al. (2006) do not provide strong support for these factors, but they suggest that illiquidity might have contributed to any mispricing of credit risk models. While accounting for most of the factors mentioned in the previous studies, Driessen (2005) states that the unexplained variation in credit spreads may be due to a risk premium that may be caused by a tendency of firms to default in waves.

While empirical studies reviewed in this chapter help to have a better understanding about the impact of various factors on corporate credit spreads, there is still a need for a further exploration of the complex relationships between corporate credit spreads and these factors.

Hypotheses:

1. Changes in credit spreads are negatively related to:
    - changes in the level of interest rates
    - changes in the slope of risk-free term structure
    - S&P index returns.
    - firm's equity returns
    - bond's issue size
2. Changes in credit spreads are positively related to:
    - changes in CBOE implied-volatility index returns
    - bond's time to maturity
    - bond's coupon

Chapter Five: Data collection and Sample analysis

The literature review undertaken in the previous chapters aims at identifying various factors that are expected to explain the behaviour of US corporate credit spreads in 2001-2007 period. Furthermore, the examination of previous theoretical and empirical studies helps identify the variables and data required to capture such factors. In this chapter we provide the steps taken for the collection of the data required to (1) test the Granger causality relationship between credit spreads and bond ratings and (2) investigate the relationship between credit spreads and other macroeconomic factors.

The chapter starts with a discussion of the criteria used for the collection of credit spreads sample to then follow with a detailed description of the data required for the estimation of all explanatory variables considered in this study. The chapter continues next with a detailed discussion of credit spreads' behaviour during a volatile economic period. This discussion is complemented by an examination of S&P rating data considering samples of both actual rating changes and credit watch lists. The chapter concludes with a discussion on the characteristics of bonds included in the sample.

5.1. Data collection process

This section starts with an explanation of the criteria used to identify US corporate bonds that are included in the final sample. It also provides a discussion of the databases used to extract the required data for the estimation of explanatory variables.

Corporate bond data are extracted from Thomson Financial Datastream database. We apply the following criteria for the identification of corporate bonds to be included in the sample:

- Bonds are issued by corporations but not Treasury.

- Bonds are actively trading. Bonds that were actively traded but either defaulted or matured before the end of December 2007 are also included in the sample to avoid any sample bias.

- Bonds are denominated in the US$ and are traded in New York stock exchange. This criterion helps limit the search only to the US bonds, although it does not guarantee that the sample includes some Eurobonds.

- Bonds do not have any embedded option or any other feature such as sinking fund, convertibility, warranty, etc.,

- Credit spread data are provided for at least 24 consecutive months.

- Bonds have more than one year to maturity. Amihud and Mendelson (1991) find that due to high transaction costs for Treasury bonds close to maturity, investors tend to lock them away in portfolios making them less tradable. Since corporate bonds are known to be less liquid than Treasury securities, it is expected that corporate credit spreads will not vary significantly especially in the last remaining year.

The initial search results in 2030 corporate bonds. The initial data collected for these bonds are month-end credit spreads for the period covering January 2001 to December 2007, the last ten S&P rating changes, bond's issue and redemption dates, its coupon rate, issue size, industry code and issuing firm's code. Based on the information about the borrower, the sample is again filtered to exclude bonds issued by various trusts and mutual funds. For each bond code, the issuer code is found. The issuer code is then used to collect issuer's financial related data. Issuers' sample includes 353 companies. The sample is further screened for bonds issued by companies whose equity data are not available from Datastream. Additionally, the sample is cleaned from bonds whose ratings are not consistent with their spreads history assuming that there have been input errors in rating history data. Bonds with negative spreads over the considered period are also excluded from the sample assuming that these are genuine errors in data calculations or input. Based on a preliminary analysis of the distribution of observed monthly spreads we decide to exclude from the sample bonds that have extremely high spreads.

The final sample of credit spreads includes a panel data set with a total number of 30771 observations represented by 421 corporate bonds. Panel data are generally classified either as balanced or unbalanced data. While balanced panel sets consist of observations for each individual unit at any time period under consideration, unbalanced panels lack information for some individual units over time. The final sample includes 274 “alive” bonds and 147 bonds which either defaulted or matured at some point during the sampling period. Hence, this data set can be categorised as an unbalanced panel for analysis purposes. Since most of the models employed in this study are based on balanced panel data samples, the final sample is further limited to 261 bonds.

Information on daily equity prices of the rated firms included in the final sample is sourced from Thomson Financial Datastream using firms’ equity codes. These codes are further used to check whether a high proportion of bonds in the final sample are issued by a few large firms. Although we find cases of firms issuing more than 5 bonds, such cases are limited to a few firms which as reported in other studies are limited to bonds of upper end of investment grade classifications. Datastream database also provides a general industry coding for each firm. These codes help classify bonds into six main groups according to firm’s industry, namely into industrial, utility, transport, bank, insurance and other financial bonds.

Our discussion in previous chapters (chapter three and four) suggests that explanatory variables for credit spreads can be grouped into three main categories: interest rate sensitive or term-structure variables (risk-free rate and the slope of the yield curve), liquidity related variables (issue size, maturity, coupon) and equity market related variables (firms' equity returns, S&P 500, Fama and French factors, CBOE volatility index). Information for each of these variables is collected from various available databases. While information on liquidity variables and S&P 500 index are gathered from Thomson Financial Datastream, data for CBOE volatility index are sourced from CBOE[14]s website. Monthly yields of Treasury bonds are collected from US Federal Reserve's webpage for a period ranging from January 2001 to December 2007[15]. Time series for Fama and French (1993) systematic risk factors (SML and HML) are collected directly from Prof. Kenneth French's website[16].

5.2. Discussion of the variables

This section provides a discussion on how all variables employed in this study are estimated. A summary of description and notations for all variables is included in the appendices (Appendix. 2).

-*Corporate credit spreads (CS_{it})*. Month-end values for corporate credit spreads are collected from Thomson Financial Datastream database for a period covering January 2001-December 2007. "These spreads are estimated as the difference between the corporate bond yield and the equivalent Treasury benchmark yield. Since the maturities of most bonds do not exactly match the maturity of available Treasury Benchmark bonds, a linear interpolation is applied to derive the equivalent benchmark yield. The following formula is applied:

$$CS_{it} = Y_1 + \left(\frac{I_3 - I_1}{I_2 - I_1}\right) \times \left(Y_2 - Y_1\right)$$

[Equation 5.1]

where:

[14] CBOE (Chicago Board of Options Exchange) http://www.cboe.com/micro/vix/historical.aspx
[15] http://www.federalreserve.gov/releases/H15/data.htm. (Accessed on 18th of June, 2008)

[16] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_bench_factor.html.

Y_1 is the yield of the benchmark with the lower maturity

Y_2 is the yield for the benchmark with the higher maturity

I_1= exact maturity in years of the lower benchmark

I_2 = exact maturity in years of the higher benchmark

I_3 = maturity of the corporate bond being analysed." (*Source: Datastream – datatype definitions)*

-S&P bond ratings ($RTNG_{it}$). Data on the latest ten S&P credit ratings are collected for each bond. Consistent with the existing literature on credit ratings (Cantor and Packer 1996, Steiner and Heinke (2001), Alsakka and ap Gwilym (2010), Güttler and Wahrenburg (2007), etc.) each S&P bond rating is converted into a linear numerical scale where 1 is assigned to the highest rating category (AAA) and 18 to the lowest rating categories of CCC. Our sample does not contain any observations for S&P rating categories of CCC-/CC/C/D (Appendix 3). Similarly to Gande and Parsley (2005) we refer to these numerical codes as explicit credit ratings (Appendix. 3, Table 3.1.).

Some of the previous studies (Chapter 2) argue that credit rating changes do not necessarily follow changes in macroeconomic factors, especially since credit rating agencies prefer stability rather than short-term accuracy when considering a rating change. Furthermore, S&P explains that watch lists provide agency's view on potential direction of a short or long-term rating. Hence, it can be argued that inclusion of watch lists in the ratings sample may increase the explanatory power of ratings models.

In a similar way to Gande and Parsley (2005), we employ a finer numerical scale which includes both actual ratings and watch lists classifications. Watch lists in this index are treated as intermediate steps between two rating categories. For example, 0.5 is added (subtracted) to (from) a given rating score when the bond is put into a negative (positive) credit watch list. We refer to these new numerical codes as the comprehensive credit ratings (CCR).

Any non-zero changes in the comprehensive credit ratings represent a rating event. Positive changes represent either a downgrade or an inclusion in the negative credit watch list, whereas negative changes represent upgrades or inclusions in positive credit watch lists. We also estimate the mode (the most frequent) rating across time for each bond in order to group bonds into investment-grade and speculative bonds.

-Leverage variable ($EQRET_{it}$). Merton (1974)'s paper argues that changes in a firm's leverage ratio are expected to have a great impact on a firm's default risk. However, employment of leverage ratios in econometric analysis of credit spreads poses its own methodological problems such as availability of information, the lack of daily data, etc. Previous studies (Collin-Dufresne et al. (2001), Avramov et al. (2007), etc.) suggest the use of firm's equity return as a proxy for firm's change in leverage ratio. Additionally, Welch (2004)'s paper on the relationship between capital structure and stock returns on U.S. firms finds that debt-equity ratios of these firms move closely to changes in stock prices. Hence, monthly equity returns of individual firms are employed as proxies for changes in firm's leverage ratio.

-Risk-free term structure variables ($INTLEV_t$ and $SLOPE_t$). Two of the variables that capture the US term structure of risk-free interest rate, as suggested by the finance literature, are the level of Treasury index yields ($INTLEV_t$) and the slope of risk-free term structure ($SLOPE_t$). Some studies (Duffee (1998), Collin-Dufresne et al (2001)) employ monthly rates of 3-month Treasury bill as a proxy for level of interest rates. Other studies (Joutz and Maxwell (2002), Avromov et al. (2007)) make use of short and long term Treasury indices as proxies for the level of interest rates variable.

Joutz and Maxwell (2002) suggest that long term indices have more explanatory power. Moreover, they note that the choice of Treasury indices with maturity higher than 10 years is insignificant to the final results. Additionally, findings from Avromov et al. (2007) suggest a higher explanatory power associated with 10-year Treasury index than with 2-year, 5-year and 30-years indices. Following these findings, monthly yields of 10-year Treasury index are collected and employed as a proxy for the level of risk free interest rates.

The slope of risk-free term structure (the other suggested variable for term structure analysis) is generally measured as the difference between yields of short and long term Treasury indices. Duffee (1998) reports weaker coefficients for the slope of yield curve for short and medium maturity bonds when the 30-year Treasury bond index is employed as a proxy for the estimation of this slope. Other studies such as (Collin-Dufresne et al. (2001), Campbell and Taksler (2003), Elton et al. (2001), Chen et al. (2001) etc.) employ the difference between 10-year and 2-year Treasury benchmark yields to estimate term structure slope.

Unlike earlier studies, Avromov et al. (2007) employ several proxies to estimate the term structure slope. Their findings suggest a higher explanatory power for slopes estimated as a difference between 30-year and 10-year Treasury yields than for slopes estimated as the difference between 10-year and 2-year Treasury yields. Unfortunately, the data for 30-year Treasury constant maturity were discounted from February 2002 till February 2006. Consequently, the slope of risk-free term structure in our study is estimated (consistently with most of the studies mentioned in Chapter four) as the difference between 10-year and 2-year Treasury yields.

-Fama and French systematic factors (SMB_t and HML_t). These risk factors are included as a proxy for systematic equity risk factors. They are collected for a period of seven years starting from January 2001. These factors are "constructed from six size/book-to-market benchmark portfolios that do not include hold ranges and do not incur transaction costs. SMB (Small Minus Big) is the average return on three small portfolios minus the average return on three big portfolios and is estimated as follows:

SMB = 1/3 (Small Value + Small Neutral + Small Growth) - 1/3 (Big Value + Big Neutral + Big Growth).

HML (High Minus Low) is the average return on two value portfolios minus the average return on two growth portfolios:

HML = 1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth).”[17]

-CBOE Volatility Index (VXO_t[18]). Collin-Dufresne et al. (2001) suggest that due to the lack of option contracts for some of the stocks considered in their study, they utilise CBOE VIX (volatility index) as a proxy for the implied volatility. This index represents the weighted measure of implied volatilities of eight near at the money put and call options on S&P 100. In September 2003, CBOE replaced the original VXO index by a new one. This new index (VIX) is estimated on a broader range of options including both near-at-the-money and out-of-the-money for both put and call contracts with an average term to maturity of 30 days on S&P 500 index.

Since VIX index measures the annualized implied volatility on a daily basis, the monthly implied volatility is then estimated as the end of month VIX observation divided by the square root of 12. Being a measure of volatility, VIX is generally referred to as the “investors fear gauge”. Generally, VIX figures over 30 indicate large amount of volatility due to investors’ fear about markets, while levels below 20 are linked to expectations of more certainty in the markets.

-Liquidity related variables (ISS_i and LIQ_{it}). Various studies have employed a bond’s issue size and bond’s age or time to maturity as proxies for liquidity. It is assumed that large issue sizes are more visible to the market and consequently have some effect on that bond’s liquidity. Elton et al (2001) find new issues to be more liquid than older bonds. Sarig and Warga (1999) also

[17] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_bench_factor.html (Accessed on 6th of June, 2008)

[18] We use the notation of VXO for the implied volatility index to be consistent with other previous studies.

suggest that bonds close to maturity tend to become more illiquid, whereas Longstaff and Schwartz (2005) claim that bond' age "parallels the notion of on-the-run and off-the-run bonds in the Treasury market." (pp. 2241)

Additionally, higher coupon rates are taxed more than low coupon bonds throughout the lifetime of the bonds. This may in turn result in low coupon bonds being more liquid than high coupon bonds. Khing and Khang (2005) argue that coupon rate may be considered as a proxy for bond's liquidity. In this study we employ a proxy for liquidity which incorporates the effect of both bond's coupon and time to maturity. This variable (LIQ_{it}) is estimated by multiplying the log of coupon by the remaining time to maturity.

The other liquidity proxy employed in this study is the log of the issued amount (ISS_i). The liquidity proxies proposed in this study aim to capture the cross-sectional differences in liquidity of corporate bonds. Such variables are generally argued to provide better results than aggregate liquidity measures.

-January seasonal effect (JANEF). Generally in the stock market, Fama and French (1993) find statistically significant January seasonal effect for bond returns. The regression coefficients for this effect appear to increase monotonically across ratings. A dummy variable is included in the analysis to account for this effect.

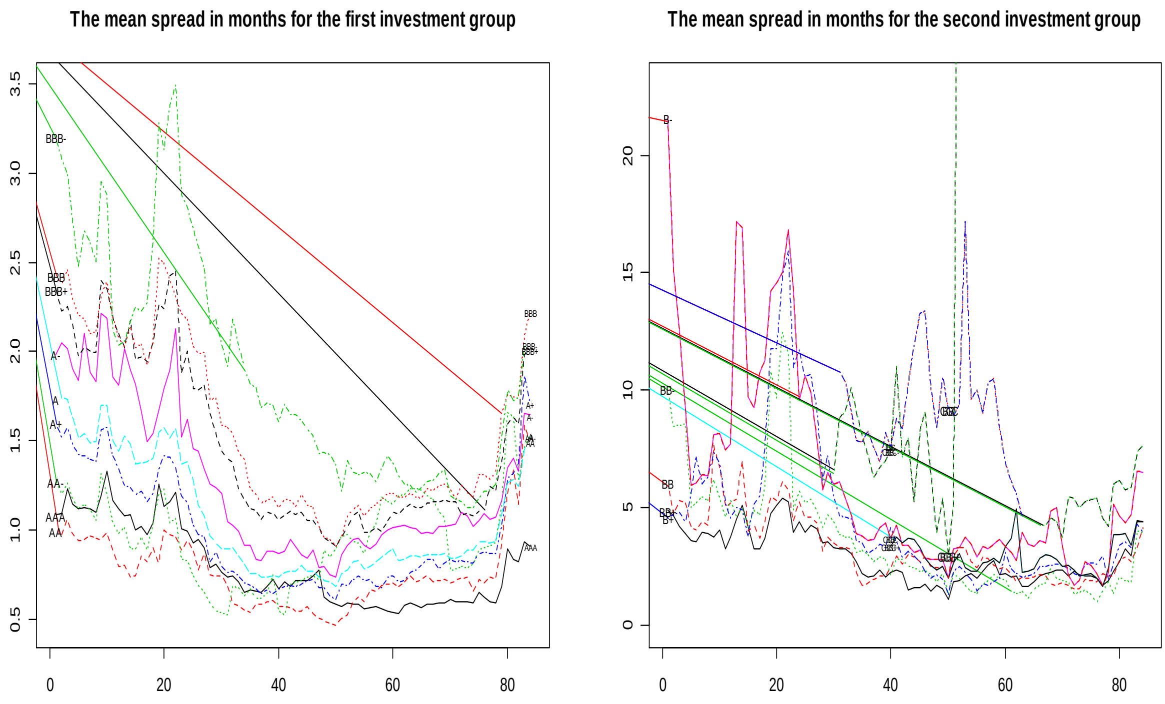
5.3. Discussion of descriptive statistics

In this section a discussion of sample descriptive statistics is provided. Firstly, we look at various events that may explain credit spread changes over the sampling period. This is then followed by a brief discussion on descriptive statistics found for various features of bonds that are included in the sample.

5.3.1. Credit spreads and bond ratings during 2001-2007

Previous studies in area of credit risk report higher credit spreads for corporate bonds of lower bond rating classifications. The following graphs represent the behaviour of credit spreads according to rating classes across 2001-2007 period. While the first graph represents credit spreads' behaviour for investment grade bonds, the second graph shows the behaviour of credit spreads for speculative bonds (or bonds with ratings lower than BBB-). This simple graphical presentation reconfirms findings of previous studies that lower-rated bonds are characterised by higher credit spreads to compensate for the high risk investors take by investing in low-rated bonds. A comparison of both graphs indicates that means of monthly spreads for speculative bonds are overall higher than means of monthly spreads for investment grade bonds.

Figure 5. 1. Monthly credit spreads during 2001-2007 period



Despite differences in levels of credit spreads between investment-grade and speculative bonds, these two graphs illustrate similar patterns in credit spreads behaviour across most of all rating categories.

It is evident from both plots that credit spreads are low for most of 2001, but widen at the end of 2001 to reach peak levels in autumn 2002. After this period, credit spreads tend to tighten. This tightening (although at different magnitudes and not across all rating categories) lasted till the end of 2006. At the start of 2007, credit spreads seem to enter into another upward slope which continues for most of 2007.

Credit spreads appear to have been low but volatile during 2001. This period is characterised by a short recession which started in March and lasted for not more than 8 months. Interestingly, our data suggest that there has been a tightening of credit spreads, more pronounced for speculative bonds especially in the second half of this year. As Tilman and Cohler (2001) suggest, this tightening in credit spreads cannot be explained by an aggressive easing Fed policy associated with poor firms' performances, declining equity markets and slower economic growth in 2001, because these events would have led to higher default rates and consequently higher spreads. Indeed, "mortgage players migrated from primarily using Treasuries to agencies and swaps for hedging … (which) likely contributed to the dramatic tightening in swap spreads. The corporate (bond) market, on the other hand, experienced unusual investor complacency and "yield grabbing" behaviour since capital that has remained on the side-lines simply had to be put to work. (Tilman and Cohler, 2001: 58)"

The narrowing of credit spreads, however, did not last for too long. Enron's filing for chapter 11 bankruptcy protection towards the end of 2001 led to turmoil in the financial markets. Its filing was followed by a high number of downgrades mainly from investment-grade bonds to speculative bonds. Our data (Appendix. 3, Table. 2) also suggest that the number of downgrades was much higher than the number of upgrades for this year, whereas both plots indicate a widening of credit spreads around this time. This may be explained by an increase in firms' default risk in general.

Although credit spreads appear to reach very high levels at the beginning of 2002, they recover slightly before peaking in autumn 2002. Interestingly, an examination of both plots and descriptive statistics for credit spreads levels (Appendix. 3, Table 3.2) indicate that credit spreads in 2002 appear to be higher for the mid and lower-end range of rating categories, but not for upper-end rating classifications. The downgrade/upgrade ratio even for this year remains quite high in levels comparable to that of 2001 (Appendix. 3, Table. A3.2). This period was characterised by a weak economy suffering from a contracted manufacturing sector, weak labour market, and a decline in the value of US dollar against other major currencies such as British pound and Euro[19]. Therefore, in 2002 investors' confidence was affected and the US stock market indices started to fall getting to very low levels particularly between July and September 2002. Hence, fallen equity prices and a weak economy may explain the widening in credit spreads in autumn of 2002.

Dionne et al. (2008) note that credit spreads were high levels during 2001-2002 and up till mid-2003. They argue that the prolonged high credit spreads till 2003 may be a result of investors not being informed about the end of 2001 recession till July 2003. Reporting similarities in credit spreads' behaviour after two recessionary periods (1991 and 2001), they suggest that in general economic cycles are followed by credit cycles that tend to linger for some time and this may also explain the high levels of spreads till the beginning of 2003.

A further inspection of the above graphs suggests that credit spreads start to slope downwards from mid- July 2003 for most of the rating categories. This narrowing of credit spreads might have coincided with the introduction of Sarbanes – Oxley Act which set stricter financial reporting standards for US corporations. This might have restored investors' confidence in corporate balance sheet information and encouraged them to look for higher returns in the speculative segment of the corporate bond market. The shift from investment-grade to

[19] http://en.wikipedia.org/wiki/Stock_market_downturn_of_2002

speculative segment of corporate bonds up till 2004 may also be a result of deleveraging in the corporate sector. Descriptive statistics of credit spreads' levels also indicate that spreads of speculative bonds narrowed at much faster speed than spreads of investment-grade bonds during this period. However, for year 2005 the evidence on credit spread behaviour is mixed with bonds of some rating categories traded at wider spreads. The presence of mixed evidences from credit spreads is also supported by the high number of both upgrades and downgrades during this year as our findings suggest (Appendix 3, Table A3.2). More surprisingly, most of downgrades and upgrades are related to classifications within the investment-grade segment of corporate bonds. This may be partly due to the event risk related to the increased activity of mergers and acquisitions during this year.

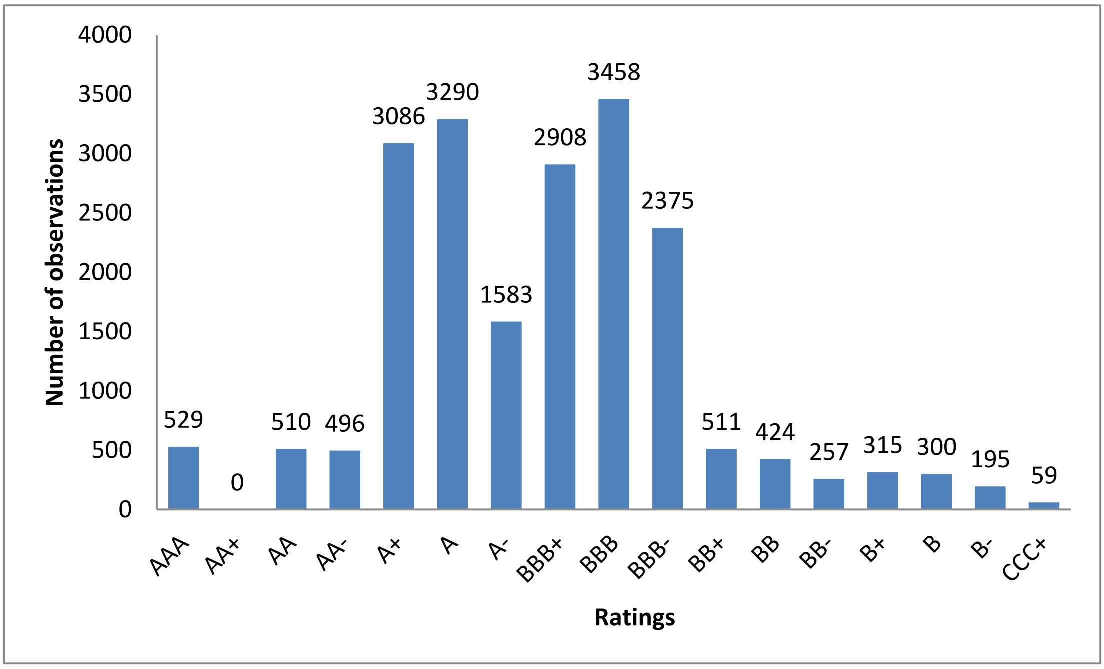
Credit spreads seem to remain low in 2006. A surge in mergers and acquisitions, leveraged buyouts as well as refinancing led to a record issue in corporate bonds during this period. Platt (2007) discloses that the "recycling of petrodollars presumably through London-based investment banks has contributed to the increased activity in the US corporate bond markets in 2006" and consequently to low credit spreads. Furthermore, our findings suggest that for the first time over 2001—2007 period the bond upgrades exceeded the number of downgrades (Appendix. 3, Table3.2). Up till the beginning of 2007, corporate bond markets were characterised by low credit spreads and the U.S. economy looked healthy. U.S. firms were benefiting from low interest rates and were in a very good position with regards to profitability and liquidity despite some firms being highly leveraged due to their "leveraged buyout" activities.

In mid-2007, the subprime mortgage market started to suffer from losses and this worried credit markets including the corporate bond market. As Brunnermeier (2008) notes during this period "investors became concerned about how to value structured products in general, whether for mortgage products or corporate credit products, and confidence in the reliability of rating agencies eroded". Our data (Appendix 3, Table 3.2) indicate an increase in the number of bond downgrades during this year. Similar to Alessandrini (1999) who reports higher changes in credit spreads for low rated bonds in recessionary periods, we find higher variances in credit spreads of speculative bonds than investment-grade bonds.

5.3.2. Descriptive statistics of corporate bonds

In this section we give a discussion of some of the features of bond included in our sample. Figure 5.2 presents distributions of monthly ratings and watch classifications for each bond over the sampling period of 2001-2007. It can be noticed that most of the ratings tend to be between A+ and BBB- categories, hence within the investment-rating group. There are only a few observations at the very bottom of the considered rating scale (CCC+), but a considerable number of observations (7%) at the top rating categories. Surprisingly, there are no observations within the AA+ category. This seems to be the case even for the watch lists (positive and negative) for this category.

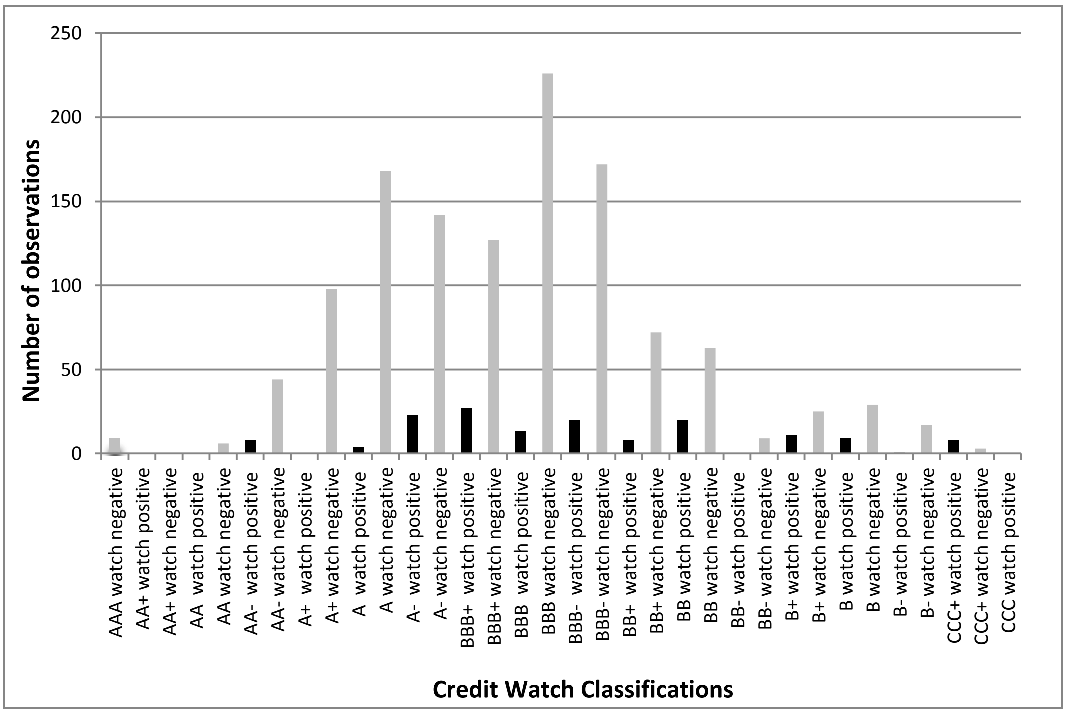
Figure 5.2. Distribution of rating observations in 2001-2007



This figure represents the distribution of rating observations according to S&P rating groups over the whole sampling period. There are no bonds rated as AA+ in our sample. Our sample does not include any observations for rating categories lower than CCC+.

A further examination of observations on watch classifications shows a much higher proportion of negative watch classifications than positive ones in the overall sample (Fig 5.3). This is consistent with previous studies because as they argue rating agencies do not put firms in credit watch positive lists as frequently as they do put them in credit watch negative lists.

Figure 5.3 Distribution of credit watch lists observations in 2001-2007



This figure represents the distribution of watch list observations for the whole sample. The grey bars represent the number of observations for negative watch observations, whereas the black bars represent the number of observations for positive watch observations. There are no observations for some of the watch lists at the upper and lower end of the watch list scale.

Not surprisingly, we find that bonds are more frequently put in BBB watch negative list. This indicates that rating agencies are hesitant to downgrade bonds to category BBB which represents the threshold for bonds being classified as speculative bonds. Furthermore, bonds in lower than A- rating when being put in a negative watch list tend not to have their rating changed on average for a period of 3-5 months. The further down we move to the rating scale towards B classifications, the longer bonds stay in the negative watch lists. Similar to other studies (Alsakka and ap Gwilym, 2010) we find a low proportion of rating changes (including watch lists) when compared to the total number of rating observations in the sample. This is plausible considering that our sample includes monthly data. Based on the discussion in Chapter two we also expect bond ratings not to change frequently, hence generating a considerable proportion of zero rating changes in the sample (Appendix 3, Table 3.2).

Our sample includes bonds issued by firms operating in various sectors (finance, insurance, telecom, utilities, manufacturing and retailing, etc.). Not surprisingly, our data indicate a higher variety in credit spreads and ratings for industrial bonds than for other bonds in the sample (Appendix. 3, Fig.3.3). One will expect firms operating in economic-sensitive industries (such as airline industry) to have extreme spreads, whereas firms operating in highly capital intensive industries (automobiles, capital goods, basic materials, defence, etc.) to have lower spreads. Similar to Khing and Khang (2005)'s findings we report credit spreads changes to be greater for industrial than utility and financial bonds especially in recessionary periods (Appendix. 3, Fig. 3.3). A further examination of differences among bonds across sectors shows that consistently with Khing and Khang (2005)' evidence firms in industrial sector tend to issue bonds characterised by larger issue size and longer maturities than financial and utility bonds. An examination of coupon rates indicates that firms in the transport sector tend to issue bonds with higher average coupons than the other sectors. As expected industrial and utilities bonds are characterized by a greater range of coupon rates than financial bonds. The average coupon rates across groups of maturities (short, medium and long-term) tend to be slightly higher for longer maturities.

Corporate bonds are generally categorised into three groups according to their maturity. These are short-term bonds with maturities of up to 5 years, medium term bonds with maturity 5-12 years and long term bonds with maturities greater than 12 years. The maturity of bonds in this study ranges from 5 to 50 years. More specifically, industrial firms are found to issue bonds whose maturities vary from 5 to 50 years, whereas utility firms, banks and other financial institutions tend to issue bonds with maturities up to 30 years.

Most of the firms tend to issue medium to long-term debt and occasionally they issue debt of maturity greater than 20 years. We find that firms with high or poor credit quality tend to issue shorter-term debt. As Diamond (1991) argues firms with higher credit ratings tend to issue short term debt because their refinancing risk is low, whereas firms with low credit ratings find it very difficult to issue long-term debt due to the adverse selection costs. Thus, short-term borrowers are represented by firms with the highest and poorest bond ratings, whereas firms in between are more likely to issue long-term debt.

In this chapter we provided an explanation of the variables to be employed in the study and an analysis of the behaviour of credit spreads included in our sample. The chapter also includes an analysis of the characteristics of corporate bonds provided in the sample.

Chapter Six: Panel Data Analysis

After the analysis of descriptive statistics for the corporate bond sample, we focus on the methodology that will be employed in this study. The aim of this chapter is to provide an overall introduction of the panel data models and discuss the benefits and limitations of these models. The discussion on this chapter will set the basis for the panel data tests that will be employed in chapter seven and eight.

6.1. Panel data analysis

One of the issues frequently encountered in economics and finance is the estimation of relationships that combine both time series and cross-sectional data. Panel data are characterised by a large sample of units (individuals, firms, households, etc.) observed over a number of periods allowing researchers to apply more complex models than ones used in cross sectional or time series analysis. For example, a panel data sample may represent multiple observations of performance on the same firms over a period of time. With panel data, researchers adequately allow for heterogeneity in behaviour over cross-sectional units as well as heterogeneity over time for a given cross-sectional unit.

Various econometrical studies have looked into the benefits and limitations related to employment of panel data sets. In the next two sections we provide an explanation of the benefits and limitations of panel data analysis based on a comprehensive summary of these points as written by Baltagi (2001).

6.1.1. Benefits of panel data sets:

- *Controls for individual heterogeneity.* Unlike in conventional cross sectional data analysis, in panel data analysis individual units are assumed to be heterogeneous. Not controlling for this heterogeneity may lead to biased results. For instance if a research considers the impact of three main inputs such as capital, labour and managerial skills on firms' profitability ratios then the main hurdle he will face is the lack of data on a non-observable variable like managerial skills. While running a regression on pure cross sectional data may be an option, the parameters given by this model will be biased since an important variable (managerial skills) is omitted. Panel data analysis help in controlling for this latent variable by introducing a fixed effect for each individual firm (assumed to be constant through time). In this way, the bias in estimates for capital and labour factors is eliminated.

- *Panel data sets provide more informative data.* Whereas time series data frequently suffer from multicollinearity between explanatory variables. The cross-section dimension added in panel data sets alleviates this econometric problem. As Baltagi (2001) suggests variation in panel data may be separated into variation between various cross-sectional units and variation within each unit. Furthermore, the additional data provided in panel samples also assist in generation of more reliable econometric estimators. Nijman and Verbeek (1990) suggest that a panel data model may provide more efficient estimators than a series of cross section models with the same number of observations.
- Hsiao (2005) notes that *panel data sets help to control for the effects of omitting variables which in econometrics is known as assertion.* He further clarifies that "it is frequently argued that the real reason one finds (or does not find) certain effects is due to ignoring the effects of certain variables in one's model specification which are correlated with the included explanatory variables. Panel data contain information on both the inter-temporal dynamics and the individuality of the entities may allow one to control the effects of missing or unobserved variables." (pp. 5)
- Panel data assist in *examination of the dynamics of adjustments* which sometimes cannot be captured by purely cross-sectional data. Unlike observations of cross sectional data

over time which may or may not include the same individuals, panel data samples provide data of the same individuals over different periods of time. This allows for an examination of individual behaviour adjustments over time. Matyas and Sevestre (1992) mention that "it is sometimes argued that cross section data reflect long-run behaviour, while time series data emphasize short-run effects. By combining the two sorts of information, a distinctive feature of panel data, a more general and comprehensive dynamic structure can be formulated and estimated. (pp. 22)" This is especially of great importance when the impact of various policy issues or the duration of economic states like inflationary periods is considered.

- Panel data enable researchers *to undertake tests of complex behavioural models.* For instance, Cornwell et al. (1989) examine time varying efficiency levels for individual airlines in a panel data model without making strong distributional assumptions for random noise.

- *No biases resulting from the aggregation of data*. Panel data samples are based on detailed information on each individual unit included. It is well known that more accurate information is collected at micro than macro-level. Consequently, estimates resulted from panel data analysis will be less biased than estimates based on tests run on aggregate data samples.

6.1.2. Limitations of panel data sets

- *Design and data collection problems.* Panel data sets are also called longitudinal surveys because more often such data come from surveys. Two most well-known examples of panel data sets in economics are National Longitudinal Surveys of Labour Market

Experience (Ohio University) and Panel Study of Income Dynamics (University of Michigan). Considering the large scale of longitudinal surveys, one may expect the following issues faced in the process of design and data collection:

- sample bias (incomplete account of the population subject of research),
- *time-in-sample bias (*Considering that in a panel data survey the same individual units are "interviewed" repeatedly during the life of the panel, there may be cases when initial individual responses may be significantly different from subsequent responses or when responses at one stage of panel's life may be influenced by previous responses.)
- *frequency of interviewing each individual* (For example, individuals living closer to the research centre may have a chance of being interviewed more frequently than those living in a considerable distance from the centre)
- collating of information over time (possible errors in referencing)

- *Possible measurement errors.* In a large scale survey required for panel data analysis there may also be cases of flawed responses due to ambiguous questions, coding inaccuracies, interviewer's capabilities in conducting the interview, misrecording of results, deliberate modification of results, etc. Trivellato (1999) notes that "measurement errors are a major concern in panel data precisely because the main aim of such studies is the measurement and analysis of change, and typically, panel data on change tend to be more subject to measurement errors than are cross-sectional data on levels. (pp. 342)" However, he adds that these errors due to longitudinal inconsistencies come to light in the context of panel but not of cross-sectional data, hence encouraging analysts to develop research strategies that may limit these errors.

- Selectivity problems include:

  - *Non-response.* At the initial wave of a panel there may be cases of no responses because some individuals may refuse to participate in the survey, they may not be present at the time of interview, they may not be traced or because of other reasons. Alongside the missing data problem, this nonresponse may raise concerns on the accuracy of identification of research population.

  - *Self-selectivity.* This relates to the issue of truncated samples in which units that do not fall within bounds of sample selection criteria are entirely omitted and no records of these omitted units are kept. Baltagi (2001) mentions that "inference from truncated sample introduces bias that is not helped by more data because of the truncation (p.8)".

  - *Attrition.* The main drawback in panel data surveys is that of individual units leaving the sample before the end of designated time period. This is known as attrition. It refers to the progressive loss of sample units during the life of the panel. As Trivellato (1999) suggests "attrition can cause serious problems. It is a delicate question because the analytic problems caused by attrition are more connected to the nature of attrition than to its amount. Indeed, random attrition affects only the efficiency of estimated. But non-random attrition especially if it associated with unobserved individual characteristics can result in unacceptable biases…that…can lead to major biases in the inferences drawn on the basis of the information provided by the surviving panel members. "(pp. 342)

- *Short*-time series dimension. Most panel samples include annual data gathered over a short period of time on each individual unit. This means that hypothesis testing relies crucially on the large number of individuals included in the sample. The researcher may increase the time span of the sample by collecting more data, but unfortunately this is not without additional costs. Furthermore, this increase may contribute to the issue of attrition as discussed previously.

6.2. Panel data models

Generally, panel data models are given as:

$$Y_{it} = \alpha_{it} + \sum^{k} \beta_{kit} X_{kit} + \varepsilon_{it} \qquad \text{[Equation 6.1]}$$

where

i = 1,2,….,N refers to a cross-sectional unit

t = 1,2,…..T refers to a given time period

Y_{it} is the value of the dependent variable for individual i at time t

X_{kit} is the value of the kth nonstochastic explanatory variable for unit i at time t.

The stochastic error term ε_{it} is assumed to be independent and identically distributed over individuals and time with mean zero $E[\varepsilon_{it}] = 0$ and constant variance $E[\varepsilon_{it}^2] = \sigma_\varepsilon^2$. Coefficients α_{it} and β_{kit} are unknown parameters or response coefficients and in most general cases they can be different for different cross-sectional units and in different time period. In the context of panel data, researchers have to include some assumptions about the degree of variability of regression coefficients.

The simplest set of assumptions is that behaviour is uniform over all individuals and in time and that individual observations are homogenous. Since in this case all the assumptions required by OLS estimation are satisfied, regression coefficients are estimated by *OLS on a pooled data sample*. Strong assumptions of both uniform behaviour and homogeneous observations deny any form of heterogeneity. If panels are characterised by significant individual differences this model should not be considered. In order to account for individual differences while assuming homogenous observations, one should assume that regression coefficients are specific to each individual (and constant through time). This model requires *OLS estimations for each individual unit* (even in the presence of individual heteroscedasticity). While this model allows for tests of differences in individual behaviour and is easily computable, it does not account for any interdependence in behaviour among individual units and provides unreliable estimates especially for panels with large N and small T.

Independence in behaviour from one individual to another in economic applications is a very strong assumption, since some non-observable factors may affect all or part of some individuals' behaviour at the same time. This causes a non-zero contemporaneous covariance between error terms of two different individual units. To account for the existence of this covariance in error terms, Zellner (1962) introduced an interdependence relationship in a regression model. This new model is known as *"seemingly unrelated regression (SUR)"* and is the most appropriate model as it accounts simultaneously for both individual specific effects and interdependence among individuals especially in panels with large T. However, this model does not work well for samples with large N and small T because it lacks the number of degrees of freedom required for its implementation. Hence, unlike OLS models, SUR models are not parsimonious.

One simple step towards parsimony is to assume that response estimators are the same for all individuals except for a generic individual (fixed) effect. This may be accomplished with the introduction of a different intercept (alpha coefficient) for each individual. If alphas are treated as the N fixed unknown parameters the regression model is referred to as *the fixed effect model.* In this model the *"least squares with dummy variables" (LSDV) or within group estimations* are employed. According to LSDV model all the observations are pooled but individual differences are captured through individual dummy variables that act as intercepts in these models. In fixed-effect within model observations are also pooled, but OLS regression in this model is run on mean corrected values because individual differences are captured via deviations of each variable values from its mean value. However, both models are parsimonious (with N+K-1 parameters) and allow for tests on individual differences.

An alternative approach assumes that the intercepts of the individuals are different but they can be treated as samples from a normal distribution with mean μ and variance σ^2. The essential assumption here is that these samples are independent of the explanatory variables x_{it}. This leads to *the random effects model* where the individual effects are treated as random. The error term in this model consists of two components: a time-invariant component and a random error term component that is uncorrelated over time. The main difference between fixed-effect and random-effect models is that while in fixed-effect approaches each individual unit has its own (fixed) intercept, in random-effect models the intercept is common for all individual units and it represents the mean value of all individual intercepts whereas the error term components represent deviations of individual intercepts from this mean value.

Matyas and Sevestre (1992) argue that several factors need to be considered to favour either fixed or random individual effects:

- The underlying causes. If individual effects are believed to be caused by a large number of random non-observable factors then the random interpretation needed to be considered.
- The number of individual units in the panel. In panels with large N and small T, the number of parameters estimated in a fixed effect model is large in relation to the total number of data points included in the panel. This raises the question of reliability of estimation of parameters. If researcher is mainly interested in the slope coefficients rather than differences among individuals (intercept coefficients), then a filtering method may be used to wash away the individual differences and consequently not estimate them.

- The nature of the sample. Panel data sample may be closed or open. When samples are closed (sample includes all possible divisions within a population like industrial sectors or geographical regions) fixed effects are of more interests, whereas when samples are open (individuals in the sample are drawn randomly from the population) then random effects are more interesting. Frees and Kim (2007) suggest that "the choice between these two models is dictated primarily by the method in which the sample is drawn. On the one hand, selecting subjects based on a two-stage sample implies use of the random effects model. On the other hand, selecting subjects based on exogenous characteristics suggests a stratified sample and thus using a fixed effects model."
- The type of inference. Based on whether inferences are made with respect to entire population or the selected sample, the researcher may choose between random or fixed specifications. A random specification is generally suggested for inferences drawn in relation to entire population, whereas a fixed specification is recommended for inferences drawn on the selected data sample.

In summary, it can be said that the fixed assumption on variable coefficients leads to dummy variable models and seemingly unrelated regression model, whereas the random assumption on these coefficients leads to error component models.

Chapter Seven: Granger Causality between Credit Spreads and Bond Ratings

In the previous chapter the main benefits and limitations of the panel data analysis are discussed. Following from this discussion we establish that a Granger causality test in the context of panel data will be appropriate to test the causal relationship between bond ratings and credit spread changes. This chapter starts with a general discussion on Granger causality methodology and then focuses on the application of such tests in the context panel data. Due to the dynamic nature of Granger tests, unit root tests on considered variables should be firstly undertaken.

This chapter also includes a discussion on unit root tests for panel data and illustrate the application of these tests in the context of credit spreads. Once the unit root tests indicate that the credit spread changes are stationary, the relationship between credit spread changes and bond rating changes is examined using a GMM method introduced by Arellano and Bond. The issues associated with the application of this method are discussed.

This chapter then follows with a detailed discussion on the findings of causality links between credit spreads and bond ratings across four main periods as identified in chapter

7.1. Granger causality methodology

Examining whether changes in ratings cause changes in credit spreads or vice versa should have been easy at first sight. However, various econometric studies suggest that questions related to causality between variables are complex. Causality may be unidirectional, for example changes in credit ratings cause changes in credit spreads but not the other way around or bidirectional so that changes in ratings and changes in credit spreads cause each other. Furthermore, a temporal ordering may not be sufficient in establishing causality relations between variables. For example, that credit rating changes occur before credit spread changes, it does not automatically imply that rating changes cause spread changes. This may also be insufficient to reject the possibility that changes in credit spreads cause changes in ratings, since expectations about changes in credit spreads may induce changes in ratings now.

Despite conceptual difficulties related to causality concept, Granger (1969) causality test has been applied extensively in economic studies. Granger causality test simply suggests which of the two considered variables (X or Y) causes changes in values of the other factor. Hence, if X is said to "Granger cause" Y, then changes in X are Useful in predicting future values of Y by adding information beyond that contained in the past values of Y. More specifically, Granger causality test is based on Vector Auto Regression (VAR) model. If we consider two stationary time series with zero means X_t and Y_t, then a simple VAR model between these two variables can be written as:

$$X_t = \sum^{m} a_j X_{t-j} + \sum^{m} b_j Y_{t-j} + \varepsilon_t \qquad \text{[Equation 7.1]}$$

$$Y_t = \sum^{m} c_j X_{t-j} + \sum^{m} d_j Y_{t-j} + \eta_t \qquad \text{[Equation 7.2]}$$

where ε_t, η_t are taken to be two uncorrelated white noise series, i.e, $E[\varepsilon_t, \varepsilon_s] = 0 = E[\eta_t, \eta_s]$ for $s \neq t$ for all s, t.

The null hypothesis $H0: b_j = 0$ for all j and $H0: c_j = 0$ for all js are tested. Classical F-test or Wald test is usually employed to test for the statistical significance of causal influences.

Granger (1969) suggests that if some b_j are significantly different from zero, then Y_t causes X_t and similarly if some c_j are significantly different from zero X_t is causing Y_t. Granger causality tests allow for checks of either causality which run in one direction (from X to Y or Y to X) or feedback systems which run in both directions simultaneously (from X to Y and Y to X). However, it is important to note that Granger causality test provides an instrument that assists research to examine the predictive ability of variables than "causality" as the word is understood.

Employment of Granger causality test requires stationary time series. A time series y_t is considered to be stationary if for any infinite period, the joint probability of any subset of this series such as $y_{t1}, y_{t1+1}, y_{t1+2} \cdots y_{t1+n}$ is identical to the probability of another subset in time such as $y_{t1+t}, y_{t1+1+t}, y_{t1+2+t} \cdots y_{t1+n+t}$. Hence, stationary implication is that the distributions of a series of random variables are invariant in time.

Stationarity is important in econometric modelling as standard linear regression estimators are based on the assumptions that (1) error terms are independent and identically distributed (IID) with mean zero and constant variance and (2) explanatory variables, if random, are stationary and independent from the error terms. This becomes particularly important when credit spreads are concerned since many credit derivative models such as the one suggested by Jarrow et al. (1997) assume spreads to follow stationary processes.

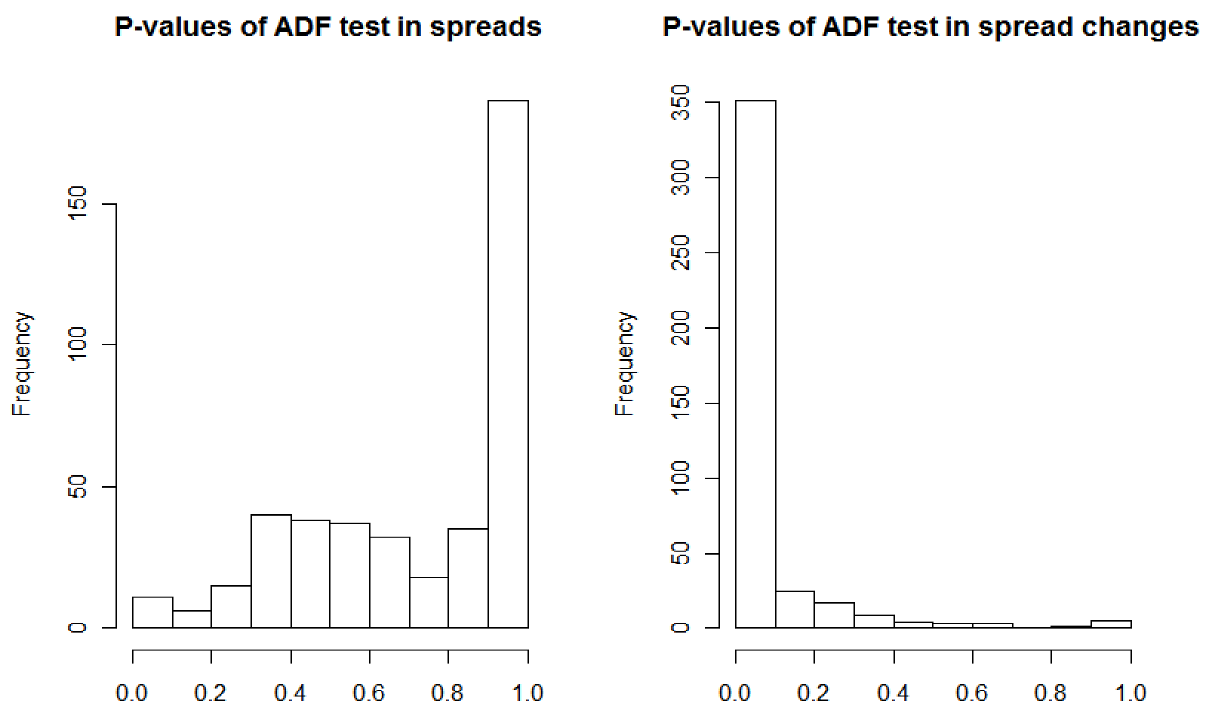
Unit root tests can be applied to check whether the data are stationary. These tests are designed to check for the order of integration of a variable. If y_t is integrated of order 1 without a drift then the value of ρ in the following equation is equal to 1.

$$CS_t = \rho CS_{t-1} + \varepsilon_t \quad \text{[Equation 7.3]}$$

The ρ parameters are estimated for levels of credit spreads of all bond issues. It is known that if the existence of a unit root cannot be rejected, the series should be at least first-differenced before used in various tests. First-differenced spreads are then checked for stationarity. The

Augmented Dicky-Fuller (ADF) test is employed to test the null hypothesis $H_0: \rho = 1$. The higher the estimated ρ-value the bigger the evidence for ρ=1, hence non-stationary is present. The following tables represent the frequency of p-values for each time series for both credit spreads' levels and their first differences.

Figure 7.1. P-values of ADF (Augmented Dicky-Fuller) tests for both levels and changes of credit spreads



These plots suggest that the original spreads produce rather large p-values (see the plot on the left), hence we have a strong unit root evidence. However the p-values for spread changes (see the plot on the right) suggest no unit root i.e. stationarity.

The null hypothesis of parameter ρ being equal to 1 is rejected when the absolute value of parameter p is significantly less than unity. Since a panel data sample is considered in this study, a panel unit root test as suggested by Choi (2001) is employed for testing many time series simultaneously. In his paper, Choi (2001) suggests various unit root tests which can be applied when panel data are heterogeneous and non-stationary by combining individual unit root tests applied on each time series. He further argues that his proposed tests can be employed for panel data with (1) finite or infinite N dimension or (2) different time dimension for each individual and that alternative hypothesis can allow for part of the time series to be stationary while the others may not. Based on Choi (2001) test suggestions, we decide to use the inverse normal Z-test (where the corresponding p-values for each issue are included) as follows:

$$Z = 1\frac{1}{\sqrt{N}}\sum_{i=1}^{N}\Phi^{-1}(p_i)$$

[Equation 7.4]

where N represents the number of bond issues, p_i indicate the p-values for an one-sided unit root statistic for the i-th bond issue, and Φ is the standard normal cumulative distribution function. Baltagi (2001) also suggests that this test seems to outperform the other ones and as such is recommended.

Since Z converges weakly to $N\sim(0,1)$, the null (unit root) hypothesis for the population is rejected if the observed value of Z is less than the critical vale of the lower tail of standard normal distribution. The corresponding Z-values for spreads and their changes are 18.55477 and -36.44285 respectively. When compared to critical values, the test statistics suggest that credit spreads levels are non-stationary at 1% significance level, whereas first-differences (changes) in spreads are stationary also at 1% significance level. We also undertake another unit root test known as Hadri test for heterogeneous panels. These findings of stationary are consistent with previous evidence provided by Pedrosa and Roll (1998) and Joutz et al (2001) who find that differences in credit spreads are stationary. While the stationarity of credit spread variable can be tested, the same cannot be said for credit rating variable ($RTNG_{it}$) which is a non-zero categorical variable.

7.2. Granger causality tests in a panel data context

Recently there have been a few studies that examine causal influences between variables in a panel data context. This examination is complex because causality is assessed not only over a period of time, but also across units. Furthermore, Granger causality test requires the application of a dynamic model since it requires the presence of a lagged dependent variable in the right hand of the regression models. Since the error terms in a panel data model include an error term characterising the unobservable effects of individual units and another remaining disturbance error term, the inclusion of a lagged dependent variable among regressors introduces correlation between this lagged variable and the error term for the individual effects. This leads to biased OLS estimators.

Sevestre and Trognon (1992) argue that there are two criteria a researcher should consider before modelling dynamic fixed effects in a panel data set. These are the degree of correlation of the error terms and the exogeneity of explanatory variables. If error terms are not serially correlated but explanatory variables are endogenous, then instrumental variable method should be preferred. In order to remove the individual effects in a dynamic model, the first differences transformation is suggested. Such transformation produces valid instruments that are not correlated with differenced remaining disturbance errors.

Arellano and Bond (1991) propose the application of Generalised Method of Moments (GMM) to get consistent estimators when instrumental variables are generated in a dynamic model. GMM is more appropriate when a consistent estimator is required and efficiency is of a secondary concern. Since it does not require any assumptions about the exact distribution of the error terms, GMM can deal with any form of heteroscedasticity and serial correlation which our data suffer from. Furthermore, Baum et al. (2003) argue that in the presence of heteroscedasticity in the model, GMM rather than instrumental variables should be employed.

Reisen and Maltzan (1999) apply a GMM model to examine the lead-lag effects of sovereign ratings on spreads between yields of central government bonds in emerging markets and yields of US Treasury bonds. In this study, we propose to follow a similar approach. In line with (Reisen and Maltzan (1999), the Granger causality test is performed based on the following equations:

$$Y_{it} = \beta X_{it-1} + \mu W_{it-1} + \alpha_i + u_{it} \qquad \text{[Equation 7.5]}$$

$$X_{it} = \gamma Y_{it-1} + \eta W_{it-1} + \lambda_i + v_{it} \qquad \text{[Equation 7.6]}$$

where i and t indicate bond issues and time periods respectively, α_i and λ_i represent bond specific intercepts (unexplained individual effects) and u_{it} and v_{it} are the respective remaining disturbance terms. Y_{it} represent credit spreads for bond i at time t, X_{it} stand for the numerically transformed bond ratings for bond i at time t, whereas W_{it} represent values of both endogenous lagged variables (on both bond ratings and credit spreads) and some exogenous risk determinants variables.

Preferably, exogenous variables should represent factors that contribute to default risk or other possible factors that may influence any changes in credit spreads such as liquidity or tax related factors. While financial accounting ratios play an important role in the rating process, financial data for US firms are provided quarterly. Granger (1969) argues that sampling period of the data is important to assert whether econometric models are simple causal models. He states that "it may be true that when quarterly data are used for example a simple causal model is not sufficient to explain the relationships between variables, while for monthly data a simple causal model will be all that is required. (pp.427)"

Another argument against inclusion of financial accounting ratios is that incorporation of ratings as an independent variable along with other financial factors in multivariate regressions where credit spreads represent the dependent variable will lead to serious multicollinearity problems. Hence, only macroeconomic time-series variables such as the level of interest rates, the slope of risk-free term structure, and stock options implied volatility index are considered as exogenous factors.

Reisen and Maltzan (1999) run GMM techniques in a balanced data sample. Due to the increased number of variables included in the regression model to represent instrumental variables, it is difficult to run GMM for an unbalanced panel as it is the case in our study. For the purpose of this study we employ a strongly balanced data sample of 231 corporate bonds. Additionally, bond ratings in the first model are included as a predetermined variable since it is assumed that their past values may be related to error terms, but their current and future values may not be correlated with the values of the errors. For the same rationale, changes in credit spreads are considered as a predetermined variable in the second model. We include three lagged values of changes in credit spreads and changes in bond ratings in both models. On the basis that bond ratings are assumed to provide information on a firm's default probability, explanatory variables such as changes in lagged values of interest rate levels, slope of risk-free term structure and VXO index are included in both models.

To check for Granger causality effects we firstly run the model with changes in credit spreads as the dependent variable and then the model with changes in bond ratings as the dependent variable. Lagged values of the dependent variable are employed as instrumental variables. As it is discussed in various econometrical papers, the choice of number of instruments is very subjective. There is not a generally accepted model that helps researchers decide how many instruments to choose. One suggestion would have been to apply Sargan test of overidentifying restrictions but as Baum et al. (2003) argue this test is not very powerful.

Robust standard errors are used for each model. This ensures that resulting standard errors are consistent with panel-specific heteroscedasticity. Furthermore, when this method is followed only AR(1) and AR(2) tests are run. Most often tests of AR(1) reject the null hypothesis of no autocorrelation. This is expected as consequent differences in error terms have one error term in common. However, AR(2) test in differences is more important as this may suggest the presence of autocorrelation in levels of error terms.

The existence of sub-periods within the sample where the market reaction may differ significantly weakens the robustness of the findings. Furthermore, considering that Arrelano and Bond (1991)'s GMM approach is designed for short panels "small T, large N", the data are grouped in sub periods. The first subsample covers the period from January 2001 till mid July 2003 (Period 1). As discussed in Chapter 5, this period is characterised by prolonged wide credit spreads. The second sub-period (Period 2) includes data from mid-2003 till the end of 2005 during which a mixed evidence of credit spreads' behaviour is noticed mainly due to a record number of upgrades and downgrades characterising the investment-grade rating category. This is then followed by the third sub-period (Period 3) from the January 2006 till March 2007. This period is characterised by a further narrowing of credit spreads occurs. The last sub-period (Period 4) covers most of year 2007 and represents another period of widening credit spreads. Given that our sample of ratings data includes information for both actual rating changes and credit watch lists, the Granger tests suggested by Reisen and Maltzan (1999) are also run on subsamples of both actual rating changes and watch lists.

7.3. Findings and discussion of Granger causality tests

The results for Granger causality tests are presented in Table 7.1. Wald test results indicate that parameters of explanatory variables in all models are different from zero thus they cannot be omitted from the model. This is the case for both regression models with changes respectively in credit spreads and bond ratings as dependent variables. One of the requirements of GMM models is non-existence of serial correlation of the second order as the first order autocorrelation of error terms is already embedded in the model. All our tests indicate no presence of second-order autocorrelation in error terms.

We firstly look at the models with changes in credit spreads as dependent variable (Table 7.1). The results indicate that lagged changes in macroeconomic factors can help explain part of the variation in credit spreads changes.

Table 7.1 Granger Causality Test for Sub-Periods (Credit spreads as Dependent Variable)

	Dependent Variable: Changes in Credit Spreads			
	Change in Credit Spreads (Period =1)	Change in Credit Spreads (Period 2)	Change in Credit Spreads (Period 3)	Change in Credit Spreads (Period 4)
Wald statistic (P-value)	191.84*	113.6*	68.66*	635.82*
Number of observations	5664	7080	3540	2124
Variables	Coefficient	Coefficient	Coefficient	Coefficient
dCS(-1)	-0.141*	-0.245*	-0.028	-0.636*
dCS(-2)	-0.120*	-0.152*	0.075	-0.646*
dCS(-3)	0.055	-0.093*	-0.066	-0.360*
dRTNG(-1)	-0.0009	-0.0001	-0.0004	0.003**
dRTNG(-2)	-0.0068**	0.0001	-0.0005	0.003
dRTNG(-3)	-0.0003	-0.0001	-0.0003*	0.001**
dINTLEV(-1)	-2.013***	0.560*	1.155*	1.199**
dSLOPE(-1)	-3.377*	2.749*	-1.094**	5.005*
dVXO(-1)	0.023*	-0.009**	0.008**	0.084*

This table represents Granger test results for the four periods when the dependent variable in the model is the change in credit spreads. Period 1 covers the data from January 2001 till July 2003, period 2 covers the data from August 2003 till December 2005, period 3 covers the data from January 2006 till March 2007 and period 4 covers the data from April 2007 till December 2007. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level respectively.

Lagged changes in the slope of risk-free term structure have statistically significant impact on changes in credit spreads, although the sign of this impact alternates as we move along the periods. Lagged changes in interest rate levels are reported to be positively related to changes in credit spreads with the exception of a negative relationship found in the first period. In line with our discussion in Chapter four, we find a positive relationship between lagged changes in implied volatility index and changes in credit spreads, with the exception of period 2 where this relationship is reported to be negative.

The results further indicate that changes in credit spreads are more dependent on their own lagged values than on lagged changes of bond ratings. Furthermore, changes in credit spreads seem to be negatively related to their lagged values of up to two months. This implies that the rate of increase in credit spreads is falling over time, suggesting a mean reversion in credit spreads differentials. The negative parameters for lagged variables of changes in credit spreads in the second period reflect narrowing credit spreads levels that characterised this period (Chapter 2). Surprisingly, we find no significant evidence of lagged effects of credit spreads changes in periods of “calmness” in corporate bond markets.

Parameters on variables of lagged bond rating changes indicate a weak explanatory power of these variables for credit spread changes. However, we find some significant impact of lagged changes of bond ratings on changes of credit spreads in periods one, three and four. Given that the significant parameters refer to the second and third lagged changes in bond ratings, we may suggest that the lagged changes in ratings have some information value for credit spreads. The sign of this relationship is not found to be consistent across the four periods.

Findings reported in Table 7.2. do not provide a strong support for the relationship between changes in bond ratings and lagged changes of macroeconomic variables such as interest rate levels, slope of risk-free term structure and implied volatility index. We find lagged changes in credit spreads of up to two months to have a positive impact on bond ratings changes indicating that past narrowing credit spreads may contribute to reclassifications of bonds into higher-quality rating classes. This impact is found to be more pronounced in the second period.

Our empirical findings further indicate that changes in bond ratings are not consistently related to their lagged values across the sampling periods. In the last two periods, lagged bond ratings of even up to three months have an impact on the most recent changes in rating reclassifications. This is not the case in the other two periods. We can argue that during good economic periods the

Table 7.2 Granger causality tests for sub-periods (Bond ratings as dependent variable)

	Dependent Variable: Changes in Credit Ratings			
	Change in Bond Rating (Period 1)	Change in Bond Rating (Period 2)	Change in Bond Rating (Period 3)	Change in Bond Rating (Period 4)
Wald statistic (P-value)	24.97**	30.55*	55.77*	37.63*
Number of observations	5664	7080	3540	2124
Variables	Coefficient	Coefficient	Coefficient	Coefficient
dRTNG(-1)	-0.072**	0.005	-0.105**	-0.061**
dRTNG(-2)	-0.007	-0.0155	-0.086**	-0.062**
dRTNG(-3)	-0.023	0.0008	-0.061**	-0.043
dCS(-1)	3.416	6.343*	55.803*	-6.994***
dCS(-2)	3.913	4.377**	0.852	0.611
dCS(-3)	-0.882	-1.264	-3.688	-8.583**
dINTLEV(-1)	32.933	29.853	6.613	27.120
dSLOPE(-1)	7.728	-69.096	43.790	33.068
dVXO(-1)	0.057	-0.657***	0.929	-1.088*

This table represents Granger test results for the four periods when the dependent variable in the model is the change in bond ratings. Period 1 covers the data from January 2001 till July 2003, period 2 covers the data from August 2003 till December 2005, period 3 covers the data from January 2006 till March 2007 and period 4 covers the data from April 2007 till December 2007. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level.

agency ratings do not upgrade or downgrade ratings very frequently. However, this is not the case in difficult economic times. Agency ratings review their ratings more frequently thus leading in more announcements of bond upgrades or downgrades or bonds being put in credit watch lists.

In uncertain and difficult economic times (periods two and three) we find that changes in bond ratings are negatively related to their lagged values of even up to three months (period two). Based on the discussion in Chapter 2 that rating agencies might want to achieve some degree of both rating stability and accuracy (Cantor and Mann, 2007), credit rating agencies may decide to put firms in credit watch lists rather than frequently change firms' ratings. Furthermore, these credit watch lists might act as implicit contracts between firms and rating agencies where firms promise to undertake recovery actions to avoid the decline in its credit quality and consequently its debt being downgraded (Boot et al, 2006). Hence, prevention of further deterioration of credit quality by putting firms in credit watch negative lists may explain at some extent the negative coefficients for lagged changes in credit ratings in periods two and three.

Theoretically, if one would expect bond ratings to Granger cause credit spreads, then there should be an expectation of an information feedback from the first lagged change in bond ratings to changes in credit spreads in Equation [7.5]. Simultaneously, unidirectional Granger causality requires that lagged variable of changes in credit spreads does not have an impact on the changes in bond ratings in Equation [7.6]. We find (Tables 7.1 and 7.2) that lagged values of bond rating changes have some explanatory power for changes in credit spreads. Additionally changes in spreads are found to be explaining part of the bond ratings. However, the results are not consistent across the four periods.

The findings on the second period indicate that credit spreads changes feed into bond rating changes, whereas in the fourth period we note that both credit spreads and bond ratings provide information for each other. Reisen and Maltzen (1999) argue that as "unforecastable shocks may simultaneously impact credit spreads and ratings, even identifying a two-way causality between ratings and spreads may be consistent with rating agencies revealing information to the market (pp.289)". Based on Reisen and Maltzen (1999)'s argument, we can suggest that bond ratings changes have some informational value for corporate bond investors. Looking across four periods, our estimates indicate that bond ratings play a more important role in periods characterised by difficult economic conditions or turbulence in the financial markets.

In order to gain a better understanding on the relationship between changes in bond ratings and changes in credit spreads, we then run the Granger causality tests (Equation 7.5 and Equation 7.6) for subsamples of downgrades, upgrades and credit watch lists. The subsample for positive credit watch lists is very small. The results for this subsample were not significant hence no results are reported. Findings for rating changes' subs-samples are provided in Table 7.3. The results provide some significant relationship between rating changes and credit spreads for the subsample of watch negatives.

Table 7.3. Granger causality tests for subsamples of watch lists, downgrades and upgrades

PANEL A	Dependent Variable: Changes in Credit Spreads		
	Change in Credit Spreads (Watch Negative)	Change in Credit Spreads (Downgrades)	Change in Credit Spreads (Upgrades)
Wald statistic	213.86*	25.32**	186.71*
Number of observations	198	224	187
Variables	Coefficient	Coefficient	Coefficient
dCS(-1)	-1.458*	-0.025	-1.005*
dCS(-2)	-.618**	-0.182	-.796*
dCS(-3)	-.185***	0.478	-0.1614
dRTNG(-1)	-.0031**	-0.003	-0.0007
dRTNG(-2)	-.0038***	-0.010**	-.0028**
dRTNG(-3)	0.0024	-0.016*	0.001
dINTLEV(-1)	-3.714	1.964	-0.639
dSLOPE(-1)	7.635**	-3.638	2.042
dVXO(-1)	-0.008	0.158**	0.0138
PANEL B	Dependent Variable: Changes in Credit Ratings		
	Change in Bond Rating (Watch Negative)	Change in Bond Ratings (Downgrades)	Change in Bond Ratings Upgrade
Wald statistic	206.22*	21.34*	169.36*
Number of observations	198	224	187
Variables	Coefficient	Coefficient	Coefficient
dRTNG(-1)	-0.420*	-0.467**	-.770*
dRTNG(-2)	-0.553*	-0.094	-.674*
dRTNG(-3)	0.208	0.517**	.330***
dCS(-1)	53.384*	-2.864	18.349
dCS(-2)	57.725*	3.76	-2.554
dCS(-3)	25.746*	16.175***	-46.352**
dINTLEV(-1)	601.882	1243.021*	-109.358
dSLOPE(-1)	1.995	-1743.9**	-541.123
dVXO(-1)	0.148	8.618	-20.140*

This table represents Granger test results for the sub-samples of watch lists, downgrades and upgrades. Panel A provides the results for rating subsamples when credit spreads change is the dependent variable. Panel B provides the results for the three rating subsamples when rating change is the dependent variable. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level respectively.

Following from the empirical findings discussed in Chapter 2, we expect credit spreads to be more closely linked to credit watch lists news than to actual rating changes and to downgrade then upgrade movements in bond ratings. Our estimates (Table 7.3) indicate a more persistent relationship between credit watch lists and credit spreads when compared to the relationship between downgrades/upgrades and credit spreads. The parameters for credit watch negative lists suggest a two-way causality between credit spreads and negative watch lists. This finding might be consistent with findings from previous studies which suggest that credit watches carry more informational value than actual reclassifications of credit quality.

We explore further the relationship between the two variables of credit rating and corporate bonds by undertaking Engle and Granger (1987)'s error correction model (ECM). This model is two-folds as it considers both short-term causality and long-term relationship between two variables. So far, the results based on Reisen and Maltzan (1999) provide mixed evidence on the impact of controlling variables (interest rate level ($INTLEV_t$), slope of risk-free rate term structure ($SLOPE_t$) and implied volatility index (VXO_t)) on bond rating changes. Hence, we decide to examine the error correction models without the presence of these controlling variables.

Based on Engle and Granger (1987)'s approach, the behaviour of credit spreads and bond ratings is examined by firstly estimating the residuals from the long-term relationship between these two variables. Then these residuals are incorporated in dynamic models as follows:

$$\Delta CS_{it} = \alpha_{1i} + \sum_{j=1}^{k} \beta_{1j} \Delta CS_{i,t-j} + \sum_{j=1}^{k} \gamma_{1j} \Delta RTNG_{i,t-j} + \lambda_1 ECT_{i,t-1} + \mu_{it} \quad \text{[Equation 7.7]}$$

$$\Delta RTNG_{it} = \alpha_{2i} + \sum_{j=1}^{k} \beta_{2j} \Delta RTNG_{i,t-j} + \sum_{j=1}^{k} \gamma_{2j} \Delta CS_{i,t-j} + \lambda_2 ECT_{i,t-1} + v_{it} \quad \text{[Equation 7.8]}$$

where:

α_{1i} and α_{2i} represent the individual effects, j represents the number of lagged variables, $\Delta RTNG_{it}$ and ΔCS_{it} represent the cointegrated variables, $ECT_{i,t}$ is the error correction term representing the residual from the long-term relationship between $\Delta RTNG_{it}$ and ΔCS_{it} when using an OLS pooled regression on these variables and μ_{it} and v_{it} are the error terms for these two models (Equation 7.7 and 7.8). λ_1 and λ_2 represent the parameters that correct for the relationship between credit spreads and bond ratings. They indicate the speed at which the equilibrium in the relationship between these two variables is restored. γ_{1j}, β_{1j}, γ_{2j} and β_{2j} represent parameters that capture the impact of lagged variables $\Delta RTNG_{it}$ and ΔCS_{it} on changes of credit spreads and bond ratings respectively. We employ Arellano and Bond (1991)'s GMM approach to test both these models. Following the AIC criterion, we decide to employ only two lagged variables of each of both variables $\Delta RTNG_{it}$ and ΔCS_{it}.

Panel A (Table 7.4) presents results for the error correction model when linear numerical ratings are employed (Appendix 2). Bartholdy and Lekka (2002) argue that logit transformations of credit ratings provide improved estimations since they help transform a bounded (with minimum and maximum categorical values) dependent variable such as credit ratings into an unbounded one. Panel B in Table 7.4 presents the results when logit-transformations[20] of bond ratings are used.

Table 7.4. The error correction model for numerical and log transformations of bond ratings.

Panel A	**dCS (it)**	**dRTNG (it)**	Panel B	**dCS(it)**	**dRTNG(it)**
dCS(-1)	-.0129	0.982	**dCS(-1)**	-0.020	0.069
dCS(-2)	-.0694*	0.0487	**dCS(-2)**	-0.073*	-0.146
dRTNG(-1)	.0029*	-0.096*	**dRTNG (-1)**	0.010*	-0.107*
dRTNG(-2)	.0001	-0.094*	**dRTNG(-2)**	0.001	-0.096*
ECT(-1)	-.774*	-0.165*	**ECT(-1)**	-0.759*	-0.180*
_cons	-.0002	0.0181	**_cons**	-0.0002	0.005
Wald-test	1413*	175*	Wald-test	1374.61*	177.91*

This table provides the results of the dynamic model that explores the relationship between bond ratings and credit spreads including the error correction component. Panel A provides the results when bond ratings are transformed into a linear numerical scale, whereas Panel B provides the results when a logit- transformation of rating is employed. This table represents Granger test results for the sub-samples of watch lists, downgrades and upgrades. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level respectively.

[20] Equation $L_{it} = \ln\left[\frac{RTNG_{it}}{18 - RTNG_{it}}\right]$ is used for logit-transformation of ratings.

Based on the negative significant coefficient for the lagged error correction term ECT(-1) in Panel A, we can suggest that credit spreads and bond rating series converge in the long-term. Changes in credit spreads and bond ratings are related in short –term. In addition, the results from both panels (panel A and panel B) are similar and suggest a strong unidirectional impact of bond rating changes on credit spreads changes. Hence, the error correction model findings indicate that bond rating changes have some informational value in the corporate credit markets.

In summary, this chapter provides a discussion on the Granger causality tests in the panel data context. It covers some of the issues related to the application of these models. It then followed with the explanation of models employed to test Granger causality between changes in bond ratings and credit spreads. The results indicate the presence of Granger causality between these two variables during difficult economic periods and for the sample of credit watch lists.

Chapter Eight: Determinants of Credit Spreads

In the previous chapter Granger causality relationship between credit spreads and bond ratings is examined. Findings suggest that the relationship between these two variables is complex. Therefore in this chapter we aim to shed more light on the impact that factors other than ratings may have on variations of credit spreads.

This chapter firstly provides a discussion of various methodological issues faced in analysis of credit spreads in a panel data context is provided. Considering the presence of clustered volatility in bond markets (Dionne et al, (2008), Pedrosa and Roll (1998), etc.), we employ a panel ARCH/GARCH process to explore the determinants of credit spreads. To our knowledge these panel data processes are not previously considered in the context of credit spreads.

This chapter then continues with a discussion of diagnostic tests undertaken to check for heteroscedasticity, cross-section correlation and autocorrelation in the model. The corrected model is run for both subsamples of investment-grade and speculative bonds. The findings are discussed for each subsample separately.

Considering that findings from previous studies have provided mixed results about factors that may explain individual differences in corporate spreads, one would be more tempted to favour random to fixed models. While Cremers et al. (2008) suggest that issuer specific factors may play an important role in explanation of credit spreads, Campbell and Taskler (2003) find that issuer-fixed effect or fixed-time effect do not add any explanatory power to changes in credit spreads. Since observations included in the sample represent a random sample of U.S. corporate bonds we need to consider in our methodology both fixed-effects and random models employing the following model:

$$\Delta CS_{it} = \alpha + \beta_1 \Delta SLOPE_t + \beta_2 \Delta INTLEV_t + \beta_3 S\&P500_t + \beta_4 EQRET_{it} +$$

$$+ \beta_5 \Delta VXO_t + \beta_6 SMB_t + \beta_7 HML_t + \beta_8 LIQ_{it} + \beta_9 ISS_i + \beta_{10} JANEF + \varepsilon_{it}$$

[Equation 8.1]

8.1. Modelling of credit spreads for investment-grade bonds

The fixed-effect results for investment-grade bonds (Table 8.1) indicate that while the variable of issue size is dropped from the model, all the other explanatory variables suggested by the model are statistically significant. The overall R-square value is low, but F-test value for R-square indicates that the model is correctly specified and regression coefficients are different from zero. The estimate of rho coefficient suggests that a low proportion of variation in changes in credit spreads is related to inter-bonds differences. The F-test following the regression model indicates that bond-individual effects are not statistically different from zero.

Table 8.1. Fixed and random effect models for investment-grade bonds

	FE model	RE model
Number of obs	16911	16911
Number of groups	210	210
R-square overall	0.0327	0.1228
F-test	268.20*	
Wald-test		2322.57*
ΔSLOPE	0.0150*	0.009*
ΔINTLEV	-0.014	-0.014*
S&P500	-0.004	-3.3E-05
EQRET	-0.005	-0.005*
ΔVXO	0.0188	0.0301*
SMB	-0.004	-0.006*
HML	-0.01137	-0.0147*
LIQ	-4.7E-06	3.91E-08
ISS	(dropped)	0.001
JANEFF	-0.001	-0.001*
_cons	0.002	-0.002

This table represents the results from both fixed and random effect models on credit spreads data of investment grade bonds.. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level respectively.

Next the random-effect model (Generalised least squares) model for investment-grade bonds is considered. In this model the correlation between individual effects and regressors is assumed to be equal to zero. The Wald test result in this case indicates that all coefficients in the model are different from zero. However, coefficients for liquidity, issue size and S&P 500 returns are statistically insignificant. The signs and statistical significance of the other regressors are not different from the ones reported for the fixed-effect model. However, the interpretation of coefficients in a random model is slightly different from the interpretation of coefficients in a fixed effect model. For example, the regression coefficient of -.00045 for the equity returns variable represents the average effect of unit change in equity returns (across time and between bonds) on changes in credit spreads.

Statistically, fixed effect models are expected to provide more efficient estimators in panel data since the emphasis is more on the heterogeneity cross-sectionally than over time. In order to decide which of these two models (fixed or random) provide consistent and efficient estimators the Hausman (1978) test is employed.

As Baum (2006) explains "if the regressors are correlated with μ_i (individual effects), the FE estimator is consistent but the RE estimator is not consistent. If the regressors are uncorrelated with μ_i (individual effects), the FE estimator is still consistent, albeit inefficient, whereas the RE estimator is consistent and efficient. Therefore, we may consider these two alternatives in the Hausman test framework, fitting both models and comparing their common coefficient estimates in a probabilistic sense. (pp. 230)"

Hence, the null hypothesis of this test is that the random effect estimators are consistent. The Hausman test result for investment-grade bonds (Appendix 3. Table A.3.5) indicates that the null hypothesis (difference in coefficients not systematic) is rejected. Hence, bond individual effects appear to be correlated with regressors. Therefore, the fixed-effect model is supposed to provide more efficient and consistent estimators than the random-effect model for the subsample of investment grade bonds. However, F-test results on the values for individual effects in fixed effect model indicate that these coefficients are equal to zero.

8.1.1. Diagnostic checks for investment-grade bonds

Before proceeding with the discussion of our findings for investment grade bonds, some diagnostic checks are undertaken to test whether our model violates any of the required underlying econometric assumptions such as constant variance and no serial correlation in error terms. We initially check for the presence of heteroscedasticity in the fixed effect model employing a modified Wald test for groupwise heteroscedasticity.

The test results (Appendix. 3 Table.6) suggest a rejection of the null hypothesis of homoscedastic error terms in fixed effect regressions for investment-grade bonds. Additionally, the results from Breusch-Pagan test confirm presence of heteroscedastic errors in the model (Appendix. 3 Table. 7). Based on the graphical presentation of credit spreads' behaviour over the sampling period in chapter 5 (Figure 5.1) we suspect error terms to be conditionally heteroscedastic.

Cermeήo and Grier (2001) argue that although OLS (Ordinary Least Squares) estimators are best linear unbiased estimators in the presence of conditional heteroscedasticity, the non-linear GARCH estimators are more efficient than OLS estimators. They further explain that GARCH panel models may provide better results for samples characterised by risk/uncertainty and lack of availability of long-term data. They state that "it therefore would be valuable to be able to test panel regressions of financial data for GARCH effects and have a more efficient panel estimator available if the error term is found to be conditionally heteroscedastic. (Cermeṅo and Grier, 2001:.2)"

Volatility clustering is the tendency for extreme returns to be followed by other extreme returns although not necessarily with the same sign. Significant economic events may be generally marked by large positive and negative moves. Volatility is often modelled as conditional standard deviation of returns based on historical information and although the conditional expected returns are consistently close to zero, the presence of volatility clustering suggests that conditional standard deviations are continually changing in a partly predictable manner. For example, if credit spreads in the last few days have been large, then it may be suggested that the distribution from which tomorrow's credit spreads is "drawn" should have a large variance. This is the rationale behind ARCH/GARCH processes.

In order to test for ARCH (AutoRegressive Conditional Heteroscedasticity) effects, one should first estimate the model

$$Y = X\beta + \varepsilon \qquad \text{[Equation 8.2]}$$

by ordinary least squares to yield the vector of residuals given by $\hat{\varepsilon}$. The artificial regression of $\hat{\boldsymbol{\varepsilon}}_t^2$ on a constant and $\hat{\boldsymbol{\varepsilon}}_{t-1}^2$ may then be used as the basis for an asymptotic test of an ARCH(1). In the absence of an ARCH effect $\hat{\boldsymbol{\varepsilon}}_{t-1}^2$ will not contribute to any significant explanation of $\hat{\boldsymbol{\varepsilon}}_t^2$ and so the resulting R^2 from this artificial regression will be low. This method may be further extended to accommodate higher orders of ARCH processes. If the error follows an ARCH (p) process, then $Y = X\beta + \varepsilon$ and $\varepsilon_t = u_t\sqrt{h_t}$ where u_t is a standard normal variable and

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \dots + \alpha_p\varepsilon_{t-p}^2 \qquad \text{[Equation 8.3]}$$

Hence in an ARCH (p) model, the conditional variance of ε_t, σ_t^2 is h_t.

In an ARCH process the error terms are not autocorrelated, but the conditional variances of ε_t are autocorrelated since they depend on previous errors. The general form of an ARCH process may be characterised as:

$$Var(\varepsilon_t|\psi_t\ ) = \sigma_t^2 \qquad \text{[Equation 8.4]}$$

Where ψ_t is the information available at time t. In the ARCH process this term depends only by the previous realized errors. However, this may be generalized so that ψ_t also includes previous conditional variances

$$\psi_t = \ \{\varepsilon_{t-j}, \sigma_{t-k}^2\ ;\ j = 1 \dots q;\ \ k = 1 \dots p\}. \qquad \text{[Equation 8.5]}$$

This is the Generalised ARCH ($GARCH$) model proposed by Bollerslev (1986). In a GARCH process:

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \dots + \alpha_p\varepsilon_{t-p}^2 + \gamma_1 h_{t-1} + \gamma_2 h_{t-2} + \cdots + \gamma_q h_{t-q} \qquad \text{[Equation 8.6]}$$

In the presence of conditionally heteroscedastic cross-sectionally correlated errors, the least-squares estimator is consistent but not efficient. This problem can be solved with the help of a MLE, (maximum likelihood estimation) approach as it is the case in ARCH/GARCH models. This is a well-known technique for statistical inference which relies on the maximization with respect to the model parameters of the likelihood (or probability) function of the observed data. It can be utilized in such a way that for a choice of parameters (which will be maximized in the function) and given the data we can calculate the residuals $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_t$ and using

$$\varepsilon_t = u_t\sqrt{h_t} \qquad \text{[Equation 8.7]}$$

Then the probability (likelihood) of observing the residual at time t (given we have observed the previous residuals up to time t) is

$$p(\varepsilon_t) = \frac{1}{\sqrt{2\pi h_t}} e^{\frac{\varepsilon_t}{2\,h_t}}$$ [Equation 8.8]

This is the density function of a normal distribution at point ε_t with mean 0 and variance

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots + \alpha_p\varepsilon_{t-p}^2 + \gamma_1 h_{t-1} + \gamma_2 h_{t-2} + \cdots + \gamma_q h_{t-q}$$ [Equation 8.9]

In the panel data context, given the data points y_{it} and x_{it} the likelihood function for a particular bond i is such that

$$y_{it}|\varepsilon_{ti-1} \sim N(\mu + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots \beta_k x_{ik}, h_{it})$$ [Equation 8.10]

where

$$h_{it} = \alpha_0 + \alpha_1\varepsilon_{it-1}^2 + \alpha_2\varepsilon_{it-2}^2 + \alpha_3\varepsilon_{it-3}^2 + \cdots \alpha_q\,\varepsilon_{it-q}^2 + \gamma_1 h_{it-1} + \gamma_2 h_{it-2} + \cdots + \gamma_p h_{it-p}\,.$$ [Equation 8.11]

Therefore since

$$\varepsilon_{it} = y_{it} - \mu + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik}$$ [Equation 8.12]

the full log-likelihood function L of our data based on the linear model with GARCH errors is the sum

$$L = \sum_{t=2}^{84} \sum_{i=1}^{N} \log \varepsilon_{it} = -\frac{1}{2} \sum_{t=2}^{84} \sum_{i=1}^{N} (\log(2\pi h_{it}) - \frac{\varepsilon_{it}^2}{h_{it}})$$ [Equation 8.13]

In our case we consider the GARCH of model with order (1,1), i.e.

$$h_{it} = \alpha_0 + \alpha_1\varepsilon_{it-1}^2 + \gamma_1 h_{it-1}.$$ [Equation 8.14]

Note that if in the above model (Equation 8.14.) $\alpha_1 = 0$ and $\gamma_1 = 0$ implies that the model is simply that of the normal panel data model. In our approach however we will estimate the parameters ($\alpha_0, \alpha_1, \gamma_1$) and compare the resulting GARCH (1,1) model with that of a simple panel data model as if $\alpha_1 = 0$ and $\gamma_1 = 0$. A statistical method to test these two models is based on the likelihood ratio test, which states that if the two models are not different from each other, then under H_0 :

$$2(L_1 - L_0) \sim \chi^2_{p}, \qquad \text{[Equation 8.15]}$$

where L_0 and L_1 are the values of the log-likelihood functions at the estimated values of these two models and p is the difference in the number of parameters among models, which in our case is 2. Therefore we can test whether the GARCH (1,1) model is valid by calculating the difference $2(L_1 - L_0)$ and if this difference is large (in the χ^2_2 scale) then we reject H_0 and accept GARCH(1,1).

The panel GARCH model is run for both subsamples of investment-grade and speculative bonds assuming that bonds within the same subsample will exhibit the same volatility structure. In order to capture the impact of economic "turbulent" period on corporate credit spreads the sample of investment-grade bonds is then sub-grouped in four sub-periods as previously discussed in Chapter seven.

GARCH panel data results for subsamples of investment grade bonds indicate the presence of clustered volatility in changes of credit spreads. Similar to the evidence provided by Pedrosa and Roll (1998), we find significant positive coefficients for most of sub-periods in investment-grade bonds subsample (Table 8.2). The ARCH coefficient ($\alpha1$) on the squared lagged observation is significantly positive for the three out of four sub-periods. We do not find a significant coefficient for the first sub-period.

Once the clustered volatility in the model is accounted for, we find changes in credit spreads to be positively related to changes in the slope of risk-free term structure across the four periods.

Hence, an increase in the slope of risk-free term structure will lead to an increase in changes of credit spreads. This relationship is stronger during “turbulent” economic periods (sub-period one and four). As Avromov et al. (2007) argue this positive relationship is consistent with the hypothesis that an increase in intermediate interest rates will reduce the net present value of future projects. This in turn will lead to a fall in value of firms and consequently to higher credit spreads.

Table 8.2. GARCH Model for Investment Grade Bonds

	Sub- Periods (months)			
dCS	Period 1	Period 2	Period 3	Period 4
α0	0.0001	0.0001	0.0001	0.0001
α1	0.190	0.546*	0.352*	0.505*
γ1	0.079**	0.454*	0.579*	0.495*
dSLOPE	0.104*	0.048*	0.026**	0.192**
dINTLEV	-0.069*	-0.008**	-0.026**	-0.019***
S&P500	-0.013**	-0.021*	-0.023**	0.043**
dVXO	-0.046**	-0.043*	-0.031**	0.146**
EQRET	-0.004**	0.001**	0.001	-0.005**
ISS	0.00001	0.005*	0.00001	-0.001**
HML	0.005***	-0.007**	-0.002	-0.028**
SMB	0.012**	0.001	-0.0002	-0.043**
JANEF	-0.001**	-0.001**	0.0007**	NA
_cons	-0.004	-0.012*	0.0006**	-0.001***

This table represents the results from GARCH models for the subsample of investment grades across four periods. Period 1 covers the data from January 2001 till July 2003; period 2 covers the data from August 2003 till December 2005, period 3 covers the data from January 2006 till March 2007 and period 4 covers the data from April 2007 till December 2007. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level respectively. Variable of liquidity (LIQ) is not included in the table due to very small parameter values generated for this variable

We find credit spreads changes to be significantly negatively related to changes in interest rates levels. This relationship is much stronger in the first sub-period. While we find statistically significant impact of other factors on changes of credit spreads across the four sub-periods, the signs of these relationships are in some cases different to what was expected. For instance, the theoretical hypotheses given in chapter four do not support a negative relationship between changes in implied volatility index returns and changes in credit spreads. We report a statistically significant negative relationship between these two variables in the first three sub-periods.

Furthermore, we find positive coefficient for equity returns in the second sub-period. The presence of these and other questionable coefficients (HML and SMB) across sub-periods in the results indicates that the GARCH model presented in Table 8.2 may have other underlying issues which still have not been accounted for.

Hoechle (2007) argues that researchers should also test for cross-section or spatial correlation when undertaking panel data analysis. If this correlation is not taken into consideration, the standard errors may not be correctly specified. Hoechle (2007) further explains that "due to social norms and psychological behaviour patterns, spatial dependence can be a problematic feature of any microeconometric panel dataset even if the cross-sectional units (e.g. individuals or firms) have been randomly selected. Therefore, assuming that the residuals of a panel model are correlated within but uncorrelated between groups of individuals often imposes an artificial and inappropriate constraint on empirical models. In many cases it would be more natural to assume that the residuals are correlated both within groups as well as between groups (p. 3)".

We employ Pesaran cross-sectional dependence test to check for spatial dependence. This test can be used in panels with large T and N panel data and is accommodating as it may also be employed in heterogeneous non-stationary or dynamic panel data models. Test result strongly rejects the null hypothesis of no cross-sectional dependence for investment-grade bonds (Appendix. 3, Table.3.6).

Hoechle (2007) suggests that in the presence of such cross-sectional dependence, the model (fixed effect or pooled OLS) should be corrected using Driscoll-Kraay (1998) standard errors. Driscoll and Kraay (1998) suggest a method that deals not only with the spatial correlation, but also allows for standard errors which are corrected for both heteroscedasticity and autocorrelation. An additional test to check for serial correlation in the idiosyncratic errors of a panel data model is employed. Drukker (2003) presents simulation evidence that this test has good size and power properties in reasonable sample sizes. Under the null of no serial correlation the residuals from the regression of the first-differenced variables should have an autocorrelation of -.5. A Wald-test is performed for this hypothesis[21]. The results of this test (Appendix. 3, Table. A3.6) indicate the presence of serial correlation for investment-grade bonds.

Considering that our model for investment-grade bonds suffers from problems of cross-sectional dependence in error terms in addition to autocorrelation and heteroscedastacity, we examine the impact of discussed factors on changes in credit spreads by employing Driscoll and Kraay (1998) standard errors in a pooled OLS model. The coefficients from the pooled OLS with Driscoll-Kraay standard errors are presented in Table 8.5. A discussion the models employed for the speculative bond sample follows before the discussion of findings for both subsamples.

8.2. Modelling of Credit Spreads for Speculative Bonds

The previous section discusses the methodological issues faced when exploring the impact of various factors on changes of credit spreads of investment grade bonds. In this section we explain the methodology followed to examine changes in credit spreads for the subsample of speculative bonds. Fixed-effect model is firstly considered followed by the random-effect estimation. The results for the fixed-effect model are given in Table. 8.3.

The overall R-square for this subsample is higher than overall R-square reported from fixed-effect model for investment grade bonds. The F-test for coefficients of the model suggests that all these coefficients are different from zero. Contrary to findings from fixed-effect model for investment grade bonds, a few regression coefficients (changes in the slope of risk-free term structure,

[21] The explanation of test on autocorrelation is taken out of STATA explanatory notes.

S&P500 returns, liquidity and January effects) for speculative bonds are not statistically significant. The signs for the statistically significant coefficients are similar to those reported for investment-grade sample where the only positive relation exists between changes in credit spreads and changes in implied volatility index.

Table 8.3. Fixed and Random effect models for speculative bonds

	FE model	RE model
Number of obs	1935	1935
Number of groups	24	24
R-square overall	0.2143	0.2156
F-test	57.88*	
Wald-test		528.96*
dSLOPE	0.021287	-0.01
dINTLEV	0.013*	-0.053*
S&P500	-0.01216	-0.010
dVXO	0.152*	0.157*
EQRET	-0.019*	-0.019*
ISS	(dropped)	0.001944
LIQ	-1.8E-06	5.78E-07
HML	-0.080*	-0.081*
SMB	-0.018**	-0.019**
JANEF	-0.0008	-0.00079
_cons	0.000828	-0.00461

This table represents the results from both fixed and random effect models on credit spreads data of investment grade bonds.. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level respectively.

The estimate of rho coefficient even for speculative bonds suggests that a proportion of the variation in changes of credit spreads is related to inter-bond differences, but this proportion is much lower than the one reported for investment-grade bonds.

Similar to findings for investment-grade bonds, the F test following regression model indicates that there are no significant individual (bond) effects for speculative bonds. Additionally, we find a negative correlation between individual effects and regressors, but this correlation coefficient is smaller than the one found for investment-grade bonds.

The results from random-effect model (Table. 8.3) for speculative bonds are not similar to those reported for investment-grade bonds. Credit spread changes for speculative bonds are found to be significantly related only to changes in the level of risk-free interest rates, changes in volatility index, equity returns and returns for Fama-French factors.

The overall R-square value is close to the one found from fixed-effect model, but higher than the R-square value reported for random effects for investment–grade bonds. We further employ the Hausman test to find which of these two models (fixed or random effect) provide consistent and efficient estimators for speculative bonds. The results of this test are given in Appendix 3, Table. A3.5. It can be suggested from results of this test that the null hypothesis of consistent random-effect estimators cannot be rejected for the subsample of speculative bonds. Hence, the random-effect model is more appropriate for this subsample.

Next, a methodological approach similar to the one explained for investment-grades is followed. The modified Wald test for group heteroscedasticity confirms the presence of this problem even in the case of speculative bonds (Appendix. 3, Table.A3.6). A panel GARCH process is then applied to account for the clustered volatility in credit spreads changes. The results (Table. 8.4) indicate that similar to the evidence from investment-grade bonds, changes in credit spreads for speculative bonds are also characterised by clustered volatility. Surprisingly, our findings indicate that there is no presence of clustered volatility in the fourth sub-period. Furthermore, changes for credit spreads of speculative bonds are not significantly related to most of the suggested factors.

However, we find evidence of a statistically significant impact of both changes in returns for implied volatility index and S&P500 returns on changes of credit spreads. The impact of term structure variables is not found to be statistically significant for speculative bonds.

Table 8.4. GARCH Model for Speculative Bonds

	Sub- Periods (months)			
DCS	(Period 1)	(Period 2)	(Period 3)	(Period 4)
α0	0.0001	0.0001	0.0001	0.0001
α1	0.610*	0.303**	0.446**	0.133
γ1	0.390*	0.099***	0.526**	0.491
dslope102n	-0.0266	-0.0119	-0.0741	-0.0717
Dintlevn	-0.182**	0.019	-0.0436	-0.0737
sp500	0.0024	-0.035***	-0.0535***	0.0186
Dvxo	0.1158***	0.0722***	0.0005	0.2886
eqret	-0.0103**	-0.0011	0.0035	-0.0071
iss	0.0101**	-0.0001	-0.0005	-0.0068
Hml	-0.1214**	-0.0656**	-0.0148	0.1896
Smb	-0.0101	-0.04***	-0.0324	-0.1196***
Janef	-0.0046***	-0.0002	-0.0148	NA
_cons	-0.0231**	-0.0003	0.0017***	0.0246

This table represents the results from GARCH models for the subsample of speculative bonds across four periods. Period 1 covers the data from January 2001 till July 2003, period 2 covers the data from August 2003 till December 2005, period 3 covers the data from January 2006 till March 2007 and period 4 covers the data from April 2007 till December 2007. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level respectively. Variable of liquidity (LIQ) is not included in the table due to very small parameter values generated for this variable.

Since GARCH model does not seem to provide robust results for speculative bonds, we employ Pesaran test to check for the cross-sectional dependence in this subsample. Pesaran test (Appendix. 3, Table.A3.6) confirms the existence of this dependence for speculative bonds across four sub-periods of the sampling period. In order to account for the cross-sectional dependence in this case we employ the feasible generalised least square (FGLS) model which allows for both heteroscedasticity and cross-sectional dependence. The tests are run for each of the four sub-periods within the sampling period. For the second and the third sub-periods we also account for panel autocorrelation. The coefficients resulted from these models are presented in Table 8.6.

8.3. Findings and Discussion

In this section we provide an analysis of the reported relationship between changes in credit spreads and their determinants for both sub-samples of investment-grade (Table 8.5) and speculative bonds (Table 8.6). We firstly start our discussion on the findings for investment-grade bonds and then compare these findings with those reported for speculative bonds.

Consistently with previous studies (Collin-Dufresne et al. (2001), Avramov et al. (2007), Duffee (1998), etc.) we find changes in interest rate level (*dINTLEV*) to be negatively related to changes in credit spreads for investment-grade bonds in three out of four sub-periods. The magnitude of this relationship is small in "tranquil" economic periods (third sub-period). Our findings on the relationship between changes in the slope of risk-free term structure (*dSLOPE*) and changes in credit spreads are similar to Collin-Dufresne et al. (2001) who also report no significant relationship between these two variables. The significant positive relationship found in the fourth period has little explanatory power.

The findings indicate that firm equity returns (*EQRET*) are negatively related to changes in credit spreads only in the first period. EQRT parameters for the other three periods are statistically insignificant. Hence, in the first period as firm's equity returns rise, the risk premium in bond markets falls as debt-holders feel more certain regarding future paybacks. Similar to changes in the slope of risk-free term structure, the size of coefficient for firm's equity returns is small.

Table 8. Pooled OLS regression with Driscoll-Kraay standard errors for investment-grade bonds

	Sub- Periods (months)			
dCS	(Period 1)	(Period 2)	(Period 3)	(Period 4)
dSLOPE	0.0241233	0.0029525	0.0039389	.0089658***
dINTLEV	-.0273884*	-0.0007048	-.0108485**	-.0443675*
S&P500	-0.000353	-0.0042585	-.012486*	-.0193823*
dVXO	0.0192351	-0.0110065	-.018477 *	.0435421*
EQRET	-.0075853*	-0.0018377	-0.0013067	-0.0044315
ISS	0.0010414	.0013609*	-0.0008069	0.000356
LIQ	1.93E-07	3.01E-07	1.77E-08	-6.01e-07*
HML	-.0110486*	-.0100604***	-.0098749**	.0303857*
SMB	-0.0011413	-.0109076*	-0.0029441	-.0266408*
JANEF	-.0009775*	-.0003747*	-.000207*	(dropped)
_cons	-0.0030321	-.0033724*	.0022551***	0.0004875

Period 1 covers the data from January 2001 till July 2003, period 2 covers the data from August 2003 till December 2005, period 3 covers the data from January 2006 till March 2007 and period 4 covers the data from April 2007 till December 2007. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level respectively.

We next consider the impact of variables related to equity market indices on changes of credit spreads. Our findings suggest a negative statistically significant impact of S&P500 index returns (*sp500*) on changes in credit spreads for the third and fourth period. Hence, an increase in S&P500 returns is linked to diminishing credit spreads during these two sub-periods. Surprisingly, we do not find a significant impact of these returns on credit spreads for the first two sub-periods.

The results for Fama-French systematic risk factors indicate that overall these two factors (HML *and SMB*) are negatively related to credit spreads changes. Consistently with previous studies (Joutz et al. (2000), Avromov et al. (2007), Huang and Kong (2003), etc.) we report significant negative coefficients for the HML factor in the first three periods. This suggests that an increase in HML returns leads to diminishing credit spreads. We also note that the magnitude of negative coefficients falls from the first to the third sub-period. Hence, HML returns lose their explanatory power in healthier economic conditions. HML coefficient sign switches to positive in the fourth sub-period.

The negative coefficients on SMB factor are statistically significant only in the second and fourth sub-periods. They seem to have similar explanatory power to HML coefficients. Hence, our study provides some supporting evidence to the argument that Fama-French factors are related to default risk premium incorporated in corporate credit spreads (Elton et al. (2001), Collin-Dufresne et al (2001), Vassalou and Xing (2004), etc.).

Coefficients on liquidity proxies of issue size (*ISS*) and liquidity (LIQ) indicate no significant relationship between these proxies and changes in credit spreads for investment grade bonds. The only significant coefficient is reported for the issue size in the second sub-period, however it lacks economic explanatory value.

Table.8.5. reports the presence of January effect in the three sub-periods. The existence of negative January coefficients (JANEFF) may be “consistent with either tax-loss selling effect, portfolio window dressing, or coupon payment flows" (Barnhill et al., 2000, Joutz and Maxwell (2002) etc.). January coefficients are statistically significant, but they have very little explanatory power for changes in credit spreads.

Overall we find regression coefficients for investment-grade bonds to be higher for the fourth sub-period when compared to previous sub-periods. This seems to be consistent with Webber and Churm (2007)'s argument that while the required compensation for both credit-related risks and non-credit risks (i.e. liquidity risk) fell significantly internationally and across segments of US, UK and European corporate bond markets between the end of 2002 and mid-2007, the required compensations for both groups of risks have risen considerably from mid-2007. They suggest that the increased premium during this period may be explained by market participants' expectations in the rise of corporate bonds defaults in the near future and the drying up of liquidity that characterised US money markets in this period.

We now discuss the findings for the subsample of speculative bonds. Similar to our results for investment grade bonds, there is a significant negative impact of changes in risk-free interest rate levels on credit spread changes. As explained in the previous chapters an increase in risk-free interest rate levels will lower the present value of expected cash flows and hence the value of the put option on the firm's asset value. This in turn will lower credit spreads.

Similar to Collin-Dufresne et al. (2001), Avromov et al. (2007), Duffee (1998), etc., our results (Table.8.6) indicate that parameters for interest rate levels for speculative bonds have a higher explanatory power than those for investment-grade bonds. From these results we can also note that changes in credit spreads for speculative bonds become more related to changes in interest rates during difficult economic periods and uncertainty in financial markets. Generally, our findings for speculative bonds do not provide support for the relationship between changes in the slope of risk-free term structure (dSLOPE) and changes in credit spreads. The only significant coefficient for this factor is found in the third sub-period. It suggests that changes in the slope of risk-free term structure are negatively related to changes in credit spreads.

Table 8.6 Feasible Generalised Least Square regression for speculative bonds

	Sub- Periods (months)			
dCS	(Period 1)	(Period 2)	(Period 3)	(Period 4)
dSLOPE	0.0411216	-0.0365496	-.0580915*	-0.0266039
dINTLEV	-.1268232*	0.0156739	-.063394*	-.1134516*
S&P500	0.0004753	-.0321313*	-.0528217*	-0.0752227
dVXO	.1348245*	.0800721***	.0287778*	0.1369343
EQRET	-.0232852*	-.0076631*	-.0091124*	-.0240965*
ISS	0.0038223	0.0010159	-0.0026883	-0.0063996
LIQ	1.18e-06 **	1.10e-06*	-3.47E-07	5.43E-06
HML	-.0775308*	-.0472781*	-.0272166*	.0471048***
SMB	0.006469	-0.0112631	-.0258295*	-0.0303155
JANEF	-0.0019955	-0.0009414	.000315*	(dropped)
_cons	-0.0106067	-0.0025217	0.0073112	0.0188728

Period 1 covers the data from January 2001 till July 2003, period 2 covers the data from August 2003 till December 2005, period 3 covers the data from January 2006 till March 2007 and period 4 covers the data from April 2007 till December 2007. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% level respectively.

Differently from findings for investment-grade bonds, the impact of equity returns (EQRET) in changes of credit spreads for speculative bonds is statistically significant across the four periods. However, the coefficients for second and third periods are smaller than coefficients for first and fourth periods. Hence, we can argue that credit spread changes for speculative bonds are less sensitive to changes in equity returns during “stable” economic conditions.

Findings for speculative bonds indicate a negative statistically significant impact of S&P500 returns on credit spreads changes in the second and third sub-periods. Most importantly, we can notice a greater dependence of credit spreads on the returns of implied volatility index for speculative bonds than investment-grade bonds. The results indicate that coefficients for this index are statistically significantly positive in the first three sub-periods. As expected the coefficients for this factor decrease monotonically as the economic environment stabilises (from the first to the third sub-period).

The findings for the impact of HML factor on credit spread changes for speculative bonds are similar to those reported for investment grade bonds. We find negative coefficients for the first three sub-periods and a positive coefficient for the fourth sub-period. With regards to SMB, we find only one significant coefficient for the subsample of speculative bonds.

We find two statistically significant coefficients for liquidity variable in the first two sub-periods. However, they do not have much explanatory power. Hence we may suggest that overall there is no evidence to suggest that the two liquidity proxies we used in this study have an impact on changes of credit spreads. Since we would expect market liquidity to have an impact on credit spread changes at least in one of the considered sub-periods, it can be argued that these two measures may not capture the liquidity impact for individual bonds.

Contrary to findings for investment-grade bonds, we do not find any significant January effect on credit spreads changes for speculative bonds. This may suggest that January effect may be more associated with bonds within investment-grade sub-sample due to reconstruction of investment portfolios.

Overall, we note that credit spreads changes of speculative bonds are more sensitive to changes in economic environment. As Dynkin et al. (2002) suggest "the main source of credit risk in higher qualities is related to specific credit events, while in the lower qualities it is driven mainly by recessions." (pp. 92) Similar to previous studies, our results indicate that yields of investment-grade bonds are affected by factors that affect Treasury bond yields, whereas yields of speculative bonds can be explained by factors that are related to equity returns.

Chapter Nine: Conclusions and Future Research

The main aim of this study is the investigation of factors that cause changes in the corporate credit spreads. The study is based on an analysis of U.S. corporate credit spreads over a seven year period (2001-2007). This period is characterised by both recessions and healthy economic environments. Our descriptive analyses indicate that credit spreads tend to widen in recessionary periods but narrow in "tranquil" economic times. Such variations in credit spreads are found to be larger for speculative than investment-grade bonds particularly in uncertain economic periods.

One of the main characteristics of a corporate bond is its rating. Ratings in general are expected to indicate a firm's ability to honour its financial obligations. The news of a bond's upgrade, downgrade or more recently a credit watch is expected to cause changes in credit spreads as it is assumed that rating events will provide new information on bond's default risk. Hence, bond rating changes are expected to have an informational value. Empirical studies investigating market reaction to changes in credit ratings provide mixed evidence regarding the informational value of rating changes or a credit watch news.

Rating agencies have recently been criticised for their slowness in announcing bond rating changes. Various studies have argued that in order to fulfil their monitoring role in the financial markets, rating agencies try to avoid assignments of ratings which may be later reversed. Thus they might tend to favour stable rather than accurate ratings. This might lead to a loss in the informational value of credit ratings, since financial investors would prefer accurate to stable ratings. In this study we question the role of bond rating changes in the corporate bond market by examining the casual relationship between bond rating changes and credit spread changes.

Granger causality tests in the context of a panel data sample are employed. The results indicate the presence of a two-way causality for the sample of negative watch list. A two-way causality relationship between changes in bond ratings and changes in credit spreads is also reported for the fourth sub-sample period which is characterised by instability in financial markets. Considering that unforeseen shocks might affect simultaneously bond ratings and credit spreads, this two-way causality might be consistent with the hypothesis that rating agencies pass information to the market. Thus, our results are consistent with the previous studies regarding the importance of watch lists in transmitting information to the market. Furthermore, we might argue that credit ratings have a higher informational value in unsettled economic periods. This might be related to “through-the-cycle” rating method which is employed by rating agencies. The results from the panel error correction model indicate the presence of a unidirectional causal impact of bond rating changes on credit spread changes.

However, we should treat these findings with care because as Loffler (2004) argues “Rating agencies use one rating method for many borrowers, and it may take considerable time until errors in the application of this method become evident to the raters. (p. 30)” In addition, our findings are based on a relatively small sample of bond rating changes and this is one of the common limitations of studies undertaken in the area of credit ratings. One future area of research is to examine in more detail the role of watch lists in the corporate bond markets in order to find out whether these watch lists are introduced to ease the tension between ratings accuracy and stability or to monitor firm’s long-time performance by giving them another chance of not having their credit rating changed.

Given the complex relationship between credit spreads and bond ratings, the second part of this study focuses on an examination of the impact that various market-related factors may have on corporate credit spreads. Unlike previous studies, we employ a panel GARCH model to explore the impact of these factors. This model has efficiency gains in estimating the conditional variance processes by using relevant information about heterogeneity across units as well as their interdependence. We find that the coefficients that control for conditional heteroscedasticity are significant. However, this model does not consider the issue of cross-sectional dependence which might lead to incoherent findings.

Petersen (2009) suggests that a considerable number of articles published in leading finance journals while report standard error estimates that are corrected for heteroscedasticity and autocorrelation, tend to ignore the issue of cross-sectional or “spatial” dependence. In this study standard errors are also corrected for cross-sectional dependence.

Consistent with previous studies, our results indicate that changes in credit spreads are negatively related to changes in risk-free interest rate levels. This relationship holds for both investment-grade and speculative bonds, but it varies in magnitude according to the state of the economy. It gets stronger in periods of economic and financial uncertainty. This sensitivity of credit spreads to risk-free interest rate levels should be taken into account not only for pricing purposes but also for risk management purposes.

Our findings reiterate suggestions from previous studies that portfolio managers will not be able to manage credit risk separately from interest rate risk. Furthermore, our study contributes to the mixed empirical evidence on the relationship between credit spreads’ changes and the slope of risk-free term structure by reporting insignificant relationship between these two variables.

Similar to previous studies (Collin-Dufresne et al. (2001), Elton et al (2001), etc.), we find empirical support for the impact of Fama and French (1993) factors for changes in credit spreads for both investment-grade and speculative bonds. Changes in credit spreads are found to be strongly related to HML returns. Their impact on credit spreads diminishes in healthy economic periods.

Another interesting finding is that credit spreads for speculative bonds are more related to equity returns. We do not find a strong supporting evidence for this relationship from the sub-sample of investment grade bonds. These results provide additional support to previous studies’ suggestions that speculative bonds behave more like equities than Treasury bonds. We also consider the

January effect on changes of credit spreads. The findings indicate a small but significant January effect for investment-grade bonds. However, we fail to find a similar evidence for the subsample of speculative bonds.

Overall, the empirical results of this study imply that credit spreads changes are driven by aggregate systematic factors that are common to corporate bonds. However, the significant presence of equity returns parameters in the sample of speculative bonds may support the view that speculative bonds behave more like equities, whereas investment-grade bonds behave more like Treasury securities.

Considering that bond-individual liquidity variables are not found to add to the explanatory power of credit spreads another possible future area of research is to look at the impact that systematic liquidity risk factors have on corporate credit spreads. Another possible area of research is the examination of corporate credit spreads in non-US corporate bond markets which are expected to be less liquid than US.

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Appendices

Appendix 1: Classification of Bond Ratings

Standard and Poor's Issuer Credit Rating
(http://www2.standardandpoors.com/portal/site/sp/en/US/page.article/2,1,1,4,1204834067208.html)

Long-Term Issuer Credit Ratings

AAA
An obligor rated 'AAA' has extremely strong capacity to meet its financial commitments. 'AAA' is the highest issuer credit rating assigned by Standard & Poor's.

AA
An obligor rated 'AA' has very strong capacity to meet its financial commitments. It differs from the highest-rated obligors only to a small degree.

A
An obligor rated 'A' has strong capacity to meet its financial commitments but is somewhat more sUSceptible to the adverse effects of changes in circumstances and economic conditions than obligors in higher-rated categories.

BBB
An obligor rated 'BBB' has adequate capacity to meet its financial commitments. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitments.

BB, B, CCC, and CC
Obligors rated 'BB', 'B', 'CCC', and 'CC' are regarded as having significant speculative characteristics. 'BB' indicates the least degree of speculation and 'CC' the highest. While such obligors will likely have some quality and protective characteristics, these may be outweighed by large uncertainties or major exposures to adverse conditions.

BB
An obligor rated 'BB' is less vulnerable in the near term than other lower-rated obligors. However, it faces major ongoing uncertainties and exposure to adverse bUSiness, financial, or economic conditions which could lead to the obligor's inadequate capacity to meet its financial commitments.

B
An obligor rated 'B' is more vulnerable than the obligors rated 'BB', but the obligor currently has the capacity to meet its financial commitments. Adverse bUSiness, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments.

CCC
An obligor rated 'CCC' is currently vulnerable, and is dependent upon favorable bUSiness, financial, and economic conditions to meet its financial commitments.

CC
An obligor rated 'CC' is currently highly vulnerable.

PlUS (+) or minUS (-)
The ratings from 'AA' to 'CCC' may be modified by the addition of a plUS (+) or minUS (-) sign to show relative standing within the major rating categories.

R
An obligor rated 'R' is under regulatory supervision owing to its financial condition. During the pendency of the regulatory supervision the regulators may have the power to favor one class of obligations over others or pay some obligations and not others. Please see Standard & Poor's issue credit ratings for a more detailed description of the effects of regulatory supervision on specific issues or classes of obligations.

SD and D

An obligor rated 'SD' (selective default) or 'D' has failed to pay one or more of its financial obligations (rated or unrated) when it came due. A 'D' rating is assigned when Standard & Poor's believes that the default will be a general default and that the obligor will fail to pay all or substantially all of its obligations as they come due. An 'SD' rating is assigned when Standard & Poor's believes that the obligor has selectively defaulted on a specific issue or class of obligations but it will continue to meet its payment obligations on other issues or classes of obligations in a timely manner. Please see Standard & Poor's issue credit ratings for a more detailed description of the effects of a default on specific issues or classes of obligations.

NR
An issuer designated NR is not rated.

Appendix 2: List of variables

Notation	Contents	Source
Dependent variable		
CS_{it}	Difference between corporate bond yields and the equivalent Treasury benchmark yield (month-end values) for each individual bond and month	Thomson Financial Datastream
dCS_{it}	Change in the variable CS from the previoUS month for each individual bond and month	Thomson Financial Datastream
DRTNG	Monthly changes in bond ratings assigned by Standard and Poor's	Thomson Financial Datastream
Determinants implied by literature review		
$EQRET_{it}$	Monthly stock returns for each individual bond	Thomson Financial Datastream
$dINTLEV_t$ (Dintlev10)	Changes in the monthly yield for 10-year Treasury bonds	US Federal Reserve webpage
$dSLOPE_t$ (Dslope102)	Changes in the difference between monthly yields of 2 and 10 years Treasury bonds	US Federal Reserve webpage
$S\&P500_t$	Monthly return on S&P 500 stock index	Thomson Financial Datastream
SMB_t	Monthly average return on three small portfolios minUS the average return on three big portfolios (monthly data)	Kenneth French's webpage
HML_t	Monthly average return on two value portfolios minUS the average return on two growth portfolios (monthly data)	Kenneth French's webpage
$dVXO_t$	Changes in monthly returns on CBOE Volatility index (monthly implied volatility)	CBOE's website
ISSi	The logarithm of issued amount for a particular bond	Thomson Financial Datastream
LIQ_{it}	This variable is measured by multiplying the logarithm of a bond's coupon by the remaining maturity months.	Thomson Financial Datastream
JANEF	Dummy variable that takes the value of unity for credit spreads in January and zero otherwise	

Appendix 3: Supplementary Tables and Figures

Table 3.1. Rating Index

Each bond rating is given a numerical value from 1 to 20 to obtain the explicit credit ratings (ECR). We then include the information on watch lists to obtain the comprehensive credit ratings (CCR). For example, if a corporate bond is rated AA without any additional information on credit watch, then both its ECR and CCR will be equal to 3. If the credit rating agency (S&P) decides to put this bond on a watch list for a possible downgrade, its ECR is still 3. However, its CCR is equal to 3.5.

S&P Rating	**Score Assigned (ECR)**
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	6
A-	7
BBB+	8
BBB	9
BBB-	10
BB+	11
BB	12
BB-	13
B+	14
B	15
B-	16
CCC+	17
CCC	18

Credit Watch	Add to ECR
Positive	+0.5
Stable	0
Negative	-0.5

Table A3.2. Descriptive Statistics on Credit spreads and Bond Ratings

This table provides the descriptive statistics for credit spreads according to the main two rating categories and across the four periods considered in this study.

	Observations	Mean	Standard Deviation	Min	Max
Time period 1			**Investment Grade Bonds**		
No Change in Ratings	6325	.0179916	.008452	.0023	.10033
Downgrades	78	.0247886	.01244	.00846	.06337
Watch Negative Lists	74	.0256307	.0129379	.00601	.06547
Upgrades	29	.0231521	.0089222	.00965	.04051
Watch Positive Lists	4	.0184975	.0054942	.01434	.02645
			Speculative Bonds		
No Change in Ratings	533	.0541053	.0304171	.01919	.26343
Downgrades	15	.094024	.0731992	.04041	.26474
Watch Negative Lists	12	.0983392	.0657228	.02876	.24256
Upgrades	8	.0456138	.019431	.01975	.0781
Watch Positive Lists	2	.036615	.0004455	.0363	.03693
Time period 2			**Investment Grade Bonds**		
No Change in Ratings	6270	.0108464	.0051427	.00051	.04809
Downgrades	81	.0134289	.0063672	.00362	.04346
Watch Negative Lists	73	.0166797	.0090396	.00642	.04575
Upgrades	76	.0114068	.0046717	.00389	.03228
Watch Positive Lists	10	.008898	.0031112	.00368	.01325
			Speculative Bonds		
No Change in Ratings	546	.0288609	.0109477	.00741	.07174
Downgrades	7	.0338614	.0109693	.02063	.0504
Watch Negative Lists	8	.0414	.012626	.022	.0533
Upgrades	9	.0253256	.0101488	.0104	.03848
Watch Positive Lists	---	---	---	---	---
Time period 3			**Investment Grade Bonds**		
No Change in Ratings	3156	.0111063	.0061005	.00077	.04193
Downgrades	29	.0180741	.0104637	.00467	.04077
Watch Negative Lists	16	.0181044	.0117073	.00459	.04149
Upgrades	38	.0107334	.0056571	.00179	.03666
Watch Positive Lists	16	.0094925	.0030369	.006	.01636
			Speculative Bonds		
No Change in Ratings	267	.0235603	.0109107	.0043	.05554
Downgrades	3	.02478	.0118157	.01685	.03836
Watch Negative Lists	4	.031455	.017466	.01688	.05417
Upgrades	8	.0161625	.005864	.00559	.02165
Watch Positive Lists	3	.0097267	.0048272	.00626	.01524
Time period 4			**Investment Grade Bonds**		
No Change in Ratings	1896	.0146061	.0074446	.00092	.09257
Downgrades	17	.0211359	.0193113	.00617	.09323
Watch Negative Lists	19	.0179684	.0127656	.00378	.05787
Upgrades	19	.0119384	.0042632	.00566	.02239
Watch Positive Lists	2	.01512	.0045396	.01191	.01833
			Speculative Bonds		
No Change in Ratings	162	.0330495	.0213022	.00153	.10496
Downgrades	5	.057186	.022406	.03323	.08526
Watch Negative Lists	1	.02265		.02265	.02265
Upgrades	2	.01577	.0102106	.00855	.02299
Watch Positive Lists	1	.01548		.01548	.01548

Figure A3.3 Credit spread changes in each sector over the sampling period

This plot represents the behaviour of credit spread changes in each sector over the sampling period of 2001-2007 (Sector codes are given as: 1= indUStrial bonds, 2 = utility bonds, 3 = transport bonds, 4=bank bonds, 5=insurance bonds, 6= other financial bonds) The figure shows that generally changes in credit spreads for indUStrial and utility bonds are more volatile than spread changes for financial bonds. However, all bonds (with the exception of bonds issued by banks) have experienced volatile spreads in 2002.

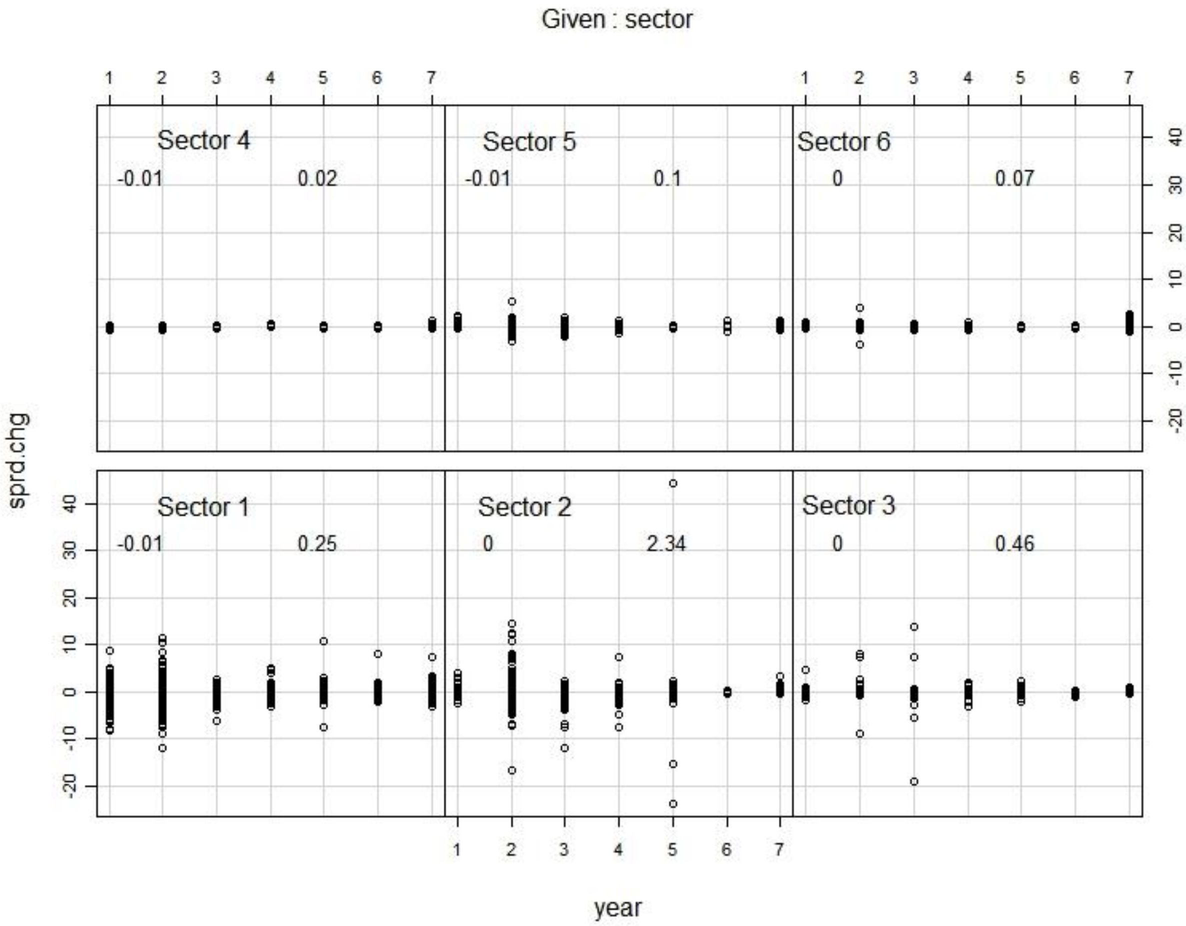

Table A3.4. Descriptive statistics for all variables included in the sample

By construction, variable code (identifying each corporate bond included in the sample) does not vary within panels. The within standard deviation of 0 suggest that this variable is time invariant. A similar conclUSion can also be drawn on variables of coupon and issued volume. These variables are not included in fixed effect models. Variable of months by construction has a between standard deviation of zero, indicating that this variable is issuer invariant. The same can be said for variables of term structure (level of interest rate and slope) and equity markets variables (S&P500 returns, returns on volatility index, SMB and HML returns). Within standard deviations for both changes in credit spreads and changes in equity returns appear to be higher than between standard deviations.

Variable	Mean	Std. Dev.	Min	Max	Observations
dCS$_{it}$ overall	-.0000129	.003863	-.07273	.1226	N = 21663
between		.0002343	-.0013311	.00072	n = 261
within		.0038559	-.0727096 .	1226204	T = 83
SMB$_{t}$ overall	.0064631	.0293946	-.0575	.0924	N = 21924
between		0	.0064631	.0064631	n = 261
within		.0293946	-.0575	.0924	T = 84
HML$_{t}$ overall	.0054857	.0271628	-.0471	.1343	N = 21924
between		0	.0054857	.0054857	n = 261
within		.0271628	-.0471	.1343	T = 84
dVXO$_{t}$ overall	.0000166	.0094999	-.02806	.02105	N = 21663
between		0	.0000166	.0000166	n = 261
within		.0094999	-.02806	.02105	T = 83
S&P500$_{t}$ overall	.0034468	.0381845	-.10868	.08802	N = 21924
between		0	.0034468	.0034468	n = 261
within		.0381845	-.10868	.08802	T = 84
EQRET$_{it}$ overall	.0063701	.0817868	-.6129227	1.2	N = 21356
between		.0084134	-.0148902	.0388375	n = 261
within		.0813614	-.6164251	1.167533	T = 82
dINTLEV$_{t}$ overall	-.0000102	.0001703	-.0003142	.0005241	N = 21663
between		0	-.0000102	-.0000102	n = 261
within		.0001703	-.0003142	.0005241	T = 83
dSLOPE$_{t}$ overall	5.68e-06	.0001079	-.000207	.0003266	N = 21663
between		0	5.68e-06	5.68e-06	n = 261
within		.0001079	-.000207	.0003266	T = 83
months overall	42.5	24.24755	1	84	N = 21924
between		0	42.5	42.5	n = 261
within		24.24755	1	84	T = 84
code overall	264.3065	129.7669	21	477	N = 21924
between		130.0133	21	477	n = 261
within		0	264.3065	264.3065	T = 84

Table A.3.5. HaUSman tests for subsamples of investment grade and speculative bonds

Investment Grade Bonds	---- Coefficients ----			
	(b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
dslope102n	.0150368	.0093213	.0057155	.0005436
dintlevn	-.0144757	-.0138264	-.0006492	.0000722
sp500	-.0039412	-.0000334	-.0039078	.0003686
dvxo	.018839	.0301715	-.0113326	.001077
eqret	-.0045822	-.0045735	-8.66e-06	.0000296
liq	-4.71e-06	3.91e-08	-4.75e-06	4.49e-07
hml	-.0113697	-.0146957	.003326	.0003177
smb	-.0040772	-.006354	.0022768	.0002176
janef	-.0005593	-.0005494	-9.86e-06	2.47e-06

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg
Test: Ho: difference in coefficients not systematic
chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 114.07
Prob>chi2 = 0.0000

Speculative Bonds	---- Coefficients ----			
	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
dslope102n	-.0071546	-.0101254	.0029708	.0067733
dintlevn	-.0542797	-.0539617	-.000318	.0014747
sp500	-.0121554	-.0102675	-.0018878	.0044586
dvxo	.151912	.1570068	-.0050947	.0129644
eqret	-.0192553	-.0193879	.0001327	.0002507
liq	-1.76e-06	5.78e-07	-2.34e-06	5.05e-06
hml	-.0805314	-.0818964	.001365	.0037148
smb	-.0188974	-.0198309	.0009335	.0025873
janef	-.0007995	-.0007897	-9.79e-06	.0000797

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg
Test: Ho: difference in coefficients not systematic
chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 0.4 Prob>chi2 = 0.9999

Table A3.6. Diagnostic tests' results for both subsamples of investment-grade and speculative bonds

Pesaran's test of cross sectional independence

Investment grade bonds	Speculative bonds
Test of cross-sectional independence = 192.99 Prob = 0.0000 Av. Abs. Val. of the off-diagonal elements = 0.182 0.210	Test of cross-sectional independence = 26.903 Prob = 0.0000 Av.Abs.Val. of the off-diagonal elements =
The null hypothesis of no cross sectional dependence is rejected.	The null hypothesis of no cross sectional dependence is rejected.

Modified Wald Test for Groupwise Heteroscedasticity in Fixed Effect Models

Investment grade bonds	Speculative bonds
H0: sigma(i)^2= sigma^2 for all i chi2 (210) = 56326.60 Prob>chi2 = 0.0000	H0: sigma(i)^2= sigma^2 for all i chi2 (24) = 2121.37 Prob>chi2 = 0.0000
The null hypothesis of homoskedasticity is rejected.	The null hypothesis of homoskedasticity is rejected.

Wooldridge Tests for Autocorrelation in panel data

Investment grade bonds	Speculative bonds
H0: no first-order autocorrelation F(1, 209) = 5.852 Prob > F = 0.0164	H0: no first-order autocorrelation F(1, 23) = 1.011 Prob > F = 0.3251
We reject the null hypothesis of no serial correlation. Hence, investment-grade bond data spreads data have first-order autocorrelation.	We fail to reject the null hypothesis of no serial correlation. Hence, speculative bond spreads do not have first-order autocorrelation.

Table A3.7. BreUSch-Pagan Lagrangian Multiplier Tests for Random Effects

This table represents the results of BreUSch-Pagan LM multiplier test for both subsamples. We employ the BreUSch-Pagan test to check for the presence of random effects in the model. This test is a Langrange Multiplier (LM) test where the null hypothesis of the one-way random *group* (time) effect model is that *variances of groups* (for time) are equal to zero. If the null hypothesis is not rejected, the pooled regression (OLS) model is appropriate.

Investment-grade Bonds

d1cs[code,t] = Xb + u[code] + e[code,t]

Estimated results:

	Var	sd = sqrt(Var)
D.cs	5.77e-06	.002405
e	5.19e-06	.0022791
u	0	0

Test: Var(u) = 0
chi2(1) = 34.72
Prob > chi2 = 0.0000

These results indicate that the null hypothesis of variances across bonds being zero is not accepted. It can be concluded from here that the random effect is more appropriate than fixed effect in this case.

Speculative Bonds

d1cs[code,t] = Xb + u[code] + e[code,t]

Estimated results:

	Var	sd = sqrt(Var)
D.cs	.0001039	.010194
e	.0000837	.009344
u	0	0

Test: Var(u) = 0
chi2(1) = 6.23
Prob > chi2 = 0.0126

Results indicate that the null hypothesis cannot be accepted implying that the random effect is more appropriate than fixed effect when credit spreads for speculative bonds are modelled.