THE INTERACTION BETWEEN
EQUITY AND CREDIT RISKS

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This thesis is dedicated to my late father

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Abstract

Equity and debt are two distinct classes of securities in terms of investing risks and potential return, but their value depends on the same underlying assets of the firm and therefore the risk-return tradeoff of each security should be systematically related. Following a review of the principal theoretical approaches to the measurement of equity and credit risks, this thesis utilizes a sample of matched firm-level equity and corporate bond data to examine three aspects of risk interaction. First, it investigates the importance of idiosyncratic and systematic equity risks in determining the credit spread on corporate bonds. Second, the thesis investigates how equity and credit risks themselves impact upon the correlation between equity and bond returns. Finally, the thesis examines whether the credit sensitive information contained within financial accounting data is fully reflected in equity prices. The empirical approach adopted in this thesis is to relate the credit spread and the conditional correlation between equity and bond returns with both equity and credit risk indicators and financial accounting variables. This methodological approach enables an extension of the existing literature on several dimensions, leading to a number of empirical results which have important theoretical and practical implications for the integrated management of equity and credit risks. Consistent with existing empirical studies, equity and credit risks are found to exert a positive impact upon the credit spread. Surprisingly, equity volatility is found to significantly outperform the distance to default in terms of explanatory power. Further, the impact of equity volatility increases monotonically as the distance to default narrows. The conditional correlation between equity and bond returns is found on average to be positive and to vary over time, peaking during the 2007 financial crisis. Finally, an increase in credit risk has a positive impact upon the correlation while an increase in equity risk is found to strengthen the correlation only if the firm's credit risk is high.

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CHAPTER 1

INTRODUCTION

1.1. Introduction

This thesis investigates three aspects of the relationship between equity and credit risks. First, it examines the importance of idiosyncratic and systematic equity risks in determining the credit spread on corporate bonds. The existing literature focuses on the relationship between the credit spread and the volatility of equity returns in excess of market return, hence ignoring the differences of firms' exposure to systematic risks. This study fills this gap in the literature by decomposing the equity volatility into systematic and idiosyncratic components and assessing their relationship with the credit spread.

Second, the thesis investigates how equity and credit risks impact upon the correlation between equity and bond returns. The existing studies investigate the unconditional relationship between the credit spread or the bond yield and the variables deriving from the structural model of Merton (1974). This study estimates the conditional correlation between equity and bond returns, and then examines the determinants of this correlation. This approach enables a more thorough analysis which extends the existing empirical evidence on determinants of the correlation between equity and bond returns.

Finally, the thesis examines whether the credit sensitive information contained within financial accounting data is fully reflected in equity prices. A limited number of existing studies that focus on the relevance of accounting data in credit markets examine the incremental information value of financial accounting data in explaining bankruptcies, credit ratings or the credit default swap premiums. This study extends the existing literature by considering the relevance of accounting data in explaining variations in the credit spread on corporate bonds.

The empirical analysis is conducted on a large US data sample covering more than 15 years and consisting of over 350 firms and 700,000 daily observations. The remainder of this chapter briefly explains the background, contributions, structure of the thesis, research methodology and main research questions.

1.2. Background and Rationale

Equity instruments (shares) are exposed to market or systematic risk, which is inherent in the entire market, as well as the specific risks associated with particular shares. However, finance theory implies that investors should only be compensated for bearing market risk. Specific risks are diversifiable and therefore exposure to these risks should not be rewarded.

Debt instruments are exposed to credit risk or the probability that the debt will not be repaid. They enjoy a higher repayment priority when compared with equity. However, this reduced risk is accompanied by limited upside potential in the value of such instruments as debt investors are generally entitled only to receive the principal amount and the stream of promised interest payments.

Whilst there are significant differences between equity and debt instruments, their value depends on the same underlying assets of the firm and therefore their risk-return relationship should be systematically related. The theoretical relationship between market and credit risk is fully defined by Merton (1974) in his groundbreaking structural approach, based on the option pricing theory of Black and Scholes (1973), which treats a firm's equity capital as a derivative instrument written on its assets.

Acknowledging the limited liability of equity holders, equity can be considered as a call option on a firm's assets with the value of debt as the strike price. The difference between the value of a firm's assets and debt indicates its credit risk. The economic incentive of equity holders to hold a firm's assets decreases as their value falls and approaches the value of debt, resulting in a higher credit risk. Bankruptcy occurs when the value of assets drops to the point where it is equal to the value of debt. At this point, equity holders have no incentive to hold firm's assets and therefore surrender them to lenders, thereby causing bankruptcy.

The structural model of Merton (1974) provides an analytical solution for the value of any security depending on the value of firm's assets as well as the probability of default and the credit spread in case of debt securities. Furthermore, the structural model fully describes the relationship between the value of equity and debt securities of the same firm. Intuitively, an increase in the market value of equity has a positive impact upon the value of debt since it decreases quasi-market value leverage by definition. The sensitivity of the value of debt relative to the changes in the value of equity increases as the leverage or the ratio of debt over equity approaches unity. In other words, the sensitivity of the value of debt to changes in equity value is highest when the firm is already in distress.

An increase in the volatility of equity increases the probability that the leverage will approach unity and trigger default. Therefore, the structural model predicts a negative correlation between the volatility of equity and the value of debt. However, this relationship is highly nonlinear. Similar to the marginal change in equity value, the marginal change in the volatility of equity impacts upon the value of debt more when the default is more probable.

The structural model is fundamentally based on the assumption that capital markets are efficient. This assumption has several important implications of which the most important is that all credit-relevant information is already reflected in equity prices. Furthermore, the credit and equity markets are perfectly integrated under this assumption.

The structural model provides a set of empirically testable predictions which have an academic as well as a practical importance. From an academic perspective, the structural model is widely utilized and it is one of the most important theoretical finance models, hence the novel evidence of its empirical performance is an important contribution to the existing literature. From a practical perspective, a better understanding of the relationship between equity and debt risk enables an improvement in the integrated management of these risks which, as Hartmann (2010) notes, remains a challenge for industry practitioners as well as financial supervisors.

1.3. Objectives and Contributions of the Thesis

There are a limited number of empirical studies which examine the relationship between equity and debt securities. Furthermore, the existing studies are in general based on a limited data samples, spanning short time periods. This thesis is underpinned by a large sample consisting of over 350 firms and 700,000 daily observations covering almost 15 years, and including the period of the recent financial crisis which, according to most recent studies, started in August 2007. The large data sample enables a more robust regression analysis and examination of empirical results.

The main objectives of this thesis are to examine the following three aspects of the relationship between equity and debt securities:

1. The relationship between the credit spread on corporate bonds and equity risk. The existing studies of the relationship between the credit spread and equity volatility focus on the volatility of equity returns in excess of the market return, implying that the sensitivity to market movements or beta is equal in cross-section. This study extends the existing literature by considering the significance of idiosyncratic as well as systematic equity risks in explaining the variations in the credit spread. The Fama and French (1993) three factor model is utilized to decompose equity volatility into its idiosyncratic and systematic components. The credit spread is then regressed on the equity volatility components in a set of panel data models. Furthermore, the structural model explicitly controls for the level of credit risk and empirically examines the interaction between the level of credit risk and equity volatility.

2. The correlation between equity and corporate bond returns. While the existing studies generally focus on the unconditional correlation, this thesis uses a bivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to estimate the conditional correlation between equity and bond returns, and then examines how equity volatility and credit risk affect the correlation in a set of panel data models. This approach enables a deeper regression analysis as well as an insight into the time properties of the correlation between equity and bond returns.

3. The relevance of accounting data in the measurement of the credit spread . This part of the thesis investigates whether financial accounting variables contain any credit sensitive information not yet reflected in equity market based measures of credit risk. The incremental information value of such accounting variables is assessed by considering their significance in explaining the variations in the credit spread in conjunction with the distance to default, and the latter, according to the structural model, is a sufficient measure of credit risk. A limited number of existing studies examine the incremental information content of financial accounting data in explaining bankruptcies, credit ratings and, more recently, the credit default swap spreads. This study makes an important contribution by documenting the incremental information content of the spread of corporate bonds in explaining the credit.

1.4. Structure of the Thesis

The thesis is divided into ten chapters. Following this introductory chapter, Chapter 2 examines the structural approach to credit risk modelling. After briefly presenting the seminal model of Merton (1974), the chapter discusses the limitations, estimation and extensions of the structural model in the extant literature.

Chapter 3 reviews the seminal approaches to the valuation of equity. After reviewing each equity value model, the chapter examines the determinant of equity premium, the time variations within it, and the estimation of the equity premium.

The study of the relationship between the credit spread and systematic and idiosyncratic equity risks is presented in Chapters 4 and 5. Chapter 4 reviews the existing literature, develops hypotheses, and presents the methodology of this thesis, along with the data sample. The empirical analysis is conducted by regressing the credit spread on equity volatility, the distance to default of Merton (1974) and a set of control variables. The regression results are presented in Chapter 5.

The study of the correlation between equity and bond returns is presented in Chapters 6 and 7. The hypotheses and methodology are developed in Chapter 6. The empirical findings, which are presented in Chapter 7, consist of an estimate of the conditional correlation between equity and bond returns, and results of regressing the correlation on equity volatility, the distance to default and common risk factors.

The study of the relevance of the financial accounting data in the measurement of credit spread is presented in Chapters 8 and 9. The literature review, hypotheses and research methodology is presented in Chapter 8. The significance of the market based indicators (i.e. the distance to default and equity volatility) and financial accounting variables in explaining variations in the credit spread is considered separately and jointly. The empirical finding are presented in Chapter 9.

Finally, Chapter 10 summarises the salient findings from the three empirical studies, discusses their theoretical and practical implications, and draws conclusions. The thesis ends with a discussion of the main limitations of the thesis and suggestions for further research.

1.5. Methodological Considerations

1.5.1. Equity Risk

A decomposition of equity returns into systematic and idiosyncratic components is required in order to examine the relationship between the corporate credit spread and the changes in the systematic and idiosyncratic equity risks. One approach to the decomposition (e.g. Campbell and Taksler, 2003; Cremers et al. 2008) is to assume that all firms' loadings on systematic risks are equal, and therefore consider equity returns in excess of a major equity index to be idiosyncratic returns. Since the assumption that all firms have equal exposure to systematic risks is unrealistic, this thesis uses a bivariate GARCH model to estimate the correlation between the firm-level equity returns and systematic risk factors. The systematic equity returns are considered to be the expected returns implied by the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966) and the three factor model of Fama and French (1993). The idiosyncratic returns are considered to be the difference between the observed returns and the expected returns.

Equity risk is measured as the volatility of equity returns, commonly estimated as the standard deviation of equity returns over an arbitrary number of preceding days. The GARCH modelling is an alternative approach to the estimation of equity volatility. A GARCH model treats the current equity volatility as a function of innovations in the equity returns and the past volatility. Unlike the standard deviation, GARCH models fully captures the time-series behaviour of equity volatility. Therefore, throughout this thesis, the equity volatility is estimated by GARCH models.

1.5.2. Credit Risk

The structural approach of Merton (1974) is the most important theoretical approach to credit risk modelling. The structural model expresses credit risk as the difference between the market value of firm's assets and the book value of firm's debt relative to the volatility of firm's assets. The basic structural model has been extended by a number of authors to account for stochastic interest rates, a mean-reverting leverage ratio and other features. The extended structural models are much more complex to estimate and there is no evidence that any of them fully address the empirical weaknesses of the basic structural model. This thesis therefore utilizes the basic structural model to estimate credit risk.

1.5.3. Regression Analysis

The data set consists of matched equity, bond and accounting variables for n different firms over t consecutive time periods. This two-dimensional feature of the dataset implies that the econometric analysis should be undertaken within the panel analysis framework. A basic panel date model assumes that the data is homogeneous in cross-section and therefore estimates a single equation for the entire dataset.

This basic panel model, referred to as the constant coefficient model, can be extended to account for differences in behaviour across firms and through time. A cross-sectional fixed effects panel model allows the intercept to vary across firms and captures the unobserved factors which are firm-specific but constant over time. Similarly, a period fixed effects panel model captures the unobserved factors which are time-specific but common across firms. Finally, a two-way fixed effects models controls for the firm and time-specific unobserved factors. The empirical phenomena this thesis focuses on are examined in a full set of panel date models.

The research methodology is fully described in chapters 4, 6 and 8.

1.6. Main Research Questions

The specific hypotheses are outlined in each of the methodological chapters (chapters 4, 6 and 8). The main research questions can be outlined as follows:

1. How do the changes in systematic and idiosyncratic equity volatility affect the credit spread on corporate bonds?

2. How do the changes in equity volatility and credit risk affect the relationship between equity and bond returns?

3. Do financial accounting data have any incremental information value in explaining changes in the credit spread, when considered in conjunction with equity volatility and the distance to default of Merton (1974)?

Answering these three research questions is the task of Chapters 5, 7 and 9 respectively. Each of these chapters is preceded by a methodology chapter. However, for completeness, major issues relating to the measurement of the credit and equity risks are reviewed first. These are dealt with in Chapters 2 and 3 respectively. The next chapter examines the structural approach to credit risk modelling.

CHAPTER 2

THE THEORETICAL FRAMEWORK FOR CREDIT RISK MEASUREMENT

2.1. Introduction

The measurement of credit risk has been one of the most important topics in finance. The earliest studies used accounting variables to assess the credit risk and classify firms into different credit groups. In one of the first studies, Beaver (1966) found that key leverage and cash flow ratios of non-defaulted firms differed significantly from the ratios of defaulted firms. He also found that these ratios were highly significant in predicting a firm's failure to service its contractual obligations. Beaver's study inspired a number of researchers to greatly improve performance of accounting-based models by using better statistical methodology and variables that serve as better proxies for credit risk.

Accounting-based and other models do not, however, take into account the fact that markets continuously assess credit risk. Market prices of shares and bonds continuously change as new information arrives. A change in a firm's outlook will immediately reflect on its share and bond prices. Therefore, all information about credit as well as equity risk is contained in market prices of securities.

This shortcoming is addressed by Merton (1974) who builds on the option pricing theory of Black and Scholes (1973) to develop the original framework for the structural approach to the valuation of credit risk.

The structural model treats debt and equity securities as derivatives written on a firm's assets, so it presents a unique framework for the analysis of interaction between credit and equity risk. The objective of this chapter is to review the basic structural model, main extensions addressing its limitations and approaches to the implementation.

2.2. The Structural Approach

The debt of a firm can be considered as a contingent claim on firm's assets. Taking into account limited responsibility of equity holders, they will have an economic incentive to keep control of the firm's assets only if their market value exceeds the value of debt. If the opposite is true, equity holders will turn the firm's assets to the creditors. Therefore, equity holders can be viewed as holders of a call option written on firm's assets with exercise price equal to the value of debt implying that the firm would go bankrupt when the market value of its assets reaches the level of debt. The value of equity at maturity of debt can be expressed as:

$$E = \max(0, A - D) \tag{2.1}$$

where

A is the value of firms' assets

D is the book value of firm's debt

Following the same logic, the creditors have an obligation to purchase firm's assets at the price that equals the value of debt. Their position, therefore, is similar to the short position in a put option. The value of debt at maturity can be expressed as:

$$D = \min(D, A) \tag{2.2}$$

This resemblance of firm's equity and debt to the call and put options enables the use of the option pricing methodology to estimate the default probability and therefore to value the debt. Under the efficient market hypothesis, the market prices of securities reflect all available information and therefore this approach gives the best possible estimate of credit risk.

Merton's (1974) model is derived based on the following assumptions:

1. capital markets are perfect, i.e.
    a. assets are divisible, there are no taxes or transaction costs
    b. there are sufficient number on investors with comparable wealth levels so that each investor believes that as many assets as wanted can be bought at the market price

c. there is a market for borrowing and lending at the same rate of interest

d. short-sale of all assets, with full use of the proceeds, is allowed

2. assets are traded continuously in time
3. the theorem of Modigliani and Miller (1958) that firm's capital structure is irrelevant to its value holds
4. the interest rate term-structure is flat and known with certainty and
5. the value of assets follows the following diffusion stochastic process:

$$dA_t = (\alpha - \delta) A_t dt + \sigma A_t dX_t \tag{2.3}$$

where

α is the instantaneous expected rate of return on firm's assets

δ is the payout rate to equity and debt holders

σ is the instantaneous volatility of the return on firm's assets and

dX is the standard Wiener process / Brownian motion

Under the above assumptions, Black and Scholes (1973), and Merton (1974) show that the value of any claim f contingent on the value of firm's assets A and time t must satisfy the following parabolic differential equation (Black and Scholes, 1973; Merton, 1974):

$$\frac{\partial f}{\partial t} + \frac{1}{2}\sigma_A^2 A^2 \cdot \frac{\partial^2 f}{\partial A^2} + rA\frac{\partial f}{\partial A} - rf = 0 \tag{2.4}$$

Solving the above equation with the boundary conditions stated in Equation (2.1), i.e. the value of equity at the maturity of debt equals the difference between the asset value and debt or zero if firm's assets are worth less than the debt value, Black and Scholes (1973), and Merton (1974) show that the value of equity is as follows:

$$E_t = A_t N(d_1) - D_t e^{-rT} N(d_2) \tag{2.5}$$

where:

A is the value of firm's assets

D is the book value of firm's liabilities

T is the time to maturity of debt

R is the risk-free rate

N is the cumulative density of the standard normal distribution

$$d_1 = \frac{\ln(\frac{A_t}{D_t}) + \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}$$

$$d_2 = d_1 - \sigma_A\sqrt{T}$$

σ is the annualized volatility of returns on firm's assets.

Acknowledging the fact that the asset value is the sum of the values of debt and equity, the value of debt is given by:

$$D_t = A_t - E_t \tag{2.6}$$

Alternatively, as shown by Black and Scholes (1973), and Merton (1974), the market value of debt can be obtained by solving Equation (2.4) with the boundary condition given in Equation (2.2):

$$D_{t,MP} = D_t e^{-rT} N(d_2) + A_t N(-d_1) \tag{2.7}$$

where all variables are as defined in Equation (2.5). The market value of debt is the principal value discounted at the risk-free rate increased by the compensation for the credit risk (i.e. the credit spread):

$$D_{t,MP} = D_t e^{-(r_t + c_t)T} \tag{2.8}$$

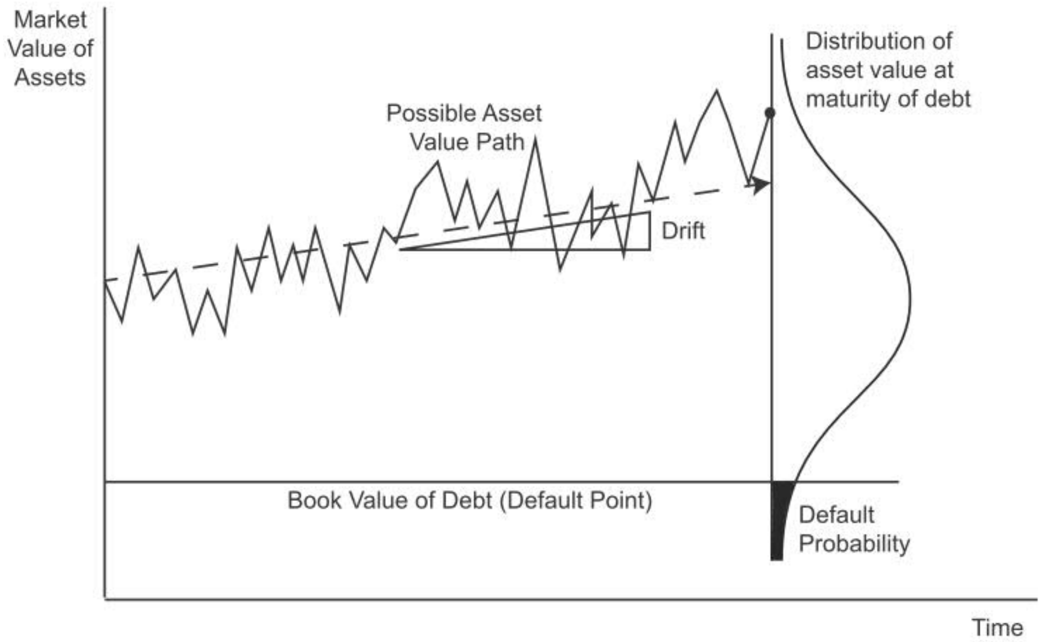
Using (2.7) and (2.8), the credit spread is given by:

$$c_t = -\frac{1}{T}\ln\left[N(d_2) + \frac{A_t}{D_t e^{-rT}} N(-d_1)\right] \tag{2.9}$$

In his seminal paper, Merton (1974) notes that the assumption of perfect capital markets can be substantially weakened and the purpose of the interest rate assumption is to clearly distinguish credit risk form interest rate risk. The Modigliani-Miller theorem is not necessary, as it is actually proved to be a part of the formal derivation of the structural model. The assumption of the assets valuation process is crucial. It requires assets returns to be serially independent in accordance with the efficient market hypothesis of Samuelson (1965) and Fama (1970).

The main concept underpinning the structural model is intuitively depicted on the following illustration.

Figure 2.1
The structural model



The distance between the current market value of assets and the book value of liabilities illustrates the initial leverage. The book value of liabilities is referred to as the default point because, it is assumed that the firm defaults when the assets value drops to the book value of liabilities. At that point, the claim the equity holders have on firm’s assets becomes worthless, so they turn firm’s assets to creditors. As the above figure clearly illustrates, the analysis of credit risk in the structural model is essentially the evaluation of the firm’s value, which is assumed to follow the diffusion stochastic process. The normal distribution of the assets value at the horizon follows from the assumption that the value of the assets evolves according to the diffusion stochastic process given in Equation (2.3). The expected rate of return on firm’s assets drifts the value of assets upward, and thus decreases the probability of default. The volatility of the assets value is, besides the leverage, the most important parameter. An increase in volatility of the assets would increase the probability that the assets value would end up below the book value of liabilities at the horizon triggering default. It should be noted that the structural model takes into account only assets insolvency, while firms usually fail to meet their debt obligations due to cash flow insolvency.

Another notable approach to the measurement of the credit risk is the reduced-form approach which, instead of modelling the process of assets value, uses debt securities directly to estimate the default probability. Classic works in this field include Jarrow, Lando and Turnbull (1997), and Duffie and Singleton (1999). Unlike the structural model, reduced-form models do not have a firm structural form. This ensures tractability and good empirical fit of reduced forms models. On the other hand, the possibility to choose a functional form of the model necessarily introduces subjectivity. This may lead to empirical results that exhibit strong in-sample fitting properties but are inappropriate for drawing conclusions about the population properties. Finally, reduced-form models do not directly link the values of firm's debt and equity. They, therefore, do not provide a comprehensive and theoretically appealing framework for the analysis of interaction between equity and credit risks.

2.3. Limitations of the Structural Approach

As Anderson and Sundaresan (2000) note, the structural model is attractive on theoretical grounds because it links the valuation of different financial claims on firms' assets with economic fundamentals. Since all claims derive their value from the same assets they are systematically correlated. It is possible, therefore, to use values of one class of securities to estimate the value of another. By theoretically explaining the relationships between claims on firm's assets, the structural model provides a framework for analysis of the relationship and interaction between different financial instruments and markets.

Despite its great appeal, the empirical evidence in support of the structural model has been mixed at best. Researchers generally report that the structural model generates much lower credit spreads than those observed. The inability of the structural model to generate realistic credit spreads can be attributed to simplifying assumptions used to derive the model, difficulties in estimation of parameters required for the implementation as well as more profound reasons that question the rationale of using the diffusion stochastic equitation given in Equation (2.3) as a model for the assets valuation process.

The most important drawback stems from the assumption that the assets value evolves continuously as described by Equation (2.3). As illustrated above, the default probability and therefore the credit spread is implied by the volatility of assets value and the difference between the asset value and the debt value. This difference divided by volatility is usually referred to as the distance to default. Due to the fact that continuously evolving value of assets needs time to change significantly, the default probability in short time is close to zero. The structural model therefore does not take into account the risk of large changes in values of assets. This is probably one of the main reasons why the structural model generates a lower credit spread than those observed.

Another drawback of the structural model is that the default can only occur at the maturity of debt and the default is assumed only when the total assets value reaches the debt value. In addition to this cause of bankruptcy, dubbed as the assets insolvency, the firm can default because of cash-flow insolvency. Ignoring cash-flow insolvency is probably another significant reason for the prediction of systematically lower credit spreads than those observed in the market.

Another obvious drawback is that the structural model is derived under the assumption that the interest rate term structure is flat and known with certainty. Besides being unrealistic, this assumption rules out the correlation between the interest rate and the value of the firm. This correlation is potentially important as the cross-sectional differences in the sensitivity of firms' values to the change in the interest rate may exist. Sweeney and Warga (1986), for example, provide evidence that the changes in the risk-free rate affect equity returns and that this effect is much stronger for the utility companies than for the whole market.

2.4. Estimation of the Structural Model

2.4.1. Estimating Unobservable Value of Firm's Assets and the Volatility of Assets

Empirical implementation of the structural model is not straightforward. The capital structure of firms is more complicated than the equity/zero-coupon bond structure used to derive the structural model. Firms usually have different forms of equity (e.g. common shares, preferential shares, restricted shares etc.) and debt (bank term debt, short-term debt, straight bonds, convertible bonds etc.) in their capital structures. Due to the fact that not all components of the firm capital are traded, the market value of a firm's assets cannot be directly observed. The empirical research is usually based on public firms with actively traded shares, so this problem is scaled down to the estimation of the market value of debt. A closely related issue is the estimation of assets volatility, which is also not directly observable. Campbell and Taksler (2003), for example, take the book value of debt as a proxy for its market value and assume two extreme scenarios for the volatility of debt. In the first scenario, the volatility of debt is assumed to be zero and in the second, it is considered to be equal to the volatility of equity. They note that these extreme scenarios are not realistic and call for further research.

A more sophisticated approach to estimating the assets value and volatility is to take advantage of the derivative nature of equity and use the option pricing theory to obtain two equations with two unknown variables (assets value and volatility). The first equation is the call option pricing formula given in Equation (2.5), i.e.:

$$E = A\,N(d_1) - De^{-rT}N(d_2)$$

where

E is the value of equity

A is the asset value

D is the debt value

σ^2 is the annualized standard deviation of asset returns

r is the risk-free interest rate

N is the cumulative density of the standard normal distribution

T is the time to maturity of debt

Assuming that the firm's equity value follows the same stochastic diffusion process as the asset value, its dynamics under the risk-neutral probability measure can be described by:

$$dE_t = rE_t\,dt + \sigma_E E_t dX_t \tag{2.10}$$

where:

r is the risk-free interest rate

σ_E is the annualized standard deviation of returns on the equity

dX is the standard Wiener process

The equity is a function of time and the asset value, i.e. $E_t = f(V_t, t)$. Therefore, Itô's Lemma can be applied to get:

$$dE_t = \left[\frac{\delta f(A_t,t)}{\delta t} + \frac{\delta f(A_t,t)}{\delta A_t} A_t r + \frac{1}{2}\frac{\partial^2 f(A_t,t)}{(\partial A_t)^2}(A_t\sigma_A)^2\right]dt + \frac{\delta f(A_t,t)}{\delta A_t} A_t \sigma_A dX_t \tag{2.11}$$

The comparison of the coefficient multiplying the Brownian processes in the two preceding equation gives the following identity:

$$\sigma_E E_t = \frac{\delta f(A_t,t)}{\delta A_t} A_t \sigma_A \tag{2.12}$$

Equations (2.5) and (2.12) form a system of two equations with two unknown variables (the asset value and its volatility). Therefore, it is possible to solve these two equations simultaneously and obtain estimates for the asset value and the asset volatility. This appears to be most frequently used method for estimation of unobservable assets value and volatility. It is advocated by major text books (e.g. Hull 2006, Saunders 1999), and widely used in academic studies (e.g. Ronn and Verma (1986), Hillegeist et al. (2004), Das and Hanouna (2009), Cooper and Davydenko (2003), Delianedis and Geske (2003), and Campbell, Hilscher and Szilagyi (2007)).

Another approach is to adopt an iterative procedure. In this approach, the volatility of equity, which can be estimated from historical daily prices of equity, is initially considered as the volatility of assets. This makes it straightforward to estimate the value of assets, which remain the only unknown variable in the equation. The standard deviation of the estimated values of assets serves as the volatility of assets in the next iteration. The procedure is repeated until the estimates of the volatility of assets from two iterations converge. This approach is used by Vassalou and Xing (2004), Du and Suo

(2003), and Duffie, Saita and Wang (2007). Also, this approach is used in a commercial implementation of the structural model by Moody's KMV (Crosbie and Bohn, 2003).

In support of the iterative approach, Crosbie and Bohn (2003) of Moody's KMV note that the estimates obtained by the system of equations method hold only instantaneously. This implies that these estimates would be acceptable if the leverage of firms was constant. However, they note that the leverage of firms is not constant, but experience significant changes. Industrial firms usually increase their leverage as they approach default, whereas the leverage of financial firms behaves exactly the opposite. Therefore, they conclude that the system of equations method is unlikely to yield reasonable results. Bharath and Shumway (2008) provide results that are inconsistent with this claim. They find that the computationally intensive iterative approach does not improve model performance.

Duan (1994) proposes a third approach. He points to drawbacks of estimating assets value and volatility by simultaneously solving two equations as presented above, and proposes using the maximum likelihood method instead. He argues that the former method considers assets volatility as constant and independent of assets value and time. Also, in his view, the two equations that are simultaneously solved are essentially the same equation which makes one of them redundant. Finally, the two equations method does not provide confidence intervals for estimated values of assets and volatility.

Duan (1994) considers observed time series of equity prices as a sample of transformed data with the call option pricing equation defining the transformation. The maximum likelihood method is used to find values of assets and volatility which maximises the likelihood of obtaining equity prices in the sample. Interestingly, Duan notes that his method provides identical estimates of as those yielded by the iteration method employed.

Wong and Li (2004) emphasize the importance of the method for estimating market value of assets and associated volatility. They point that the use of book value of debt as a proxy for its market value overestimates the value of assets and therefore the implied bond values, and conclude advocating the maximum likelihood method.

Ericsson and Reneby (2005) estimate three versions of the structural model and run simulations to investigate whether the performance of models depend on the method for estimating assets value and volatility. They find that the maximum likelihood method clearly dominates the system of equations method and that the latter performs so poorly that it may be a cause for empirical failures in implementation of the structural model. In addition to yielding unbiased and relatively efficient parameters, they point to the maximum likelihood method that allows straightforward derivation of the probability distribution and thus confidence intervals of parameters.

Suo and Wang (2006) use the maximum likelihood method to estimate the assets value and volatility using equity as well as bond prices. When bond prices are used, they find that estimated assets volatility is unreasonably high and that the estimation process does not converge for most of the observations in their sample.

2.4.2. Choosing Default Point and Time Horizon

The structural model envisages a firm with simple capital structure consisting of equity and a zero coupon bond. In this setting, the firm defaults if its assets are worth less than the bond's face value when the bond matures. As already mentioned, firms' capital structures are much more complex. Virtually all balance sheets contain current liabilities, short-term loans, long-term loans, bonds and other classes of liabilities. Maturities and other details on firms' liabilities are not easily accessible. Therefore, a choice of the default point and the maturity of liabilities is not straightforward, and may influence empirical results.

As a minimum, the default point should include all liabilities that are due during the period for which the default probability is modelled. The other extreme is to include total liabilities, because the firms usually pay interest or coupons on all liabilities. It should be also taken into account that the ability of firms to refinance their debt depends on the total leverage.

A review of the literature shows that the most common choice for the default point is the book value of total liabilities. This choice is adopted by Campbell and Taksler (2003), Huang and Zou (2008), Eom et al. (2004), Tarashev (2005), Ericsson et al. (2005), and

Hillegeist et al. (2004). In its commercial implementation of the structural model, Moody's KMV assumes that the default point amounts to the short-term liabilities and a portion of long-term liabilities (Dwyer and Su, 2007). Following this approach, Vassalou and Xing (2004) use the short-term debt plus half of the long-term debt and argue that this choice adequately captures the financing restraints of firms. They examine the sensitivity of their results to the choice of the proportion of the long-term debt included in the calculation and find it not large enough to significantly alter their results. Das and Hanouna (2009) also take into account only fifty per cent of the long-term debt.

The choice of default point should be related to the choice of the time horizon over which the default probability is modelled. If the long-term liabilities are included in the default point then their maturity should play an important role in choosing the time horizon. Otherwise the model would potentially overestimate the default probability of firms financed with more long-term liabilities. Although the extension of the structural model to longer terms is pretty straightforward, the literature review shows that it is common to estimate a default probability for a period of one year, e.g. Du and Suo (2003), Hillegeist et al. (2004), Bharath and Shumway (2008).

The relationship between the time horizon and the default probability is highly nonlinear. It is initially positive and then turns negative as the growth in assets values outweighs the increase in assets volatility due to the extension of the time horizon. Therefore, the time extension from the standard one-year model is likely to impact empirical results. Campbell, Hilscher and Szilagyi (2007) provide a similar empirical support for this argument. They report that the significance of the distance-to-default variable in their logit regression depends on the time horizon. Also, the coefficient of the distance-to-default variable takes the expected negative sign only when the time horizon is extended for two or three years. Delianedis and Geske (2003) try to overcome this issue by assuming that a maturity of firms' short-term and long-term liabilities is one year and ten years respectively. Huang and Huang (2003) use the duration of liabilities and Cooper and Davydenko (2003) consider the timeframe as an endogenous variable and choose the value which makes the modelled credit spread consistent with the observed credit spread.

2.4.3. Estimating the Expected Growth in the Assets Value

According to the assumed dynamic of the value of assets, described by the stochastic differential Equation (2.3), the expected growth in the value of assets or drift per unit of time is α-δ, where α is the instantaneous expected rate of return on firm's assets and δ is the payout rate to the equity and debt holders. The expected rate of return on firm's assets α can be considered to consist of two components, the risk-free rate r and the assets risk premium ξ. This expands the expression for the expected assets growth rate to r+ξ-δ and brings down the estimation of assets growth rate to the estimation of the assets risk premium and the assets payout ratio.

A higher assets growth rate implies that the value of assets drifts away from the value of debt at a faster pace. This causes the distance to default to widen and therefore lowers the probability of default as clearly depicted in Figure 2.1. Similarly to the assets value and volatility, the expected asset premium and payout rates are not directly observable. In his seminal paper, Merton (1974) shows that the value of a derivative written on a firm's assets does not depend on the expected growth in the asset value or the risk preference of investor. In this risk-neutral setting, returns are discounted at the risk-free rate which makes the estimation of the asset risk premium unnecessary. This argument provides the theoretical justification for the use of risk-neutral probability of default.

The literature identifies different approaches to estimation of the asset value growth rate. Using the risk-neutral probability and therefore avoiding the estimation of the asset risk premium is the most straightforward approach. The payout rate is computed as the weighted average of bond's coupon rate and dividend yield where the weights are derived from the leverage ratio. This approach is utilized by Ericsson et al. (2005), Huang and Zhou (2008), and Campbell and Taksler (2003).

An alternative approach, used by Vassalou and Xing (2004) and Eom et al. (2004), is to use the average change in the estimated value of assets as a proxy for the drift parameter. This approach eliminates the need for estimation of the expected growth rate and the payout ratio separately, because both rates are reflected in the average change in the asset value. Bharath and Shumway (2008) follow a similar approach. They estimate the asset value, volatility and the drift parameter, which is computed as the average change in the estimated asset value, in the iterative procedure discussed in the previous section. Similarly, Suo and Wang (2006), as well as Ericsson and Reneby (2004) use the maximum likelihood method to estimate the drift parameter alongside the assets value and the volatility of assets.

Another notable approach is found in the widely cited paper of Huang and Huang (2003). They derive the asset risk premium from the equity premium estimated in the regression analysis by Bhandari (1988). As the payout rate, they take the weighted average between the average historical dividend yield (four per cent according to Ibbotson Associates, 2002) and the average historical coupon rate which they estimate at nine per cent. Applying weights given by the average leverage ratio for S&P 500 index firms provides them with the payout rate of six per cent. Leland (2004) follows a similar approach and assumes a payout rate of six per cent and an asset risk premium of four per cent. Besides computing the payout rate in the usual manner, Ericsson et al. (2005) consider it to be an exogenous variable taking values of zero or six per cent. Finally, a proxy for the rate of return on firm’s assets may be an accounting variable. Patel and Pereira (2005) use the ratio of earnings before interest and taxes to total assets as a proxy for the expected rate of return on firm’s assets and they follow Huang and Huang (2003) in assuming the six per cent payout rate.

2.5. Extensions of the Structural Model

Merton’s (1974) seminal paper inspired further research on credit risk modelling based on the asset valuation process. As a result, a number of extensions of the original structural model have been proposed. Major works aimed to improve the model’s performance by relaxing the model’s assumptions and a better modelling of the asset valuation process. Although the mathematical derivation of these models is to a great extent more complex than that of the original structural model, the basic idea remains the same: once the stochastic process for the asset value is specified, it is possible to compute the probability that the asset value will be lower or higher than the pre-specified default point over any period of time.

All major models assume that the asset value evolves according to the following stochastic diffusion equation:

$$dA_t = (r_t + \lambda_t - \delta_t)A_t dt + \sigma V_t dX_t + dJ \tag{2.13}$$

where

r is the risk-free interest rate

λ is the asset premium (in the risk neutral probability measure δ = 0)

δ is the payout rate

σ is the annualized standard deviation of returns on firm’s assets

dX is the standard Gauss-Wiener process

dJ is the asset value jump process

This specification is the same as in the original structural model of Merton (1974) with the jump component dJ.

2.5.1. Early Default

In the structural model of Merton (1974) the default occurs at the maturity of debt if the asset value falls below the debt value. The model therefore predicts that the default will not happen even if the firm’s assets become worthless before the debt matures. An appealing extension is to allow the default to happen if the asset value reaches a barrier before the debt matures. This feature would enable the model to also incorporate cash flow insolvency as well as to take into account bond covenants concerning the firm’s performance that might stipulate default if certain performance standards are not met.

A down-and-in option must be introduced in the analysis. This is a call option that comes into existence if the underlying asset price reaches a certain barrier level. Adding a barrier to the structural model implies that the equity holders still have a call option on firm’s assets but they have given up a down-and-in option with the barrier value as the strike price. Therefore, the equity value can be expressed as:

$$E = \text{regular call option} - \text{down-and-in-option} \tag{2.14}$$

Since the down-and-in option has a positive value it is clear that the equity is worth less in the structural model with a barrier than it is worth in the original structural model.

This implies a higher debt value and therefore lower credit spreads in the barrier model. The down-and-in call option pricing equation when the barrier value is less or equal to the strike price is as follows (Hull 2006, p. 533):

$$C_{di} = A_t e^{-rT}(B/A_t)^{2\lambda} N(y) - D_t e^{-rT}(B/A_t)^{2\lambda-2} N(y - \sigma_A \sqrt{T}) \qquad (2.15)$$

where

A is the asset value

D is the debt value

B is the barrier level (bellow the initial debt value)

N is the cumulative density of the standard normal distribution

r is the risk-free rate

σ is the annualized volatility of returns on firm's assets

T is the time to maturity

$$\lambda = \frac{r + \sigma_A^2/2}{\sigma_A^2}$$

$$y = \frac{\ln\left[B^2/(A_t D_t)\right]}{\sigma_A \sqrt{T}} + \lambda\sigma\sqrt{T}$$

Black and Cox (1976) were first to introduce a barrier to the structural model. They argue that it is reasonable to assume that the barrier increases exponentially and specify the barrier as $Be^{-\lambda T}$ where B is the barrier value, T is the remaining life of the bond and gamma is the rate of increase. The equity value in this model is given by:

$$E_t = A - \left\{ \begin{array}{l} De^{-r(T-t)}N(z_1) - De^{-r(T-t)}y^{2\vartheta-2}N(z_2) + Ae^{-a(T-t)}N(z_3) \\ +Ae^{-a(T-t)}y^{2\vartheta}N(z_4) + Ay^{\vartheta-\zeta}N(z_5) + Ay^{\vartheta-\zeta}N(z_6) \\ -Ae^{-a(T-t)}y^{\vartheta+\eta}N(z_7) - Ae^{-a(T-t)}y^{\vartheta-\eta}N(z_8) \end{array} \right\} \qquad (2.16)$$

where, for the sake of completeness:

$$y = \frac{Be^{-\gamma(T-t)}}{A} \qquad \vartheta = \frac{(r - a - \gamma + \frac{1}{2}\sigma_A^2)}{\sigma_A^2}$$

$$\delta = \frac{(r - a - \gamma - \frac{1}{2}\sigma_A^2)}{\sigma_A^2 + 2\sigma_A^2(r - \gamma)} \qquad \zeta = \frac{\sqrt{\delta}}{\sigma_A^2} \qquad \eta = \frac{\sqrt{\delta - 2\sigma_A^2 a}}{\sigma_A^2}$$

$$z_1 = \frac{\ln A - \ln D + (r - a - \frac{1}{2}\sigma_A^2)(T - t)}{\sqrt{\sigma_A^2(T - t)}} \qquad z_2 = \frac{\ln A - \ln D + 2\ln y + (r - a - \frac{1}{2}\sigma_A^2)(T - t)}{\sqrt{\sigma_A^2(T - t)}}$$

$$z_3 = \frac{\ln D - \ln A - (r - a - \frac{1}{2}\sigma_A^2)(T - t)}{\sqrt{\sigma_A^2(T - t)}} \qquad z_4 = \frac{\ln A - \ln D + 2\ln y + (r - a + \frac{1}{2}\sigma^2)(T - t)}{\sqrt{\sigma_A^2(T - t)}}$$

$$z_5 = \frac{\ln y + \zeta\sigma_A^2(T - t)}{\sqrt{\sigma_A^2(T - t)}} \qquad z_6 = \frac{\ln y - \zeta\sigma_A^2(T - t)}{\sqrt{\sigma_A^2(T - t)}}$$

$$z_7 = \frac{\ln y + \eta\sigma_A^2(T - t)}{\sqrt{\sigma_A^2(T - t)}} \qquad z_8 = \frac{\ln y - \eta\sigma_A^2(T - t)}{\sqrt{\sigma_A^2(T - t)}}$$

2.5.2. Stochastic Interest Rate

A more careful modelling of the risk-free rate process is another notable extension of the original structural model which assumes that the risk-free rate is constant with a flat term structure. Kim, Ramaswamy and Sundaresan (1993) propose a model with constant default barrier and a stochastic process for evaluation of the interest rate. They use the Cox, Ingersoll and Ross (1985) process to model the interest rate dynamics:

$$dr = \kappa(\mu - r)dt + \sigma\sqrt{r}dX \tag{2.17}$$

where

r is the risk-free interest rate;

μ is the long-run mean of the interest rate

κ is the speed at which the interest rate reverts to its long-term mean

σ is the instantaneous standard deviation of the interest rate

dX is the standard Wiener process

In this model, the asset value and the interest rate processes may be correlated. The strength and sign of this correlation can play a significant role in the debt valuation. Therefore, firms with similar leverage and asset volatility may have different credit risk depending on the sensitivity of their asset value to the changes in the interest rate. The authors also add the assumption that the firm's assets cannot be sold to pay dividends. Bondholders have priority and receive interest payments continuously. The firm defaults if its cash flow is insufficient to cover interest payments to bondholders. The bond price is obtained by solving the following pricing equation of Brennan and Schwartz (1980):

$$\frac{1}{2}\sigma_A^2 A^2 \frac{\partial^2 D}{\partial A^2} + \rho\sigma_A\sigma_r\sqrt{r}A\frac{\partial^2 D}{\partial r\partial A} + \frac{1}{2}\sigma_r^2 r\frac{\partial^2 D}{\partial r^2} + \kappa(\mu - r)\frac{\partial D}{\partial r} + (r-\delta)A\frac{\partial D}{\partial A} - rD + c = \frac{\partial D}{\partial t} \tag{2.18}$$

where

A is the value of firm's assets

D is the value of risky bond

r is the risk-free rate

μ is the long-run mean of the interest rate

κ is the speed at which the interest rate reverts to its long-term mean

δ is the firm's net cash outflow resulting from optimal investment decision

c is the bond coupon rate

σ_A is the instantaneous standard deviation of the asset value

σ_r is the instantaneous standard deviation of the interest rate

ρ is the instantaneous correlation coefficient between diffusion components of the asset value and interest rate processes

The value of risky bond is fully described by assuming that, upon bankruptcy, the bondholders will receive the full value of assets or a fraction of the value of a comparable risk-free bond and specifying the following boundary conditions:

$$\begin{aligned} &\lim_{A\to\infty} = D(A,r,t;c) = P(r,t;c) \\ &D(A,r,\tau=0;c) = \min\left[A,F\right] \end{aligned} \tag{2.19}$$

The first boundary condition states that, as the asset value approaches infinity, the bond value approaches the value of a comparable risk-free bond. The second condition specifies the terminal condition when bondholders receive the minimum of the asset value or the face value of the bond. The authors provide a numerical solution for the above valuation equation and note that a closed-form solution is not available.

Longstaff and Schwartz (1995) propose a model with the same extensions but with a closed-form albeit approximate solution. They opt for a constant default threshold and argue that a more sophisticated specification of the default barrier makes the model more complex without adding more insight into the valuation. The interest rate is modelled as the Vasicek (1977) process:

$$dr = (\mu - \kappa r)dt + \eta\, dX \qquad (2.20)$$

where:

μ is the long-run mean of the interest rate

κ is the speed at which the interest rate reverts to its long-term mean

η is the spot-rate volatility

dX is the standard Wiener process

A notable feature of the Longstaff and Schwartz (1995) model is how it deals with the default payoff. At default, bondholders receive risk-free bonds in the amount of 1-w times the face value of the bond. They derive the following valuation expression for risky debt:

$$D(X,r,T) = P(r,T) - wP(r,T)Q(X,r,T) \qquad (2.21)$$

where

X is the leverage ratio

r is the risk-free interest rate

T is the time to maturity

$D(r,T) = e^{A(T)-B(T)r}$ - value of risk-free bond according to Vasicek with

$$A(T) = \left(\eta^2/2\beta^2 - \alpha/\beta\right)T + \left(\eta^2/\beta^3 - \alpha/\beta^2\right)\left(e^{-\beta T} - 1\right) - \left(\eta^2/4\beta^3\right)\left(e^{-2\beta T} - 1\right)$$

$$B(T) = \frac{1 - e^{-\beta T}}{\alpha}$$

$Q(X,r,T,n)=\sum_{i=1}^{n} q_i$, risk-neutral probability of default with

$$q_1 = N(a_1)$$

$$q_i = N(a_i) - \sum_{j=1}^{i-1} q_j N(b_{ij}),\ i = 2,3,\ldots\ldots,n$$

N is cumulative density of the standard normal distribution

$$a_i = \frac{-\ln X - M(iT/n,T)}{\sqrt{S(iT/n)}}$$

$$b_{ij} = \frac{M(jT/n,T) - M(iT/n,T)}{\sqrt{S(iT/n) - S(jT/n)}}$$

$$M(t,T) = \left(\frac{\alpha-\rho\sigma\eta}{\beta} - \frac{\eta^2}{\beta^2} - \frac{\sigma^2}{2}\right)t + \left(\frac{\rho\sigma\eta}{\beta^2} + \frac{\eta^2}{2\beta^3}\right)\exp(-\beta T)\left(\exp(\beta t)-1\right)$$
$$+\left(\frac{r}{\beta} - \frac{\alpha}{\beta^2} + \frac{\eta^2}{\beta^3}\right)\left(1-\exp(-\beta t)\right) - \left(\frac{\eta^2}{2\beta^3}\right)\exp(-\beta T)\left(1-\exp(-\beta t)\right)$$

$$S(T) = \left(\frac{\rho\sigma\eta}{\beta} + \frac{\eta^2}{\beta^2} + \sigma^2\right)t - \left(\frac{\rho\sigma\eta}{\beta^2} + \frac{2\eta^2}{\beta^3}\right)\left(1-\exp(-\beta t)\right) + \left(\frac{\eta^2}{2\beta^3}\right)\left(1-\exp(-2\beta t)\right)$$

The bond valuation equation is very intuitive. P(r, T) represents the value of the equivalent risk-free bond. The present value of write downs in case of default, wP(r, T) multiplied by the risk-neutral default probability is deducted to take into account the default risk. The asset value and the default boundary impact the bond valuation equation only through their ratio. An important implication is, as Longstaff and Schwartz (1995) note, that it is not necessary to specify the asset value and the default boundary to conduct the bond valuation.

2.5.3. Stochastic Default Barrier

Briys and Varenne (1997) introduce a structural model with a stochastic barrier which takes the following form:

$$B(t) = \alpha F P(t,T) \tag{2.22}$$

where:

F is the face value of the bond

α =is the coefficient $0 \le \alpha \le 1$ and

$P(t,T)$ is the value of a riskless zero-coupon bond maturing at time T.

The above equation is stochastic because it is a function of the interest rate, which is modelled as a stochastic variable. The authors derive the following pricing equation:

$$D = FP(0,T)\begin{bmatrix} 1 - P_E(l_0,1) + P_E(q_{0,}\dfrac{l_0}{q_0}) \\ -(1-f_1)l_0(N(-d_3) + \dfrac{N(-d_4)}{q_0}) \\ -(1-f_2)l_0\left(N(d_3) - N(d_1) + \dfrac{N(d_4)-N(d_6)}{q_0}\right) \end{bmatrix} \qquad (2.23)$$

where:

$$d_1 = \frac{\ln l_0 + \dfrac{\sum(T)}{2}}{\sqrt{\sum(T)}} \qquad d_2 = d_1 - \sqrt{\sum(T)}$$

$$d_3 = \frac{\ln l_0 + \dfrac{\sum(T)}{2}}{\sqrt{\sum(T)}} \qquad d_4 = d_3 - \sqrt{\sum(T)}$$

$$d_5 = \frac{\ln \dfrac{q_0^2}{l_0} + \dfrac{\sum(T)}{2}}{\sqrt{\sum(T)}} \qquad d_6 = d_5 - \sqrt{\sum(T)}$$

$$\sum(T) = \int_0^T \left[(\rho\sigma_A + \sigma_P(t,T))^2 + (1-\rho^2)\sigma_A^2\right]dt$$

$$l_0 = \frac{A_0}{FP(0,T)} \qquad q_0 = \frac{A_0}{\alpha FP(0,T)}$$

$$P_E(l_0,1) = -l_0N(-d_1) + N(-d_2) \qquad P_E(q_0,\frac{l_0}{q_0}) = -q_0N(-d_5) + \frac{l_0}{q_0}N(-d_6)$$

The valuation equation has familiar and intuitive interpretation. The value of risky debt is the value of riskless bond corrected for values of the standard put option to account for the possibility of default at maturity and the barrier option to take into account the possibility of an early default. The last two terms in the equation capture the effects of deviations from the priority rule. This rule implies that debt holders should be paid first in case of default, but there is strong empirical evidence indicating that deviations from the priority rule are commonplace (e.g. Franks and Torous, 1989). The coefficients f_1 and f_2 indicate a fraction of the asset value debt holders receive in case of default. Setting them to the value of one implies that the priority rule is fully enforced. Otherwise, the default risk is increased which has a negative impact upon the bond value.

2.5.4. Mean-Reverting Leverage Ratio

The models considered so far estimate firms' default risk based on their current leverage. Because of the expected growth in the asset value, the leverage is predicted to decrease over time. This implies a downward-sloping term structure of credit spreads for highly leveraged firms. This is not consistent with the empirical findings of Helwege and Turner (1999) who report that the term structure of credit spreads on high-risk bonds usually has a positive slope. Collin-Dufresne and Goldstein (2001) note that leverage ratios at the industry level did not significantly change although equity indices increased 10-fold during the past 20 years. This empirical evidence (that an increase in the asset value does not automatically lead to a drop in the leverage but to an increase in borrowings) implies that credit risk models should take into account the firm's current capital structure as well as the possibility for its change. In an important paper, Collin-Dufresne and Goldstein (2001) propose a structural model with a stochastic interest rate that leads to stationary leverage ratios. The previously considered model of Briys and Varenne (1997) also features a stochastic default boundary. However, their model does not lead to stationary leverage ratios because the default boundary is linked to the interest rate process rather than the asset value process.

Collin-Dufresne and Goldstein (2001) assume that the log-default boundary is described by:

$$dk_t = \lambda(y_t - v - k_t)dt \tag{2.24}$$

where:

y is the log of the asset value A

v and λ are the constants

According to this specification, firms issue more debt when the leverage falls below some target (i.e. when k < y-v) and reduce the leverage when it is above the target (i.e. when k > y-v). They show that a structural model with this feature produces significantly higher credit spreads in comparison to a model with the constant default boundary.

2.5.5. Jump Diffusion

The main limitation of the original structural model is in its assumption that the asset value follows a diffusion process. Under a diffusion process, the asset value changes continuously so it should be possible to predict when the asset value will reach the default barrier. It follows that the default is completely predictable because the unexpected significant changes in the asset value are not possible. This is the reason why the structural model predicts a zero credit spread for very short-term debt. Needless to say, a large body of empirical evidence contrasts with these implications of the structural model. One way to overcome this limitation is through allowing the possibility for jumps in the asset value. Merton (1976) proposes the jump-diffusion model in which the jump probability is modelled as a Poisson process:

$$dJ = \begin{Bmatrix} 0 \ \text{with probability}\ 1-\lambda dt \\ 1 \ \text{with probability}\ \lambda dt \end{Bmatrix} \tag{2.25}$$

The dynamic of the asset value is described by:

$$dA_t = (r_t + \zeta_t - \delta_t) A_t dt + \sigma A_t dX_t + (X-1) A_t dJ \tag{2.26}$$

It is assumed that the correlation coefficient between dX and dJ is zero. If there is a jump then the asset value falls by 1-X. Zhou (1997, 2001) proposes a structural model which assumes that the asset value evolves according to the jump-diffusion process and derives a closed-form solution for the value of zero-coupon bond under the assumption that the default can only happen at maturity.

Closely related to the jump diffusion is the concept of volatility jumps which was put forward by Naik (1993). Instead of jumps in the asset value, this extension of the structural model allows for large discrete shifts in the volatility of the asset value. The shifts in the volatility can be modelled as a Poisson process in a similar manner as the jumps in the asset value.

2.5.6. Stochastic Volatility

Allowing jumps adds flexibility to the modelling of volatility but does not fully mitigate the limitations of the original structural model's assumption that the volatility is constant. The hypothesis of the constant volatility of a financial security's price has been rejected in most of the existing empirical tests. Attempts at forecasting the equity volatility yielded mixed results (e.g. Frances and Van Dijk, 1995). A regression of realized volatility on forecasted volatility produces R-squared statistics in a range of 10 per cent. Finally, the volatility is not even observable. These empirically supported arguments call for the modelling of the volatility as a random variable. Hull and White (1987) consider the pricing of European call option when the volatility is stochastic. The volatility is assumed to evolve according to the following stochastic diffusion equation:

$$d(\sigma^2) = \mu\sigma^2 dt + \xi\sigma^2 dw \tag{2.27}$$

They show that the Black and Scholes (1973) pricing equation overvalues at-the-money and undervalues deep in and out-of-the-money call options written on a security with stochastic volatility. In the credit risk context, the equity of a firm is treated as a call option written on its assets. An at-the-money call option means that the firm is close to the default point, i.e. the value of a firm's assets is close to the value of the debt. Overvaluation of the equity means underpricing of the debt and therefore upward biased credit spreads. On the other hand, the equity of low-level credit risk firms (deep in-the-money call option) is underestimated which implies overvalued debt and hence downward biased credit spreads. Heston (1993) derives a closed-form pricing equation for the price of a European call option written on an asset featuring stochastic volatility.

Another approach to incorporating time-variations of the volatility into the structural model is the use of the Generalized Autoregressive Conditional Heteroskedasticity

(GARCH) model. GARCH is an econometric model that uses lagged values of the volatility and lagged values of errors from autoregressive models for estimation of the asset value. A GARCH(p,q) model can be written as:

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \qquad (2.28)$$

where

α(L), β(L) are the lag polynomials of order p and q respectively

ε is the error term from $A_t = \phi_0 + \phi_1 A_{t-1} + \varepsilon_t$

The degree of persistence of the volatility, which indicates how long shocks take to dissipate, is a function of the two lag polynomials. The most parsimonious GARCH(1,1) model is usually sufficient to capture the time behaviour of the volatility:

$$\sigma_t^2 = \omega + \alpha_j \varepsilon_{t-1} + \beta_j \sigma_{t-1}^2 \qquad (2.29)$$

Wilmott (2000) notes that the GARCH(1,1) model becomes the same as the stochastic volatility model when the time step tends to zero.

2.5.7. Endogenous Default Barrier

All of the previously considered models assume that the default occurs when the asset value reaches an exogenously set default barrier. An alternative to this approach is to assume that equity holders choose when to stop the debt servicing in order to maximize the equity value. In this setting, the firm will continue to service its debt even when the asset value is less that the principal debt value, but exceeds the endogenous default boundary. Leland (1994) uses the structural model to relate the debt value and the optimal capital structure to firm risk, taxes, bankruptcy costs, bond covenants and other parameters. His analysis shows that debt renegotiation can simultaneously increase debt and equity value, but it is in equity holders' interest to hold renegotiation until the brink of bankruptcy. Under the assumption that the debt is perpetual, he derives the optimal endogenous default point. Leland and Toft (1996) extend the analysis by relaxing the assumption of infinite debt. They show that the optimal default boundary decreases with the maturity of debt, the asset volatility and the risk-free rate. On the other hand, it increases with the principal value of debt.

Following this line of research, Anderson and Sundaresan (1996) argue that the default boundary and the allocation of firm's cash flows are determined endogenously as the equilibrium of the non-cooperative game between debt holders and equity holders. The equity holders may opt to underperform debt servicing even if the firm can meet all debt payments. The authors define this as the strategic debt service that has a potential to persuade creditors to renegotiate the debt contract because of the costliness of formal bankruptcy. In this non-cooperative game, creditors initiate the bankruptcy when it is best for them.

2.6. Summary

The structural model of Merton (1974) treats all securities as contingent claims on firms' assets. In this setting, the equity resembles a call option and the debt is considered as a put option written on firm's assets. Building on the option pricing theory of Black and Scholes (1973), the structural model provides an analytical solution for the value of debt securities, the probability of default and the associated credit spread. Since the value of equity and its volatility are the major inputs in the structural model, it provides a unique framework for the analysis of the relationship between the value of equity and credit spreads.

Despite the great appeal, empirical evidence in support of the structural model has been mixed at best. The structural model is generally found to underestimate credit spreads which is attributed to its rigid assumptions as well as implementation issues. It should also be noted that some authors (i.e. Ericsson, Reneby and Wang, 2005) argue that the structural model performance in explaining credit spread related to the credit risk is quite satisfactory when taking into account that a large part of the observed credit spread is related to the liquidity risk and tax issues.

The structural model is derived under strict assumptions of which the most consequential one is that the asset value follows a diffusion process, which is continuous and therefore rules out the jumps in the asset value. Assumptions of a constant risk-free rate and volatility of assets are also not empirically supported. A number of authors propose extensions of the structural model to relax those assumptions as well as take into account specific features of debt instruments and empirically established facts. Eom, Helwege and Huang (2004), and Huang and Zhou (2008) find the mean reverting leverage feature of the Collin-Dufresne and Goldstein (2001) model to have the best performance among competing structural models.

Empirical implementation of the structural model is not straightforward. The market value of assets and its volatility, which are required for the estimation, are not observable. Most authors assume that the volatility of debt is zero and the value of assets is the sum of the market value of equity and the book value of debt. Campbell and Taksler (2003) note that these assumptions are not realistic and call for a more careful estimation of the value of assets and associated volatility. A more sophisticated approach, which is also widely used (e.g. Das and Hanouna, 2009; Cooper and Davydenko, 2003), involves simulations solving of two equations implied by the Black and Scholes (1973) option pricing model for unknown assets value and its volatility.

The next chapter reviews the seminal approaches to the valuation of equity.

CHAPTER 3

THE THEORETICAL FRAMEWORK FOR EQUITY RISK MEASUREMENT

3.1. Introduction

Since the value of corporate debt fundamentally depends on the firm's leverage, all factors that influence the equity value and therefore the leverage should influence the debt valuation in a systematic manner. This implies that excess returns on equities or returns above the risk-free rate should be systematically related to the credit spreads or excess returns on corporate debt.

The objective of this chapter is to examine equity pricing models, the main determinants of the equity premium, and approaches to estimating and analysing equity volatility, which is a major parameter in the structural debt pricing model.

3.2. A Basic Model for Equity Prices

The first step in developing a model for equity prices is to assume that all available information up to time t is fully reflected in the equity price E_t. In other words, the past equity prices have no role in predicting the future prices. This assumption is enough to build the following simple model:

$$E_t = E_{t-1} + \varepsilon_t \tag{3.1}$$

where ε_t is independently and identically distributed with mean zero and variance σ^2, i.e. $\varepsilon_t \sim$ IID $(0,\sigma^2)$. The above model states that equity price changes are completely random and unpredictable. The price change is simply a white noise process ε_t. The price change over time is simply the accumulation of random shocks, i.e. $E_T - E_t = \sum_{t=1}^{T} \varepsilon_t$

This is the essence of the random walk hypothesis first formulated by Bachelier (1900) and further developed into the efficient market hypothesis by Fama (1970).

According to this simple model, changes in ε have permanent, non-decaying effects on equity prices. Therefore, equity prices do not have a particular long-term equilibrium. This non-stationary feature makes the price series inadequate for most aspects of the time series analysis. As a result, virtually all empirical research is conducted on returns or the first-difference of the price series.

Under the assumption of normality, the returns are given by:

$$R_i = \frac{E_{t+1} - E_t}{E_t} = \mu_i + \sigma_R \phi \tag{3.2}$$

where

μ_i is the expected return or drift

σ_R is the standard deviation of returns, i.e. $\sigma_R = \sqrt{\frac{1}{n-1}\sum_{i=i}^{n}(R_i - \bar{R})^2}$

ϕ is a standardized Normal variable

The expected return grows linearly in time and therefore the standard deviation grows like the square root of time. This implies that over a short timescale the standard deviation or volatility of returns is the most important determinant of the equity value, whereas the expected return dominates in the long run.

Putting this time dimension into the above model gives:

$$R_i = \frac{E_{t+1} - E_t}{E_t} = \mu_i \delta t + \sigma_R \phi \sqrt{\delta t} \tag{3.3}$$

Taking the time step to zero ($\delta t = 0$) the above equation becomes:

$$R_i = \frac{E_{t+1} - E_t}{E_t} = \mu dt + \sigma_R dX \tag{3.4}$$

where dX is the standard Wiener process ($dX = \phi\sqrt{\delta t}$) or a random variable drawn from a normal distribution with the zero mean and the variance dt. Rewriting the above equation, gives the process for the equity value:

$$dE_t = \mu E_t dt + \sigma_E E_t dX \tag{3.5}$$

This is the diffusion stochastic process at the core of the structural model for credit risk pricing, which is stated in Equation (2.3). As the main assumption of the structural framework, it is fundamental for understanding the relationship between equity and debt values.

The above equity value process has two components: the deterministic expected growth rate and the stochastic component which describes the uncertainty of the expected growth rate. Both components are empirically unobservable and thus subject to an estimation error.

3.3. Equity Risk and Return Trade-Off

Investors whose objective is the maximization of the expected return would invest all of their funds in a security promising the highest rate of return. In the same manner, investors wishing to minimize the risk would invest all proceeds into government securities with the lowest volatility of returns. The optimal choice between these two extremes is not obvious and requires analysis of each security's contribution to the portfolio risk.

The breakthrough in the analysis of the risk-return trade-off is made by Markowitz (1952) who developed the portfolio theory. Markowitz recognized that the volatility of portfolio's returns depends not only on the volatility of individual securities' returns but also on the correlation between their returns. The expected return of the portfolio is the weighted average of individual securities' returns:

$$R_P = \sum_{i=1}^{N} \omega_i R_i \tag{3.6}$$

where ω_i is the weight of the security i in the portfolio.

The variance of the portfolio return depends on the individual securities' variances and also on the correlation between the returns on individual securities. It is given by the following expression:

$$\sigma_P^2 = \sum_{i=1}^{n} \omega_i^2 \sigma_i^2 + \sum 2\omega_i \omega_j \operatorname{cov}(R_i, R_j) \tag{3.7}$$

where

$i \neq j$

ω_i is the weight of the security i in the portfolio

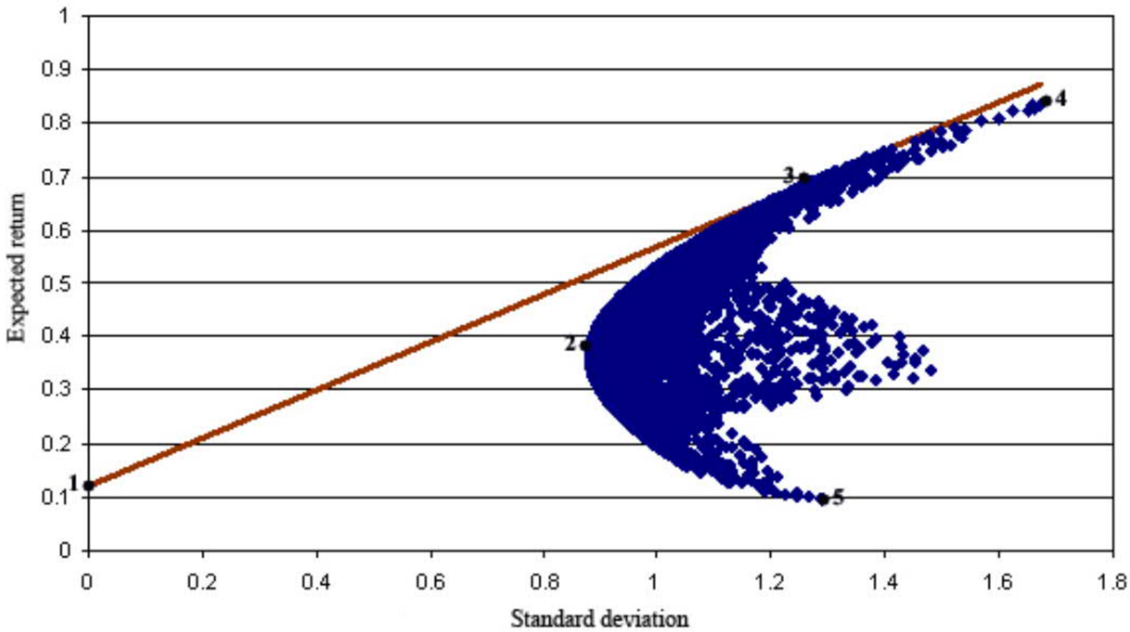
σ_i^2 is the variance of returns on the security i

$\operatorname{cov}(R_i,R_j)$ is covariance between returns on securities i and j, i.e.

$$\frac{\sum (R_i - \overline{R_i})(R_j - \overline{R_j})}{n-1}$$

Portfolio theory assumes that the objective of investors is to maximize the portfolio return to variance ratio (max $I_p = \frac{R_P}{\sigma_P}$). An optimized or mean-variance efficient portfolio offers the highest expected rate of return given the volatility of returns. This is shown in the following illustration:

Figure 3.1
The efficient mean-variance portfolio



The efficient mean-variance portfolios are graphically shown in the upper edge (i.e. from point 2 to point 4) of the region of all possible expected return/standard deviation combinations. These portfolios offer the highest expected return given the standard deviation. The portfolio at the point 5, for example, is not mean-variance efficient because there is another portfolio offering a higher expected return with the same standard deviation of returns. Therefore, investors aiming at optimizing their portfolios will end up holding portfolios from the point 2 to the point 4 in the figure above. If the risk-free asset exists and investors are able to borrow at the risk-free rate, it is always optimal to hold the tangency portfolio of risky assets (point 3). In this case, the adjustments of the risk level to individual preferences are made by investing a portion of available funds in the risk-free asset or borrowing and investing in the risky portfolio to increase the risk exposure. The relationship between the expected return and the standard deviation of portfolios formed in this process is linear, and is referred to as the capital allocation line:

$$E(R_P) = r_{rf} + \sigma_P \frac{E(R_T) - r_{ft}}{\sigma_T} \tag{3.8}$$

where:

$E(R_P)$ is the expected return on portfolio with risk-free asset and risky tangency portfolio

$E(R_T)$ is the expected return on the tangency portfolio of risky assets

σ_P is the standard deviation of $E(R_P)$

σ_T is the standard deviation of $E(R_T)$

r_{rf} is the risk-free rate of return

The capital allocation line implies that the standard deviation of returns is a complete measure of the equity risk. This is true if the returns are normally distributed as implied by the basic model for equity prices given in Equation (3.5). The major justification for the mean-variance analysis is provided by Samuleson's (1970) proof that the moments of the returns distribution beyond the variance can be ignored in the portfolio optimization process. However, it should be emphasized that the variance does not capture the risk of huge changes or jumps in equity prices.

Finally, a breakthrough implication of the portfolio theory is that total equity risk can be divided into two components. The first component is related to the idiosyncratic risks or the risks that are specific to one security, whereas the second component consists of risks that are common to all securities in the portfolio. Common risks affect all securities, so they cannot be avoided and investors should be compensated for exposure to those risks. On the other hand, the idiosyncratic risks are specific risks associated with individual firms. They can be diversified away by investing in sufficient number of firms, so exposure to those risks should not be rewarded.

3.4. Equity Value Determinants

The current value of any assets is equal to the discounted value of cash flows it generates. Campbell (2000) notes that a unique stochastic discount factor for all assets in the economy must exist to rule out the arbitrage opportunities in complete markets. Assuming linearity, the relationship between the stochastic discount factor and the equity values can be described by the following model:

$$E_{t+1} = \alpha + \sum_{i=1}^{n} \beta_i X_{i,t} \qquad (3.9)$$

where:

X_i are the factors describing the equity value

α and β_i are free parameters

This specification also applies for the equity returns, i.e.: $E(R_{t+1}) = \alpha + \sum_{i=1}^{n} \beta_i X_{i,t}$.

Theoretical and empirical identification of factors X_i has been a major theme in the finance literature.

3.4.1. Capital Assets Pricing Model

Portfolio theory assumes that the variance of a portfolio's return is a complete measure of risk. Furthermore, it introduces a notion of the correlation with other assets in the portfolio as a major source of securities risk. Sharpe (1964) and Lintner (1965) generalized the theory by adding the key assumption that all investors have identical expectations of future returns. With an unrestricted borrowing and lending at a risk-free rate, all investors will end up holding the same tangency portfolio of risky assets illustrated by point 3 in Figure 3.1. The prices of assets in the tangency portfolio will inevitably rise, because all investors will attempt to purchase them. On the other hand, prices of assets not in the tangency portfolio will be falling until they become attractive enough to enter the tangency portfolio. This process will continue until each asset in the market is priced such that its weight in the tangency portfolio is its share in all risky assets combined. If follows that the tangency portfolio is the market portfolio.

Since idiosyncratic risks in a well-diversified portfolio cancel out, an individual asset's contribution to the portfolio risk depends on its correlation with other assets in the portfolio or the market portfolio in this case. This implies a constant relationship between the expected return and the standardised covariance between the market return and the return on each asset.

An asset whose returns are uncorrelated to the market return is usually a risk-free asset. When the assumption of a risk free asset is relaxed, such an asset is called a zero-beta asset. In any case, investing in a zero correlation (zero-beta) asset should provide an expected return equal to the risk-free rate when it exists. Furthermore, investing in the market portfolio provides an expected return $E(R_M)$ with a variance σ_M. The CAPM prescribes the following relationship between the expected return on individual assets and systematic risk:

$$E(R_i) = R_0 + \beta_i \left[E(R_M - R_0) \right] \tag{3.10}$$

where

R_0 is the return on a risk-free asset

$E(R_M)$ is the expected market return

$$\beta_i = \frac{Cov(R_i, R_M)}{\sigma_M^2}$$

Assuming a single-period horizon, in the equilibrium expected return of all individual assets must satisfy the above equation. An increased demand for assets with a higher expected rate of return would increase their price. Similarly, selling off assets offering a lower rate of return would diminish their value. This process would continue until all prices are in equilibrium or as implied by the above equation.

This breakthrough model, named the Capital Assets Pricing Model (CAPM), was the first theoretical model describing the risk-return relationship of an individual asset. Furthermore, the CAPM provides clear and empirically testable predictions. The two most important predictions are: 1) the beta is a complete measure of risk that should be priced in the returns, and 2) the relationship between the asset's beta and expected return is linear. The first prediction implies that the beta coefficient in the linear regression model given in Equation (3.10) is positive and significant. Furthermore, the model should explain a significant portion of the variation in returns. The second prediction implies that no other variable should be incrementally significant in explaining the variation in returns.

Since the CAPM is stated in terms of expectations, a practical implementation requires translating expectations into observable variables. An obvious approach is to use realized returns on assets as a proxy for expected rates of return, and the realized rate of return on a broad stock index as a proxy for the expected rate of return on the market portfolio.

From a theoretical point of view, the use of a broad stock index as a proxy for the market portfolio has been challenged, because the CAPM assumes that the market portfolio includes all possible assets. In a major study, Roll (1977) argues that since the market portfolio is unobservable, the CAPM cannot be tested. In other words, the results of empirical tests of the CAPM may be due to the choice of a proxy for the market portfolio rather than the validity of theoretical predictions of the CAPM. This critique has a valid point, but this implies only that the CAPM cannot be unambiguously confirmed of rejected empirically. For all other purposes, the appropriate test of the CAPM is how successful it is in explaining returns of individual securities.

A great body of literature documents that the CAPM does not explain the variation in returns reasonably well. In an early study, Friend and Blume (1970) analyse three portfolio performance measures derived from the CAPM. All three measures are directly derived from Equation (3.10) and indicate the excess return on portfolio relative to the CAPM (Jensen, 1968), the excess return on portfolio in relation to the beta coefficient (Treynor, 1965), and the excess portfolio return in terms of the total risk (Sharpe, 1966). The CAPM implies that these risk-adjusted measures should be independent of the risk level. However, Friend and Blume (1970) find that the relationship between the performance measures and the portfolio risk level is highly significant. Furthermore, the relationship is inverse, i.e. low-risk portfolios are considered to perform better than high-risk portfolios. This implies that the CAPM fails to capture significant portion of the risk.

The unrealistic assumption of unlimited lending-borrowing at the risk-free rate may contribute to the CAPM empirical failings. Black (1972) relaxes this assumption by replacing the risk-free rate in the CAPM with the rate of return on a zero-beta portfolio or a portfolio with zero correlation with the market portfolio (i.e. $cov(R_Z,R_M)=0$).

Black, Jensen and Scholes (1972) test the CAPM using returns of all stocks on the New York Stock Exchange spanning more than 40 years. They group the stocks in ten portfolios to minimize measurement errors that occur in the estimation of beta coefficients. Their finding is that the risk-return relationship is linear as predicted by the theory. However, contrary to the theoretical prediction, they report that time-series regressions of the portfolio excess returns on the market returns have intercepts significantly different than zero. Consistent with Friend and Blume (1970), the low-beta securities have positive intercepts, whereas the high-beta securities have negative intercepts. Black, Jensen and Scholes (1972) empirical results can be reconciled with the Black's (1972) version of the CAPM implying that the intercept is equal to the expected return on a zero-beta portfolio, which is not necessarily zero.

Blume and Friend (1973) also find the risk-return relationship of equities to be linear, and that the Black (1972) version of the CAPM explains the variations in stock returns reasonably well. Fama and MacBeth (1973) also confirm that the relationship between the return on equities and the associated risk is linear and positive.

These empirical studies confirm that the strength of correlation with the market portfolio or the beta coefficient is significant in explaining the equity returns variations. The second, even more important prediction of the CAPM is that the beta coefficient is a complete measure of risk. Banz (1981) examines whether the firm size can explain the differences in returns unexplained by the CAPM. He finds that the firm size measured as the market value of firm equity is highly significant in explaining the differences in risk-adjusted returns. The correlation between the firm size and the risk adjusted return is negative. In other words, the average returns on small firms are higher than the average returns on large firms.

Bhandari (1988) reports that the risk-adjusted equity returns are positively correlated with the leverage after controlling for the firms size. Furthermore, he provides evidence that the leverage does not act as a proxy for beta but that it is a source of risk not captured by beta. The importance of leverage in determining equity returns is underscored by Vassalou and Xing (2004) who find that small firms have higher returns than big firms only if they have a high leverage. [1]

Other variables are also found to be incrementally informative in explaining equity returns. Basu (1977, 1983) finds that the risk-adjusted returns depend on the equity earnings yield. Portfolios with a high earnings yield ratio deliver higher risk-adjusted returns. Fama and French (1992) document the importance of the book-to-market equity in this regard. The book-to-market equity ratio is found to be even more significant in explaining the equity returns than the earnings yield, leverage and size.

Lo and MacKinlay (1990) argue that using portfolios formed of the basis of some variable known to be correlated with returns to test the CAPM may produce biased results. Results of such tests may be due to correlation between the variable and the measurement error of beta rather than the correlation between the variable and portfolio returns. The above-mentioned studies report that the CAPM fails to capture the size, the book-to-market and other variables are subject to this critique. However, it can be concluded that the empirical support for the CAPM is weak. Although there is some evidence of a positive and linear relationship between the beta coefficient and average returns, the overwhelming evidence suggests that beta is not a complete

[1] Vassalou and Xing (2004) examine the importance of the default risk (measured by the structural model of Merton, 1974) in determining equity returns. Since the leverage is a major determinant of the default risk their results should hold for leverage as well.

measure of risk. According to Fama and French (2004) it is unlikely that these empirical shortcomings are caused by the use of an inadequate proxy for the market portfolio. Therefore, this one-factor model does not appear to be robust enough to capture all dimensions of equity risk.

3.4.2. Multi-Factor Models

The poor empirical record of the CAPM has spearheaded a number of studies aimed at developing better theoretical and empirical models. As a large body of literature suggests that the beta factor is not a complete measure of risk, other major models attempt to describe the risk or variations in returns with multiple factors. Merton (1973) argues that investors require compensation for bearing the risk of shifts in investment opportunities in addition to the compensation for an exposure to the systematic risk. Ross (1976) proposes the arbitrage pricing theory which can accommodate multiple systematic risk factors. Finally, Fama and French (1992) develop a purely empirical three-factor model and document its ability to explain the variations in equity returns.

3.4.2.1 Intertemporal Capital Assets Pricing Model

Merton (1973) argues that investing with a multi-period horizon assumes exposure to risk of unfavourable changes in the investment opportunity set in addition to exposure to the systematic risk measured as the strength of correlation with the market portfolio. This implies that multi-period investors take into account not only the expected returns in the current period but also the correlation of the expected returns in the current period and the returns in subsequent periods.

Merton (1973) shows that an investor will hedge the risk of unfavourable changes in the investment opportunity set by purchasing assets whose value increases when such changes occur. Therefore, the total demand for financial assets will be the sum of investor demand for assets stemming from attempts to optimize the mean-variance performance and the demand for assets needed for the purpose of hedging. Guo and Whitelaw (2006) find that expected returns are primarily driven by the latter component of the total demand.

If the case of the constant investment opportunity set, Merton's (1973) model, or the Intertemporal Capital Assets Pricing Model (ICAPM), predicts the same risk-return relationship as the CAPM. Therefore, the CAPM may be considered as a special case of the ICAPM. The well documented fact that the risk-free interest rate is not constant is sufficient to rule out the possibility that the investment opportunity set is constant. In the more plausible case of changing investment opportunities, the risk-return relationship is as follows:

$$E(R_i) = E(R_0) + \beta\,\sigma_{iM} + \lambda\sigma_{iX} \tag{3.11}$$

where

$E(R_0)$ is the expected return of a risk-free asset

σ_{iM} is the covariance between the expected return on the risky asset i and the market portfolio

σ_{iX} is 1 x n row of covariances between the expected return on the risky asset i and n state variables x that govern changes in the investment opportunity set.

Merton (1973) does not specify the state variables which determine the investment opportunity set. He notes, however, that the interest rate is an obvious candidate for a state variable. Lintner (1975) also identifies interest rate as related to equity returns in a systematic and highly significant manner. Fama and French (1988) provide empirical evidence that the market dividend yield is also a strong candidate for a state variable. In another research study, Fama and French (1989) document that the term spread on the junk bond yield is significant in predicting the future equity returns. Kothari and Shanken (1997) suggest the book-to market equity as another state variable.

A number of empirical studies examine the empirical validity of ICAPM's implications. French, Schwert, and Stambaugh (1987) study the relationship between returns and volatility of the equity market portfolio. Using an autoregressive integrated moving average model (ARIMA) they decompose volatility into predictable and unpredictable components. Regressions of monthly excess return on volatility provide results contrary to the ICAPM's prediction. The predictable component of the volatility is not significantly related to the excess returns, whereas the relationship between the unpredictable component and the excess returns is found to be negative.

Campbell (1987) finds that returns on Treasury bills are positively correlated with their conditional variance, but the relationship between equity returns and the conditional variance is found to be negative. Glosten, Jagannathan and Runkle (1993) also find a negative correlation between returns on the equity market portfolio and its volatility.

Brandt and Kang (2004) model equity returns and associated conditional volatility as a vector-autoregressive process (VAR) and find the relationship to be strongly negative. Furthermore, they document how returns and volatility change throughout business cycles. The changes in volatility precede the changes in the mean return. In other words, the conditional volatility rises immediately when the economy passes the peak of a business cycle, while the conditional mean return rises gradually. At the end of a business cycle, the volatility drops to a normal level while the lagging mean of the returns is still rising. This effect may explain the negative return-volatility relationship. To investigate this possibility, Brandt and Kang (2004) also estimate the unconditional relationship between the returns and the volatility and find it to be positive.

Lundblad (2007) argues that the mixed results about the risk-return correlation are due to the use of a limited data sample. He employs a data sample of equity returns spanning nearly two centuries and finds a significantly positive return-variance tradeoff.

Bali and Engle (2008) also find a significantly positive risk-return trade-off by pooling together time series and cross-sectional data. Furthermore, they provide evidence that sensible empirical results can be obtained by estimating the conditional or time-varying variance in a multivariate GARCH-in-mean modelling framework. In examination of potential state variables, Bali and Engle (2008) report that the aggregate dividend yield and the inflation rate are significant proxies of the investment opportunity set. On the other hand, the default spread, term spread and short-term interest rate appear not to be priced in the equity market. This insignificance of the default spread is in contradiction with abovementioned results of Bhandari (1988), and Vassalou and Xing (2004). Bali (2008), however, estimates a positive slope for the default spread which in the ICAPM context can be interpreted that an increase in the default spread implies a favourable shift in the investment opportunity set. He also finds a positive co-variation with the aggregate dividend yield, and negative premiums for the size factor (the difference between equity returns of large companies and equity returns of small companies) and the risk-free rate.

Guo and Neely (2008) also find the positive risk-return tradeoff in their study of international stock markets. They employ the component GARCH model of Engle and Lee (1999), and find it to be superior to the standard GARCH model. This approach enables examining the effects of long and short-run volatility on returns. They find that the long-run volatility is a much more important determinant of equity returns than the short-run volatility.

Guo and Whitelaw (2006) confirm that the risk-return trade-off is positive. They argue that the conflicting results of previous studies are due to weaknesses in modelling of the hedge component of the model. Their results show that the demand for securities is primarily driven by hedging activities of investors. Therefore, an omission or inappropriate modelling of the hedge component strongly influences the empirical results. This evidence, which downplays the importance of the market variance, may have serious implications one of which is the rejection of the market beta as a proxy for expected returns. In line with these results, Goyal and Santa-Clara (2003) find that the market variance has no forecasting power for the market return. On the other hand, they document a significant relationship between the average stock variance and the market return. This implies that idiosyncratic risks are priced in the equity market and contradicts the major premise of the asset pricing theory that only un-diversifiable or systematic risk should be priced. Goyal and Santa-Clara (2003) explain that investors hold undiversified portfolios for various reasons, hence they take into account idiosyncratic risks.

3.4.2.2. Arbitrage Pricing Theory

Ross (1976) exploits the arbitrage argument to develop an asset pricing theory. The theory assumes that the capital markets are perfectly competitive so any opportunity to make riskless profit is immediately arbitraged away. The second fundamental assumption is that, as in the CAPM and the ICAPM, the relationship between expected return and systematic risk factors takes a linear form. This assumption implies that the stochastic process generating asset returns is as follows:

$$R_i = E(R_i) + \sum_{i=1}^{n} \beta_{in}\delta_n + \varepsilon_i \tag{3.12}$$

where:

R is the return on asset i

E(R) is the expected return on asset i

β is the sensitivity of return in asset i to change in the systematic risk factor δ

δ is the systematic risk factor

ε is the effect of idiosyncratic risks on return of asset i

Assuming that idiosyncratic risks can be diversified away the expected return on any asset is given by:

$$E(R_i) = \alpha_0 + \sum_{i=1}^{n} \beta_{in}\delta_n \tag{3.13}$$

The term α can be interpreted as the expected return on a riskless asset and coefficients β_n represent premiums for exposure to risk factors δ_n.

The similarity between the above pricing equation and the previously considered equations of the CAPM and the ICAPM is striking. It can be shown that when the only systematic risk factor is the market return APT' pricing equation is reduced to the CAPM equation. However, a major difference is that the CAPM is derived assuming an unobservable portfolio of all assets whereas the APT assumes a diversified portfolio that is large enough to render idiosyncratic risks irrelevant.

The main difference between the APT and the ICAPM is in the theoretical justification for using the multi-factor linear model. All factors in the APT represent systematic or common risk, whereas the systematic risk in the ICAPM is fully captured by the co-variation with the market portfolio while additional variables serve as a proxy for changes in the investment environment.

The APT does not specify common factors driving equity returns so empirical testing and implementation are not straightforward. Factor analysis is usually used for testing purposes. This methodology identifies a number of unspecified common factors in variables of interest, which are the equity returns in this case. In an early test, Roll and Ross (1980) find at least three factors to be significant for pricing. Furthermore, they examine whether the variance of returns on individual securities has a role in explaining the returns in addition to the common factors identified by the factor analysis. The APT implies that the variance of individual securities returns or any other variable at the firm level should play no role in determining the returns. However, Roll and Ross (1980) find the variance to be significant. The authors discount this evidence against the APT on the basis that the skewness in the distribution of individual returns can be responsible for the return-variance relationship. In another critical examination of the APT, Reinganum (1981) finds that the APT's risk factors do not account for empirical anomalies such as the size effect.

The second approach is to select potential state variables and estimate a regression model. Campbell (2008) recommends using finance theory to identify variables and estimate a parsimonious model. In a major empirical study Chen, Roll and Ross (1986) use the simple discount valuation model to show that systematic factors are those that influence expected cash flows and the discount rate. They identify the inflation rate and changes in industrial production as common risk factors. Unexpected changes in industrial production are measured with changes in growth of industrial production, bond credit spreads, bond term spreads, changes in equity market indices, changes in real consumption and oil prices. They report that industrial production, credit and term spreads are highly significant. Surprisingly, these economic variables are found to be far more significant in the cross-section analysis than the return on the value-weighted New York Stock Exchange index. In a follow up study, Shanken and Winstein (2006) fail to reproduce results of Chen, Roll and Ross (1986). Shanken and Winstein (2006) find only industrial production to be a factor priced in the returns. On the other hand, the significance of the bond credit spread could not be confirmed.

The APT offers a theoretical justification for a multi-factor approach to the modelling of systematic risk. The studies above provide evidence that identification of factors or state variables is an elusive task. Different determinants of returns may be identified for different exchanges in the same market. In an interesting study, Goyal, Perigon and Villa (2008) find that the factors determining the returns of equities listed on the NYSE and NASDAQ are not the same. In fact, only two out of three identified factors appear to be common for both exchanges.

3.4.2.3. Fama and French Three-Factor Model

Fama and French (1992) document that firm size and equity book-to-market capture cross-sectional variations in equity returns. This finding suggests that size and book-to market are powerful proxies for equity risk. Fama and French (1993) show that the market premium, the difference in returns on equities of big and small firms, and the difference in returns on firms with high and low book-to-market equity capture cross-sectional differences in equity returns very well. Consistent with the previously considered asset pricing theories, the relationship between these risk factors and returns takes the linear form, i.e.:

$$R_{i,t} = R_{f,t} + \beta_1(R_{M,t} - R_{f,t}) + \beta_2 SMB_t + \beta_2 HML_t + \varepsilon_t \qquad (3.14)$$

where

$R_{f,t}$ is the risk-free rate of return at time t

$R_{M,t}$ is the market rate of return at time t

SMB_t is the difference in returns on big and small firms at time t

HML_t is the difference in returns on high and low book-to-market equity firms at time t

ε_t is the zero-mean error term at time t

Fama and French (1993) divide firms in three groups based on the book-to-market equity and two groups based on the market value. In order to track the underlying risk factors in returns related to the book-to-market-equity and the size, they construct six portfolios based on the intersections of the previously formed groups (i.e. big size/high book-to-market equity, small size/high book-to-market equity, etc.). They report that the excess return on the market portfolio or the market factor explains about 90 per cent of the variations in returns on big firms with low book-to-market equity. For small firms with high book-to-market-equity R-squared drops to 61 per cent.

The SML and HML factors alone (i.e. without the excess return) explain a substantial proportion of variations in returns. In most regressions, coefficients of determination are above 20 per cent. This clearly shows that these factors capture underlying risks missed by the market factor. The model containing all three factors typically explains more than 90 per cent of variations in returns.

It is still not clear which underlying factors are responsible for variations in equity returns related to the size and the book-to-market equity. Chan, Chen and Hsieh (1985) find that the credit spread or difference in returns on long-term government bonds and low-grade bonds is highly significant in explaining the size effect. The credit risk, therefore, may be the underlying risk factor that is priced in the returns.

In another attempt to explain the economic rationale behind the significance of the firm size and the book-to-market equity in explaining the equity returns Fama and French (1995) investigate the relationship between these two variables and firm profitability. They confirm that the size and the book-to-market factors explain variations in firms' earnings. High book-to-market equity firms are less profitable than low book-to-market equity firms. After controlling for the book-to-market equity, small firms are found to have lower earnings than big firms. However, they could not confirm that the size and the book-to-market factors in returns are caused by common factors in earnings.

In a recent study, Simpson and Ramschander (2008) examine macroeconomic announcements related to the consumer demand, inflation, interest rates, economic growth and the real estate market. They find that the SMB and HML factors strongly respond to macroeconomic news which suggests that they proxy for changes in the underlying economic fundamentals. In comparison to the CAPM, Simpson and Ramschander (2008) report that the three-factor model is superior in tracking macroeconomic variables. Petkova (2006) finds a significant relationship between the SMB and HML factors and variables predicting changes in excess market return and its variance. The HML proxies unexpected changes in the term factor whereas the SMB factor is related to the credit spread. This suggests that the HML and the SMB factors can be considered as state variables capturing changes in the investment opportunity set in the context of the ICAPM. In a related research study, In and Kim (2007) confirm that the SMB and HML factors proxy for changes in the long-term investment opportunity set, but are not related to the changes in the investment opportunity set in the short-term.

These findings suggest that one of the underlying variables behind the SMB and HML factors is the credit risk. Combining this evidence with the results of Vassalou and Xing (2004) implying that the credit risk is systematic risk and therefore priced in equity returns, provides the theoretical justification for the SMB and HML factor relevance in asset pricing. Ghargori, Chan and Faff (2007) provide evidence against this conclusion. They examine returns on portfolios mimicking credit risk and reach the opposite conclusion, i.e. the credit risk is not priced in equity returns and the SMB and HML factors are not the proxies for credit risk.

Fama and French (2004) note that the three factor model does not capture the momentum effect documented by Jegadeesh and Titman (1993). The performance of equities exhibits a degree of persistence. Securities that historically performed well continue to do so over the next few months whereas poorly performing securities continue to perform poorly. Jegadeesh and Titman (1993) document that the strategy of buying past winners and selling past sellers yields an abnormal return. They argue that the momentum effect is not related to systematic risk or the delayed reaction of the equity market to innovations in common factors. To capture the momentum effect, Carhart (1997) adds to the pricing equation the difference in returns between portfolios of the past winners and portfolios of the past losers. Ghargori, Chan and Faff (2007) find that the momentum effect is priced in the equity market but its inclusion in the three-factor model only marginally improves model explanatory power.

3.5. The Equity Premium

As the major measure of compensation for exposure to the systematic risk, the equity premium or return on the market portfolio in excess of the risk-free rate has a major role in the valuation of individual securities. The CAPM models excess returns on individual securities as the product of the equity premium and correlation between the market return and returns on individual securities (i.e. the beta coefficient). This makes the equity premium, in addition to the beta coefficient, the most important determinant of equity returns. It is therefore not surprising that Fama and French (1993) find the market return explains significant portion of variations in return on individual securities.

3.5.1. Equity Premium Determinants

Since the equity premium is a compensation for bearing systematic risk, it should depend on macroeconomic conditions. Expected risk premiums should be countercyclical. In other words, when economic prospects are good expected risk premiums should be low. On the other hand, high risk premiums are required to induce investors to take risks during challenging economic times. Fama and French (1989) provide empirical evidence for this argument. In the same line of research, Chen (1991) finds that the default spread, the term spread, the dividend yield and industrial production growth are important determinants of the future equity premium. He argues that the significance of these variables stems from their correlation with macroeconomic conditions. This argument is empirically supported by Estrella and Hardouvelis (1991) who document that the term spread is a strong predictor of changes in the economic activity. Lettau et al. (2008) explore the link between the equity premium and macroeconomic risks or the volatility of the aggregate economy. They find that the decline in the equity premium at the end of the last century can be explained by the decline of macroeconomic risks.

Another critical determinant of the equity premium is the risk aversion of investors. If risk aversion increases, the investors will demand a higher compensation for the risk exposure, which would lead to lower asset prices and thus a higher risk premium. In the opposite case, a decrease in the risk aversion would put upward pressure on the asset prices and lower the risk premiums. Building on this argument to model the equity premium has been challenging. While estimating the direction of the relationship between the risk aversion and the risk premium is straightforward, a full specification of this relationship requires knowledge of the utility function of investors. By investing today investors sacrifice current consumption in exchange for future consumption. In equilibrium, therefore, assets should be priced to make equal the current loss and the expected future gain in investors' marginal utility, conditioned on the expected future level of consumption. This conditioning is necessary because the marginal utility of consumption may be different when the investment is made and when it is liquidated. The value of additional consumption is inversely related to the level of consumption. In other words, the marginal utility of consumption is low in good times when the level of consumption is high and vice versa. It follows that the assets, which pay off during the good times or when the level of consumption is high, are less desirable and therefore have to offer a higher rate of return to attract investors. This prediction corresponds to the prediction of the CAPM, implying that high-beta assets should offer higher expected rate of return to compensate investors for exposure to the risk of disproportionate loss in market downturns.

Building on the consumption pricing framework, Mehra and Prescott (2008) show that, under the assumption of a perfect correlation between the equity return and consumption growth rate, the equity premium is given by:

$$\ln R_E - \ln r_{rf} = \alpha\sigma_X^2 \qquad (3.15)$$

where:

α is the risk aversion coefficient

σ^2_x is the variance of the growth rate in consumption

Variations in the growth rate of consumption are not large enough to justify the historically observed equity premium with a reasonable value of the risk aversion coefficient. Mehra and Prescott (1985) were the first to discover and emphasize this fact. Their model generates the equity premium below 0.5 per cent, which is significantly lower than the observed value of about six per cent. This finding can be interpreted as the equity premium not being a compensation for a non-diversifiable risk.

The large proportion of unexplained equity premium reported by Mehra and Prescott (1985) has stimulated a large number of theoretical and empirical studies. Rietz (1988) argues that accounting for low-probability events that have highly negative consequences can explain the observed levels of the equity premium. In other words, a significant portion of the equity premium is the compensation for exposure to risk of rare market crashes that, when they happen, have disastrous effects on the wealth of investors. Barro (2005) suggests that incorporating stochastic variations in disaster probabilities is a natural way to extend this approach, and that far-out-of-the-money options can be used to measure disaster probabilities.

Longstaff and Piazesi (2004) propose a model with three components. The first component is the variance of the consumption growth as in Mehra and Prescott (1985). The second component is the probability of a jump in asset prices and the consumption level which is in line with Rietz (1988) and Barro (2005). Finally, the third component is the firm-risk premium which is the most important because the cash flows of firms are highly correlated with consumption growth. Longstaff and Piazesi (2004) show that their model explains about a half of the historically observed equity premium, which is high when compared to other studies but is still far from a complete understanding of the equity premium.

Finally, an important determinant of the equity premium appears to be liquidity. Based on data spanning a century, Jones (2002) finds the variation in the aggregate liquidity to be an important determinant of equity returns. Bekaert, Harvey and Lundblad (2007) reach the same conclusion for emerging markets.

3.5.2. Time Variation of the Equity Premium and its Implications

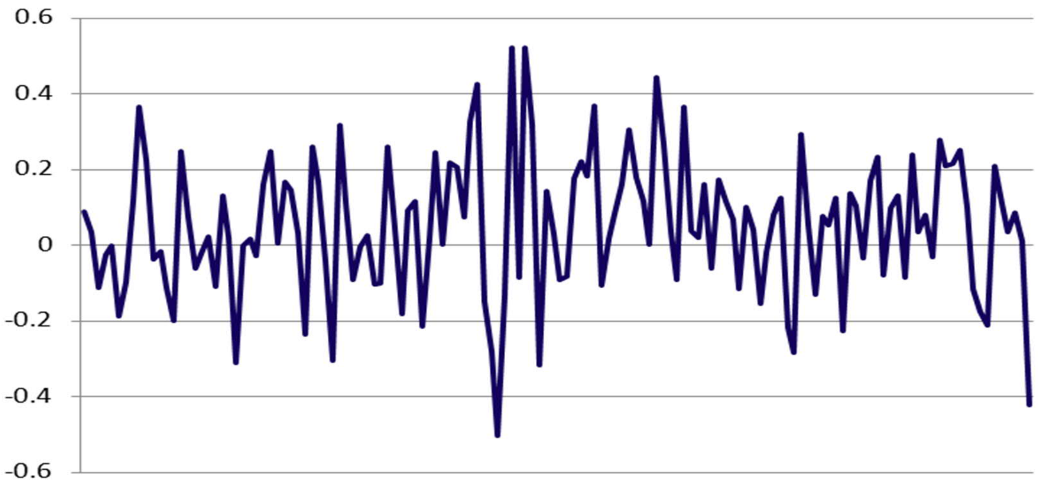
The equity premium is essentially the price of risk. As with any price, the price of risk is determined by its supply and demand. The demand for risky securities changes as investors adjust their portfolios to match targeted risk levels. During market crises which are characterized by sharp declines in asset prices, for example, the overall demand for risky securities tends to vanish as inventors rush towards the safety and liquidity of government securities. The supply of risk embedded in securities also changes as the business conditions change and the firms issue or repurchase securities.

If changes in the supply and the demand are not perfectly correlated, the equity premium is not constant but varies over time. The historical data support this argument.

Figures 3.2 and 3.3 depict the difference over annual return of the S&P Composite Index and one-year interest rate from 1871 to 2009.

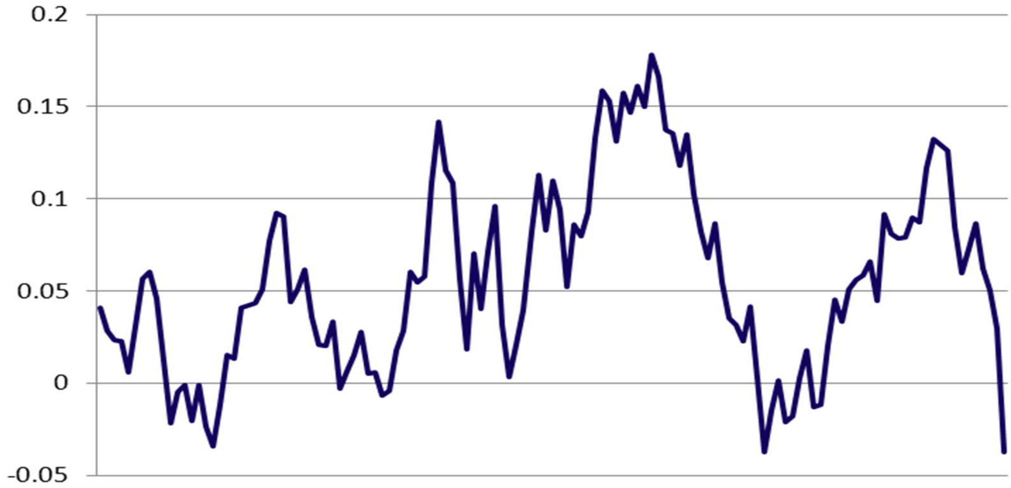
The examination of the time properties and the research of variables which are significant in predicting the equity premium has come under a lot of attention. Rozeff (1984) presents a case for using the dividend yield as an indicator for the future equity premium. He finds that the dividend yield is significant in predicting the subsequent equity premium.

Figure 3.2
Time variations in realized equity premium (annual, 1871-2009)



Data source: Robert Schiller's Website: http://aida.econ.yale.edu/~shiller/data.htm

Figure 3.3
Time variations in realized equity premium (1871-2009, 10-year moving average)



Data source: Robert Schiller's Website: http://aida.econ.yale.edu/~shiller/data.htm

Fama and French (1988) find that the explanatory power of dividend yields increases as the return horizon widens. They report that lagged earnings are also significant in explaining the equity returns. The explanatory power of earnings is smaller than that of the dividend yield, this attributed by Fama and French (1988) to the noise in the earnings yield. In other words, the earning yield is a noisier measure of expected returns than the dividend yield. Lamont (1988) argues that the higher variability in earnings is related to expected earnings, so it should not be disregarded as the noise.

Dimson, Marsh and Staunton (2006) decompose the equity premium into dividend growth, dividend yield, changes in the real exchange rate, the expansion of multiples, or a decline in risk. They find the dividend yield and the expansion of multiples to be most significant components of the equity premium.

Mehra and Prescott (2008) divide the time period from 1929 to 2005 into sub periods when the aggregate market value of equity relative to national income was below its mean value, and find that the subsequent equity premium is high.

These empirical results suggest that the equity premium is not constant but varies over time. The direct consequence is that static models such as the unconditional CAPM are unable to satisfactorily explain the equity returns. In their successful implementation of the CAPM, Jagannathan and Wang (1996) allow betas and the equity premium to vary over time. They show that the conditional CAPM translates into the unconditional model with two factors: the expected beta and beta-premium sensitivity. Their results indicate that the conditional version of CAPM significantly outperforms its static counterpart. Donaldson, Kamstra and Kramer (2008) reach a similar conclusion. They find models of the equity premium which allow for time-variations to significantly outperform static models for the equity market in the United States, and conclude that the time variation is the most important feature of the equity premium process.

The interaction between betas and the equity premium is likely to be responsible for empirical anomalies detected in empirical studies based on the unconditional CAPM. Firms with betas highly correlated with the equity premium will deliver abnormally high returns relative to the static CAPM. Campbell (2000) notes that this phenomenon may explain findings of Fama and French (1993, 1996) indicating that the credit risk is priced in equity returns because the betas of distressed firms may be high when the equity premium is high.

3.5.3. Estimation of the Equity Premium

The equity premium is the equity market return in excess of the risk-free rate that investors expect to earn. The equity premium is, therefore, a variable of investors' expectation of future equity returns which are not observable.

The simplest approach to estimating the equity premium is to assume that the historical or realized equity premium is equal to the expected equity premium. The return on a broad market index such as the S&P 500 is usually used as a proxy for the market return, whereas the Treasury bill or bond rate is used as a proxy for the risk-free rate. Then the equity premium is simply calculated as the difference between the index return and the Treasury bill or bond rate. The implicit assumption inherent in this approach is that the equity premium is constant. This is an obvious weakness as the previous section pointed to the overwhelming empirical evidence of time-variability in the equity premium. Therefore, the equity premium estimated in this way will be sensitive to the time period used.

To overcome this weakness, the equity premium should be estimated by a model relating the equity premium to changes in underlying risks. The CAPM and the ICAPM [2] imply that the relationship between the equity premium and its variance is positive and linear:

$$(R_M - r_{rf}) = \beta \sigma_M^2 \tag{3.16}$$

As previously discussed, empirical studies have not unanimously confirmed this prediction. Some studies find the relationship to be as expected (e.g. Bali and Engle, 2008), others report no significant relationship (e.g. Chan, Karolyi and Stulz, 1992) and some even document a negative relationship (e.g. Nelson, 1991).

[2] Assuming that the investment opportunity set is constant in the case of ICAPM

An alternative approach is to estimate the equity premium from fundamentals. The expected equity return must be equal to the expected dividend yield and the expected rate of capital growth, i.e.

$$R_t = \frac{D_t}{E_{t-1}} + \frac{E_t - E_{t-1}}{E_{t-1}} \tag{3.17}$$

where:

D_t is the amount of dividends to be paid during the period t

E_t is the equity price

Fama and French (2002) note that if the dividend yield is stationary then the dividend growth rate approaches the capital growth rate in the long run. Campbell (2008) suggests that the accounting growth of equity may be used as an approximation for the capital growth rate.

Fama and French (2002) find that the historically observed equity premium is in line with the estimation from fundamentals during the first half of the 20 th century, whereas more recently the realized equity premium is significantly higher than the dividend growth model predicts. Fama and French (2002) attribute this difference to unexpected capital gains. In other words, investors expected significantly lower returns that they actually earned. Claus and Thomas (2001) use a similar methodology to estimate the equity premium for the six largest equity markets and reach a similar conclusion as Fama and French (2002). Pastor, Sinha and Swaminathan (2009) use the implied cost of capital as a proxy for the expected equity return. Their results suggest that the implied cost of capital outperforms the dividend yield as a proxy for the expected equity returns.

Goyal and Welch (2008) examine out-of-sample performance in forecasting the equity premium of dividend yields, price-earnings ratios and other variables used in empirical studies. Contrary to expectations, they find that none of these variables outperforms the historical equity premium. Campbell and Thompson (2008) challenge their results. They impose theoretically motivated restrictions on regression models for prediction of the equity premium. The first imposed restriction is that the coefficients can only take the theoretically expected sign and the second restriction is that the estimated values of equity premium must be positive. Under these restrictions Campbell and Thompson (2008) show that most of the variables predict better than the historical equity premium.

3.6. Equity Volatility

As shown previously, the volatility of equity returns is commonly assumed to be a complete or sufficient measure of equity risk. Since it is not observable it must be estimated from historical data. It is well documented that equity volatility varies over time, so estimation methods that account for time variations are likely to provide more robust estimates. Bali and Engle (2008), for example, attribute their uncovering of the positive return-variance trade off to the use of GARCH-based estimation method. The importance of volatility modelling is emphasized by the finding of Bollerslev and Zhou (2009) that the difference between the implied and realized variations, or the variance premium, explains more than 15 per cent of the time-series variations in returns on the market portfolio.

Akin to these returns, the equity volatility at the firm-level can be decomposed into two distinct components: the systematic and the idiosyncratic component. Also, given that the persistence of various types of shocks is different, the volatility can be decomposed in the short-term and long-term components. There is a growing body of literature exploring the time properties and the pricing implication of volatility components.

3.6.1. Estimation of the Equity Volatility

The simplest approach to the estimation of equity volatility is to assume that it is equal to historical volatility. In this case, volatility is given by:

$$\sigma_i = \sqrt{\frac{\sum_{t=1}^{n}(R_{i,t} - \bar{R}_i)^2}{n}} \tag{3.18}$$

where

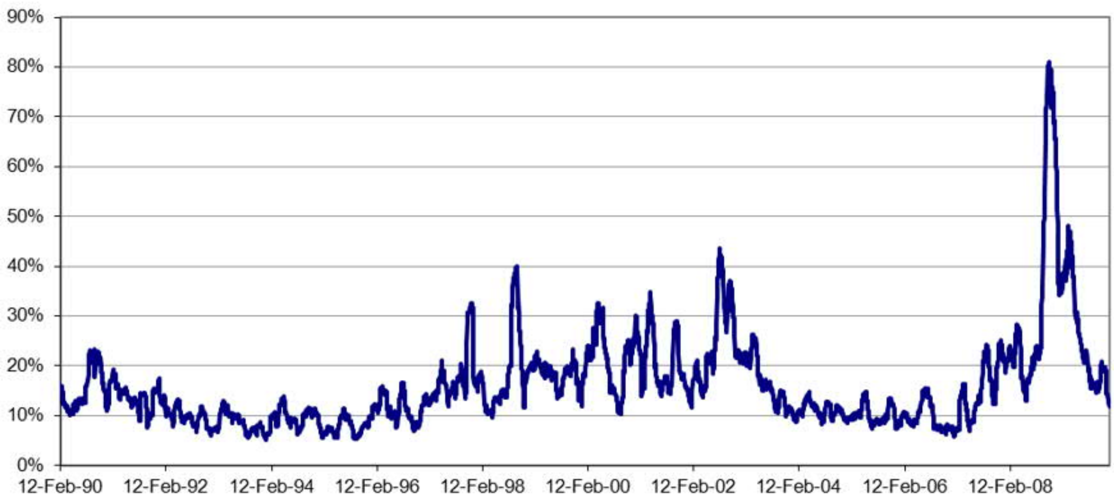
$R_{i,t}$ is return on security i in period t

$\overline{R}_i$ is the average return

n is the number of observations

It should be emphasized that this simple method implies that volatility is constant. That may be an unrealistic assumption and can cause significant errors in the estimation, if volatility varies over time. To illustrate this point, Figure 3.4 depicts a 30-day moving average volatility of the S&P 500 index.

Figure 3.4
Moving average volatility of the S&P 500 index from January 1990 to January 2010



A casual examination of the above chart challenges the constant volatility assumption. This is particularly true during market crises when volatility drastically increases. A more sophisticated method to estimate the volatility, which takes into account the time-series behaviour of volatility, involves the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models.

The most parsimonious GARCH (1,1) model, which was introduced by Bollerslev (1986) as a generalization of Engle (1982), is given by:

$$\sigma_t^2 = \gamma V + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3.19}$$

where

V is the long-run volatility

ε is the error term from the return model $R_t = \phi_0 + \phi_1 R_{t-1} + \varepsilon_t$

σ is the conditional volatility

The coefficient γ can be interpreted as the weight given to the long-run volatility, α can be understood as the extent to which the volatility reacts to market movements, and finally, β can be considered as a measure of significance of the lagged volatility in the estimation of the current volatility (persistence). The above GARCH (1,1) model can be easily generalized to a GARCH (p,q) model or a model with p and q lag terms.

In the GARCH specification, the returns process is modelled as a simple autoregressive process. Consistent with the theoretical implication that the risk-return trade-off is positive, and assuming that the conditional variance is a good proxy for the risk, Engle, Lilien and Roberts (1987) model the return as a function of its conditional variance, i.e.:

$$R_t = \phi_0 + \phi_1 \sigma_{t-1} + \varepsilon_t \qquad (3.20)$$

This model, termed GARCH-in-mean, explicitly imposes the linear relationship between the return and its conditional variance, hence a higher volatility implies higher returns.

The previously considered GARCH specifications implicitly assume that negative and positive news impact the equity returns in an equal manner. Contrary to this assumption, Brown, Harlow and Tinic (1988) show that equity prices respond more strongly to bad than to good news. In the presence of imperfect information, they argue that investors overreact to bad news and under react to good news. Black (1976) and Christie (1982) attribute this asymmetry to the leverage effect. Negative returns lower the firm value and therefore increase financial leverage which in turn increases risk and volatility.

Campbell and Hentschel (1992) argue that the leverage effect cannot alone explain this phenomenon of asymmetric volatility. They show that any news, positive or negative, increases volatility which puts negative pressure on equity prices. This volatility effect offsets the positive effect good news produces. In the case of bad news, the volatility effect reinforces the negative pressure on equity prices. Wu (2001) finds that this effect, called the volatility feedback, is significant statistically as well as economically.

If negative shocks produce more volatility as the above studies suggest then the GARCH volatility estimates are biased upwards following good news and biased downwards following bad news. To remedy this Nelson (1991) proposes a modified GARCH specification which allows that positive and negative news have different effects on volatility. His model is termed the exponential GARCH or EGARCH and is given by:

$$\log\sigma_t^2 = \omega + \beta\log\sigma_{t-1}^2 + \alpha\left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right] + \eta\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{3.21}$$

The significance of coefficient η indicates the asymmetry effect. It is expected to have negative value as the negative shocks are hypothesized to have a greater impact upon the volatility. On the other hand, if η is found to be insignificant then positive and negative shocks have the equivalent effect on volatility. Furthermore, the EGARCH specification allows big shocks to have an outsized impact upon volatility relative to the standard GARCH model.

An alternative GARCH specification is proposed by Glosten, Jagannathan and Runkle (1993) to capture the asymmetry effect, the threshold-GARCH or TGARCH.

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2 + \eta I_{t-1}\varepsilon_{t-1}^2 \tag{3.22}$$

where

$$I = \begin{Bmatrix} 1 \text{ if } \varepsilon_{t-1} < 0 \\ 0 \text{ if } \varepsilon_{t-1} > 0 \end{Bmatrix}$$

In this case, a greater impact of negative shocks on the volatility is indicated by a significant and positive value of the coefficient η.

Another competing GARCH specification is the quadratic-GARCH or QGARCH proposed by Sentana (1995):

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\left(\varepsilon_{t-1} - \eta\right)^2 \tag{3.23}$$

Similar to the TGARCH, a positive value of the coefficient η in the QGARCH model indicates that negative shocks have a greater impact upon volatility than positive shocks. The QGARCH model reduces to the GARCH model if the coefficient η is zero. Franses and Van Dijk (1996) report that the QGARCH significantly outperforms the standard GARCH and the TGARCH model in volatility forecasting.

As Engle and Ng (1993) propose a methodology to analyse how shocks impact the volatility in these competing models. Plotting the volatility against the last shock ε_{t-1} while holding all other variables at their unconditional means, illustrates how the last shock influences volatility. Engle and Ng (1993) term this illustration the news impact curve. The equation of news impact curve for the GARCH(1,1) model is:

$$\sigma_t^2 = A + \alpha\varepsilon_{t-1}^2 \tag{3.24}$$

where

σ_i is the conditional variance at time t

ε is the unpredictable return or shock at time t-1

$A \equiv \omega + \beta\sigma^2$

σ is the unconditional standard deviation

ω is the constant term and

β is the parameter corresponding to σ_{t-1} in the GARCH equation

For comparison sake, the news impact curve for TGARCH is given by:

$$\begin{aligned} &\sigma_t^2 = A + \alpha\varepsilon_{t-1}^2 \text{ for } \varepsilon_{t-1} > 0 \text{ and} \\ &\sigma_t^2 = A + (\alpha+\gamma)\varepsilon_{t-1}^2 \text{ for } \varepsilon_{t-1} < 0 \end{aligned} \tag{3.25}$$

Figure 3.5
News impact curve of the GARCH and the TGARCH models

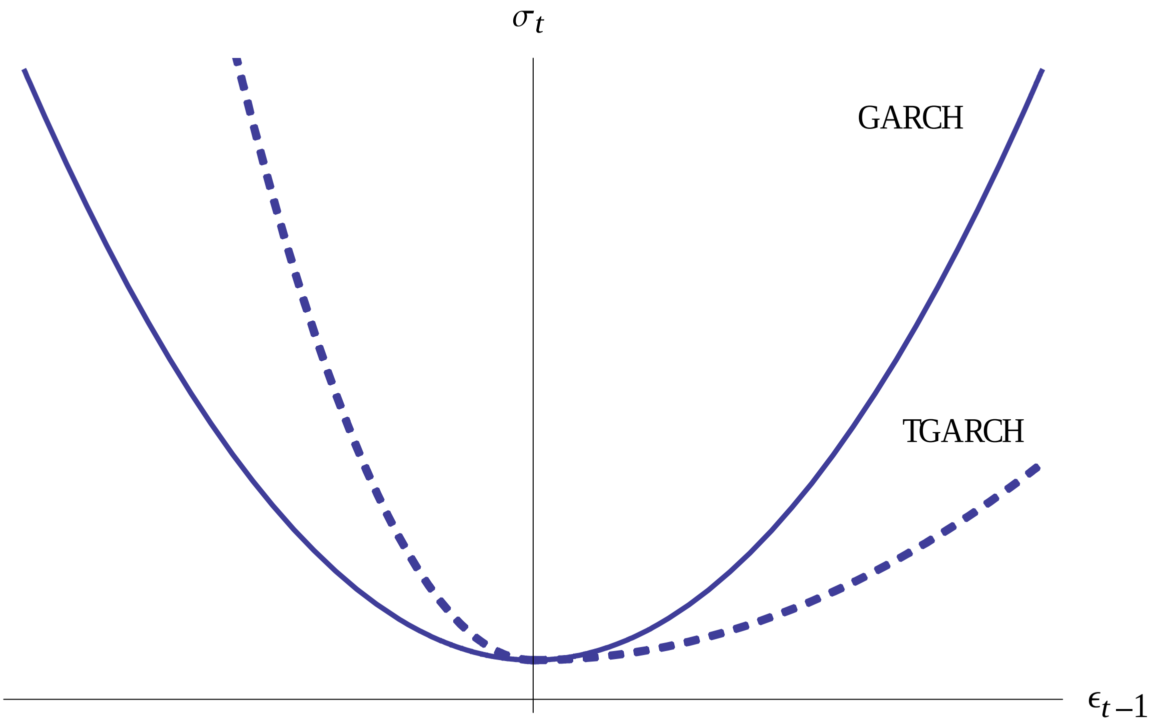


Figure 3.5 clearly illustrates how a volatility estimate can be biased if the standard GARCH model is used when positive and negative shocks impact volatility in an asymmetric manner. The choice of appropriate model specification is ultimately an empirical matter. In other words, a model producing the best volatility estimate for a given data sample should be chosen.

3.6.2. Volatility Components

There are two distinctive components of variations in equity returns. The first is the market or systematic volatility, driven by market-wide events and risks. The second is the idiosyncratic volatility or variations in returns due to firm-specific risks. Campbell et al. (2001) document that these two components of total volatility behave differently over time. The idiosyncratic volatility trended upward, while there was no trend in the systematic volatility over the same period. The market volatility leads the idiosyncratic volatility and increases in recessions. Brandt et al. (2008) point to a sudden drop in the idiosyncratic volatility during the last few years and argue that the time-series behavior of idiosyncratic volatility documented by Campbell et al. (2001) is due to sporadic highly volatile periods rather than the time trend. Firms with low equity prices and mostly owned by retail investors are found more likely to have high and rising volatility. Bennett, Sias and Starks (2003) also link the rise of firm-specific risks to ownership but they argue that the growth in institutional ownership is responsible for the increase in the idiosyncratic volatility. Guo and Savickas (2008) provide another explanation unrelated to ownership. They show that idiosyncratic volatility is significant in predicting the market return and argue that the idiosyncratic volatility is a proxy for changes in the investment opportunity set.

The market volatility can be measured as described in the previous section. On the other hand, since the idiosyncratic volatility is not observable, its measurement is not so straightforward. The simplest and most parsimonious measure would be the variation in the excess returns (i.e. returns in excess of the market return).

$$\sigma_{i,t} = \sqrt{\frac{\sum_{i=1}^{n} (\eta_{i,j,t} - \bar{\eta}_{i,j})^2}{n}} \tag{3.26}$$

where

$\eta_{i,j,t}$ is the equity return in excess of the market return ($\eta_{i,j,t} = EP_{i,j,t} - EP_M$).

$\bar{\eta}_{i,j}$ is the average excess return

The major weakness of this simple measure is that it ignores the difference in risk factor loadings among securities and assumes that expected returns for all equities are the same. This issue can be addressed by estimating the expected returns with one of the previously considered models and then measuring the idiosyncratic volatility as a sum of squared errors of the model.

Taking into account that persistence of shocks may vary from very short-term to permanent, another potentially useful decomposition of the equity volatility is to consider it as a sum of the short-term and long-term components. Engle and Lee (1999) propose the following specification:

$$
\begin{aligned}
\sigma_t^2 &= l_t + s_t \\
s_t &= (\alpha + \beta) s_{t-1} + \alpha(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \\
l_t &= \omega + \rho l_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)
\end{aligned} \tag{3.27}
$$

where

σ_t^2 is the conditional variance at time t

s_t is the short-term component of the conditional variance

l_t is the long-term component of the conditional variance

ε is the unexpected return

Assuming that $0 < (\alpha+\beta) < 1$, the short-term component mean-reverts to zero at a rate of $(\alpha+\beta)$, while the long-term component follows an auto-regressive process and if $0 < \rho < 1$, it converges to $\omega/(1-\rho)$. Since the long-term component should mean-revert at a slower rate, it is assumed that $0 < (\alpha+\beta) < \rho < 1$. Engle and Lee (1999) find that this model produces results consistent with the highly volatile period surrounding the October 1987 market crash. Using the same methodology, Adrian and Rosenberg (2008) find a positive trade-off between returns and both volatility components. The risk premium for the long-term component is estimated to be about 35 per cent higher than the compensation for the short-term component. The authors argue that the short-term component is related to the market skewness risk, whereas the long-term component is closely related to the business cycle risk. Zhu (2009) finds that only the short-term volatility component is positively and significantly related to returns in ten Asia-Pacific equity markets. The long-term component is found to account for about 75 per cent of the total volatility while the short-term component is responsible for the remaining 25 per cent. The empirical results are consistent with the Asian market crisis, using the 1997 data.

3.7. Summary

Markowitz (1952) shows that only the systematic risk, inherent in the entire market or entire market segment, should be priced in the equity markets. Specific risks associated with individual securities are diversifiable and therefore the exposure to these risks should not be rewarded. Building on this insight, Sharpe (1964) and Lintner (1965) develop the Capital Assets Pricing Model (CAPM) which implies that the expected return of a security only depends on its correlation with the market return. Despite the strong theoretical underpinning of the CAPM, a large body of literature shows that is does not fully explain variations in equity returns. Furthermore, contrary to the CAPM main implication, variables such as the firm size (Banz, 1981), leverage (Bhandari, 1988) and earnings yield (Basu, 1077, 1983) are found to be significant in explaining the variations in returns unaccounted for by the CAPM. These findings spearheaded the development of multi-factor models for equity pricing. Fama and French (1992) propose an empirically inspired model which shows a notable success in explaining the equity returns with three risk factors: the market rate of return, the difference in returns on big and small firms and the difference in returns on high and low book-to-market equity firms.

The models discussed above estimate the expected excess return of individual securities relative to the excess return of the entire market or the equity premium. Fama and French (1989) provide the evidence that the equity premium is countercyclical, i.e. low when economic prospects are good and high during the challenging economic times. In line with this, a number of authors (e.g. Mehra and Prescott, 2008) shows that the equity premium varies over time. Therefore, the static models such as the unconditional CAPM should not be able to satisfactorily explain equity returns. Donaldson, Kamastra and Kramer (2008) argue that the time variation is the most important feature of the equity premium process.

The equity volatility is a major measure of risk. The simplest approach to estimate the equity volatility is to assume that it is constant. In this case, the equity volatility is estimated as a standard deviation of historic equity returns. This approach is widely used although it is an empirical fact that the volatility is not constant but varies over time. Given the importance of equity volatility as a risk measure, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models should be used for the estimation of the equity volatility to ensure that time series properties are taken into account.

Finally, decomposing the equity volatility provides an opportunity to analyze how each component of the equity volatility impacts equity returns. Campbell et al. (2001)

decompose the volatility into systematic and idiosyncratic components, and document their different time behaviours. Engle and Lee (1999) propose decomposition into short-term and long-term components.

The next chapter reviews the existing literature, develops hypotheses and presents the research methodology for the empirical study of the relationship between the corporate credit spread and changes in the systematic and idiosyncratic risks of corresponding equities.

CHAPTER 4

SYSTEMATIC AND IDIOSYNCRATIC EQUITY RISKS AS DETERMINANTS OF THE CREDIT SPREAD

4.1. Introduction

The structural model of Merton (1974) provides a theoretical foundation for the analysis of the relationship between the values of equity and debt securities. The model treats the firm's equity and debt as derivatives written on the firm's assets, and implies that the default probability is defined by the difference between the value of assets and the value of debt relative to the volatility of the firm's asset value. As a result, the most important determinants of the difference in the yields on corporate and government bonds, known as the credit spread, should include leverage and asset volatility. Since the latter is unobservable, it is usually derived from equity volatility.

Despite a strong theoretical foundation, the existing empirical evidence on the determinants of credit spread is far from conclusive. Collin-Dufresne, Goldstein and Martin (2001) note that changes in the yields of governmental bonds and equity returns explain about 60 per cent of the variation in the corporate bond yield, and only five per cent of changes in the credit spread. They report that the theoretically relevant variables such as the leverage and equity volatility fail to explain the majority of changes in the credit spread. Furthermore, they find that the residuals from regressing changes in the credit spread on the theoretically derived variables are highly correlated, which leads them to conclude that the credit spread is driven by a common factor. In a widely cited paper, Elton et al. (2001) show that this factor can be proxied by the Fama-French factors (Fama and French, 1993) which are known to be the common factors priced in equity returns. After showing that the Fama-French factors explain as much as 85 per cent of the credit spread not accounted for by the expected default loss and higher taxes paid on corporate bonds relative to governmental bonds, the authors conclude that the risks inherent in corporate bonds are systematic and, by extension, rewarded with a risk premium.

As noted above, the structural model links the values of the firm's equity and debt by considering them as options written on the firm's assets. As in option pricing, the total volatility of assets, which represents systematic as well as idiosyncratic risks, is used to measure the probability that the firm's asset will fall to the level of debt, thereby triggering bankruptcy. If the credit risk cannot be diversified away as indicated by the above studies, then the systematic risks should be the major drivers of the credit spread. This is important in light of Campbell et al. (2001) who find that idiosyncratic volatility has been trending upwards in recent decades while the market-wide volatility has been stationary.

The purpose of this chapter is to review existing studies on the relationship between the corporate credit spread and changes in the systematic and idiosyncratic risks of the corresponding equities. This literature review guides the formation of this study's hypotheses, empirically tested on firm-level data covering almost 15 years, including the period of the recent 2007 financial crisis. This chapter goes on to present the research methodology and the dataset. The empirical results are presented in Chapter 5.

The existing literature focuses on the relationship between the credit spread and the volatility of equity returns in excess of the market return. This study aims to extend the literature findings in several ways. First, conditional equity volatility models, such as the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model, are employed to account for the time series behaviour and the asymmetric nature of equity volatility. Second, systematic and idiosyncratic expected equity returns are estimated using the CAPM and the Fama and French (1993) three factor model. This removes the limitation imposed by the commonly used assumption that all firms' loadings on systematic risks are equal, i.e. all betas are equal to one. Finally, in addition to using individual theoretically derived variables in the regression analysis, the structural model is explicitly estimated to control for the level of the credit risk, as well as to provide an insight into its performance as compared to individual variables.

4.2. Literature Review and Development of Hypotheses

It is commonly accepted that equity and credit risks are intrinsically linked. In their ground-breaking work, Modigliani and Miller (1958) show that a change in the firm's leverage gives rise to the expected returns on the firm's equity. This approach recognizes that debt and equity securities are simply different claims on the same firm assets. Building on this insight, Merton (1974) applies the option pricing theory of Black and Scholes (1973) to develop a structural model with analytical formulas for the values of debt and equity. In his seminal work, he shows that the value of equity is the value of a call option, whereas the market value of risky debt exceeds the value of risk-free debt by the value of a put option written on the firm's assets with the exercise price equal to the book value of debt.

Finance theory implies that only systematic risks, which cannot be diversified away, should be priced in the valuation of financial securities. Sharpe (1964), Lintner (1965) and Mossin (1966) show that a security's exposure to systematic risks is captured by the strength of its correlation with the market portfolio, that is, the return on the market portfolio in excess of the risk-free rate. Fama and French (1993) find that, in addition to the market premium, the difference in returns on equities of big and small firms, and the difference in returns on firms with high and low book-to-market equity, capture the exposure to systematic risks in the cross-section. Due to its empirical success, the three-factor model of Fama and French has become the most widely employed model to measure equity risk and expected equity returns.

Unlike in equity pricing, idiosyncratic risks have a role in determining the credit spread or expected returns on debt securities in excess of the risk-free rate. Because bonds are fixed income instruments, the major determinant of the credit spread should be the probability of default. In the structural model of Merton (1974), this is the probability that the value of the firm's assets will reach the book value of debt. In Merton, then, the value of the firm's assets is assumed to follow the standard diffusion stochastic process with the volatility of asset value as the diffusion component. As a result, the default probability depends on the total volatility of the value of the firm's assets, which encompasses systematic as well as idiosyncratic risks.

The structural model provides a theoretical framework for the analysis of the relationship between equity and bond securities. Based on its strong theoretical foundations, it fully describes how equity volatility and other variables should affect the corporate bond spread, thereby providing guidelines for empirical research. The major implication of the structural model is that the default probability is defined by the difference between the market value of assets and the book value of debt relative to the volatility of the market value of assets.

4.2.1. Relationship between the Credit Spread and Equity Volatility

An increase in asset volatility or leverage implies a higher probability that the value of assets will fall to the value of debt, triggering bankruptcy. As a result, the volatility of equity returns and the corporate credit spread should be always positively correlated.

Campbell and Taksler (2003) focus on the relationship between idiosyncratic equity volatility and the credit spread. They estimate idiosyncratic equity volatility as the standard deviation of daily returns in excess of returns on the CRSP value-weighted index over 180 days prior to each monthly observation of the credit spread in their sample. It should be noted that calculating excess returns in this way implies that the betas of all firms are equal to one. The idiosyncratic equity volatility is reported to account for between six per cent and ten per cent of the variation in the credit spread levels.

Cremers et al. (2008) use option-based volatility to explain the credit spread level. Following Campbell and Taksler (2003) they calculate idiosyncratic equity volatility as the second moment of excess returns relative to the CRSP value-weighted index. They confirm that the relationship between the credit spread and equity volatility is positive. Further, they report that option-implied volatilities are more significant than historical volatilities. However, models with option-implied volatility do not give a substantially better fit than the same models with historical volatility.

In a recent study, Ericsson, Jacobs and Oviedo (2009) find a positive relationship between equity volatility and credit default swap premia. Zhang, Zhou and Zhu (2009) attempt to explain the variations in credit default swap premia using equity volatility as well as jump measures constructed from high-frequency data. They report that short-run weekly realized volatility and annual historical volatility explain 68 per cent of the variation in default credit swaps premia levels. Short-run weekly volatility marginally improves the explanatory power of a model with annual volatility. Jump measures explain about 15 per cent of the variations and appear to impact the credit default swap premia.

The above discussion leads to the following hypothesis:

H1: The credit spread and equity volatility are positively correlated, as implied by the structural model.

This hypothesis is tested by regressing the credit spread of corporate bonds on the corresponding (conditional) equity volatility obtained from a GARCH process. Let V_t be the estimated volatility and CS_t be the credit spread at time t. Then the hypothesis is tested by assessing the coefficient b in the following regression:

$$CS_t = a + bV_t + \varepsilon_t \tag{4.1}$$

Collin-Dufresne, Goldstein and Martin (2001) report that credit spreads respond asymmetrically to changes in the VIX index, which represents a weighted average of eight implied volatilities of near-the-money options on the S&P 100 index. Zhang, Zhou and Zhu (2009) find that negative jumps in equity prices have an effect on credit default swap spreads three times larger than positive jumps. These findings lead to the following hypothesis:

H2: The relationship between the credit spread and equity volatility is asymmetric, i.e. an increase in equity volatility has a bigger impact upon the credit spread than a decrease in volatility of a similar magnitude.

This hypothesis is examined by extending Equation 4.1. The test for symmetry is conducted by testing for the statistical hypothesis that the coefficient c is equal to zero against the alternative that it is positive in the following regression:

$$CS_t = a + bV_t + cV_t^+ + \varepsilon_t \tag{4.2}$$

where $V_t^+ = V_t \ I(\Delta V_t \ \geq 0)$ and $I()$ is the indicator function which equals 1 if the condition is satisfied and zero otherwise.

4.2.2. Relationship between the Credit Spread and Distance to Default

Equity volatility is considered as a theoretical determinant of credit spread because of the structural model's implication that the volatility of the value of a firm's assets is fundamentally important for the measurement of credit risk. It should be noted that, according to the structural model, the full measure of credit risk is the distance to default which incorporates information on volatility as well as information on leverage and the risk-free rate. This single measure, therefore, should in principle outperform equity volatility and any other single variable as a determinant of the credit spread.

However, despite its strong theoretical underpinning, the performance of the structural approach in explaining variations in the credit spread has been mixed at best. Empirical studies (e.g. Lyden and Saraniti, 2001; Eom, Helwege and Huang, 2004; Ericsson, Reneby and Wang, 2005) generally find that the structural model overprices bonds or predicts lower than observed credit spreads. The inability of the structural model to generate realistic credit spreads can be attributed to the simplifying assumptions used to derive the model. A major simplifying assumption that Merton (1974) makes to derive the original structural model is that asset volatility is constant. This assumption is used to justify the use of unconditional volatility in empirical studies despite the overwhelming evidence that volatility varies over time.

Another explanation for the inability of the structural model to generate realistic credit spreads may be that the credit spread is not entirely a compensation for bearing the credit risk. In fact, Huang and Huang (2003) find that only a fraction of the credit spread can be linked to the credit risk. Elton et al. (2001) emphasize the importance of the difference in the tax treatment of corporate and government bonds. Longstaff, Mithal and Neis (2005) find that the non-default component of the credit spread is related to individual bond liquidity as well as market-wide liquidity.

A growing body of literature indicates weaknesses of the structural model in explaining the credit risk in particular. Du and Suo (2007) show that distance to default does not outperform the model with equity volatility, equity value and leverage, in predicting credit ratings. They note, however, that their conclusion is based on the assumption that credit rating is a true indicator of credit risk. Campbell, Hilscher and Szilagyi (2008) report the weak performance of distance to default in predicting corporate bankruptcies. Bharat and Shumway (2008) find that the default probability implied by the structural model, which is obtained as N(- distance to default), is a significant but not a complete predictor of corporate failure. Furthermore, they find that the default probability is weakly correlated with the credit spread. Default probabilities implied by the distance to default appear to be unrealistically low. Therefore, Vassalou and Xing (2004) do not convert the distance to default into default probabilities and use it instead as an indicator of credit risk in their study of the relationship between equity returns and credit risk.

Based on this discussion the following hypotheses are formulated:

H3: The credit spread and the distance to default of Merton (1974) are negatively correlated.

H4: The distance to default of Merton (1974) is a more economically significant determinant of the credit spread than equity volatility.

The third hypothesis (H3) is tested by regressing the credit spread on corporate bonds on estimated values of the distance to default. Let DD_t be the estimated distance to default and let CS_t be the credit spread at time t. The hypothesis is tested by assessing if the coefficient b is statistically negative in the following regression:

$$CS_t = a + bDD_t + \varepsilon_t \tag{4.3}$$

The fourth hypothesis (H4) is examined by comparing the magnitude of the estimated coefficient to the magnitude of the coefficient of a corresponding equation with equity volatility as the explanatory variable.

4.2.3. Systematic and Idiosyncratic Equity Risks as Determinants of Credit Risk

The major theoretical determinant of credit risk is the volatility of the total value of the firm's assets, which is influenced by idiosyncratic as well as systematic risks. The importance of systematic risks is emphasized by Elton et al. (2001) who report that the credit spread is strongly related to systematic risks captured by the Fama and French factors commonly associated with equity risk. Cheyette and Tomaich (2003) provide evidence that idiosyncratic and systematic risks may affect the credit spread differently. They report that the bond yields of high quality issuers are primarily explained by interest rate factors, while the bond yields of firms with smaller credit quality are determined by equity returns. Surprisingly, the bond yields of firms with intermediate credit quality are neither related to interest rate factors nor to equity returns. The only significant determinants for bond yields of these companies appear to be bond specific factors. Furthermore, the authors decompose equity returns into systematic and idiosyncratic components, and examine the strength of their correlations with bond yields. The relationship between bond yields and positive/negative systematic equity returns and negative idiosyncratic returns are found to be similar, while the relationship between bond yields and positive idiosyncratic returns is reported to be substantially lower. A possible explanation for this finding is the agency conflict whereby managers take actions that increase equity value at the expense of debt value (Maxwell and Stephens, 2003; Alexander, Edwards and Ferri, 2000).

Existing empirical studies involving equity volatility commonly focus on the relationship between the volatility of equity returns in excess of a major index (e.g. Campbell and Taksler, 2003; Cremers et al., 2008) and market-wide equity volatility. Cremers et al. (2008) unexpectedly obtain a significant negative relationship between the credit spread and the S&P 500 index volatility. Campbell and Taksler (2003) report that idiosyncratic volatility is much more statistically and economically significant than the market-wide volatility. This is surprising because, according to the structural model, it is total volatility that should determine the credit spread. The authors note that changes in idiosyncratic risk are more persistent than changes in market risk (Campbell et al., 2001) so lagged idiosyncratic volatility receives a greater weight in predicting total volatility.

Campbell and Taksler (2003) also explore how market volatility and average idiosyncratic volatility affect A-rated bond yield indexes in the US market through time. This analysis is motivated by Campbell et al. (2001) finding that idiosyncratic volatility has been trending upwards in recent decades while market volatility has been stationary. The results presented by Campbell and Taksler (2003) are mixed. Idiosyncratic volatility for the Standard and Poor's bond yield index is reported to be significant while market volatility is not. However, market volatility is by far more statistically and economically significant for the Moody's bond yield index.

Bednarek (2006) reports that lower rated firms on average have equity returns that are more volatile. Both components of volatility, market-wide and idiosyncratic, are found to be significantly different for each credit rating from AAA to CCC. The author finds that investment grade bonds are primarily influenced by market volatility, whereas the credit spread on low-rated bonds is related to firm-specific volatility.

In contrast to the structural model prediction, the studies above in general suggest that idiosyncratic equity volatility has a larger impact upon the credit spread than systematic volatility. However, it should be noted that the importance of systematic volatility in these studies is biased downward because of ignoring cross-sectional differences in exposure to systematic risks. Thus, the following hypothesis is formulated:

H5: Idiosyncratic and systematic equity risks are equally important determinants of the credit spread.

This hypothesis is examined in two steps. In the first step, equity volatility is decomposed into its systematic and idiosyncratic components, and, in the second step, the credit spread is regressed on the volatility components, that is, the economic and statistical significance of coefficients b and c in the following regression is examined.

$$CS_t = a + bV_t^{sys} + cV_t^{idio} + \varepsilon_t \tag{4.4}$$

4.2.4. Interaction between Equity Volatility and the Distance to Default

The structural model implies a non-linear relationship between equity volatility and the credit spread. The importance of equity volatility as a determinant of credit spread should increase, economically and statistically, with the level of credit risk. Campbell and Taksler (2003) use an accounting based ratio to divide firms in their sample into four leverage groups. Although they do not find a monotonic relationship, their results indicate that equity volatility is more important for firms with higher leverage. Cremers et al. (2008) use credit ratings to classify firms according to their credit risk exposure and also provide some evidence that the importance of equity volatility increases with risk. However, they obtain statistically insignificant results for the group with the lowest ratings. The reason behind these inconclusive results might be that the data samples are mostly populated with investment grade bonds, so there may be a limited number of observations for high-risk firms. This leads to the following hypothesis:

H6: The strength of the relationship between the credit spread and equity volatility is positively related to the level of credit risk.

This hypothesis is examined by estimating the distance to default of Merton (1974), which is an indicator of credit risk, and extending Equation 4.1 to control for the distance to default. First, the hypothesis is tested by examining the significance of the coefficient c in the following regression:

$$CS_t = a + bV_t + c\, V_t\, DD_t + \varepsilon_t \tag{4.5}$$

Additionally, Equation 4.1 is extended as follows:

$$CS_t = a + bV_t + \sum_{i=1}^{k} c_i V_t^i + \varepsilon_t \tag{4.6}$$

where $V_t^i = V_t\ I(x_i \leq DD_t < x_{i+1})$ and $I()$ is the indicator function which equals one if the condition is satisfied and zero otherwise. The x_i are pre-selected thresholds, and k is the number of risk classes in the sample. This specification allows examination of the statistical and economic significance of equity volatility for different ranges of the distance to default. In order to avoid the dummy variable trap, the last category is excluded (as it will be accounted for by the coefficient b). Model 4.6 is a discreet version of model 4.5.

4.2.5. Relationship between the Credit Spread and Common Factors

Collin-Dufresne, Goldstein and Martin (2001) document that the variables which should in theory determine credit spread changes in fact have limited explanatory power. They report that leverage, equity returns, changes in the VIX index, S&P 500 index returns and the risk-free rate explain only about 20 per cent of the credit spread changes. Instead of using an estimate of firm-level equity volatility, the authors use changes in the VIX index which represents a weighted average of eight implied volatilities of near-the-money options on the S&P 100 index. They find leverage and equity returns to be statistically significant, but note that their economic significance is rather limited. In fact, the factor loading on the S&P 500 index returns appears to be significantly larger than the loading on the firm-level equity returns. These findings, together with results of the principal component analysis, showing that the regression residuals grouped into maturity and leverage portfolios are highly correlated over time, lead the authors to conclude that most of the variations in credit spread are driven by a common factor rather than firm-specific factors, as implied by the structural model.

Longstaff, Mithal and Neis (2005) analyse the differences between credit default swap spreads and corporate bond credit spreads. By assuming that credit default swap spreads are a direct measure of credit risk, they find that a major part of bond credit spreads is due to credit risk. However, they also confirm that the credit spread contains a non-default component of credit which is related to market-wide liquidity. The authors interpret this finding to be consistent with the findings of Collin-Dufresne, Goldstein and Martin (2001). A regression analysis shows that firm-specific liquidity variables (such as coupon, bid-ask spread, and the principal amount) explain only about 20 per cent of variations in the non-default component of credit spreads. Interestingly, a dummy variable which takes the value of one if a firm is rated AAA or AA and zero otherwise is also statistically significant and the most economically significant variable. The negative regression coefficient implies that bonds issued by AAA/AA rated firms have lower credit spreads after controlling for credit risk. This may be interpreted as the flight-to-quality premium or premium investors are willing to pay to hold the highest quality assets.

Elton et al. (2001) show that the credit spread is strongly correlated with the systematic risk factors priced in equity returns. As a result, the authors conclude that the risks inherent in corporate bonds are systematic and, by extension, are rewarded with a risk premium.

However, King and Khang (2005) find that systematic factors are less relevant for bond pricing than idiosyncratic factors. Ericsson, Jacobs and Oviedo (2009) find little evidence that the residuals from regressing the credit spread on the theoretical variables are driven by a common factor. The first principal component accounts for about 30 per cent of variations in the residuals which is much lower than the 76 per cent reported by Collin-Dufresne, Goldstein and Martin (2001). Similar results are reported in Cremers et al. (2008).

This discussion leads to the following hypothesis:

H7: Firm-specific risk measures are more important determinants of the corporate credit spread than the aggregate risk factors.

This hypothesis is consistent with the prediction of the structural model and contrasts with the growing empirical evidence that the credit spread is primarily influenced by aggregate factors. Firms' exposure to systematic risks should be picked up by firm-level variables, so that aggregate variables should not contain any information that is not already reflected in the firm-level variables.

The empirical testing is conducted by including the returns and volatility of a major equity index in the model. Let V_t^{idio}, V_t^{sys}, R_t^{idio} and R_t^{sys} be firm-level idiosyncratic equity volatility and returns, and V_t^m and R_t^m be volatility and returns of the S&P 500 index, respectively. Then the hypothesis is tested by assessing the statistical and economic significance of coefficients b to g in the following regression:

$$CS_t = a + bV_t^{idio} + cV_t^{sys} + dR_t^{idio} + eR_t^{sys} + fV_t^m + gR_t^m + \varepsilon_t \qquad (4.7)$$

4.3. Methodology

4.3.1. Credit Spread

Before the final payment, which will include the principal amount, bonds usually make semi-annual coupon payments. Denote CF_t as the cash flow a bond is expected to generate in year t. The market price of bond B equals the value of all future cash flows discounted to present value.

$$B = \sum_{i=1}^{n} \frac{CF_t}{(1+y)^t} \tag{4.8}$$

where

CF_t is cash flow in year t

y is the discount rate

The redemption yield or yield to maturity is obtained by solving the above equation for y. The solution is found via optimization because the bond price equation is not linear and analytical solutions for it do not exist.

The redemption yield consists of two components. The first is the cost of capital which can be measured by the equivalent (in maturity) yield of a government bond which is considered to be risk-free. Since in practice an equivalent-maturity governments bond, also referred to as the benchmark bond, is not always available, a simple interpolation technique is used:

$$Y = Y_1 + \left(\frac{L_3 - L_1}{L_2 - L_1} \right) (Y_2 - Y_1) \tag{4.9}$$

where

Y_1 is the yield of the benchmark bond with the lower maturity

Y_2 is the yield of the benchmark bond with the higher maturity

L_1 is the exact maturity in years of the lower benchmark bond

L_2 is the exact maturity in years of the higher benchmark bond

L_3 is the exact maturity in years of the bonds being analysed

The second component of the firm's bond yield is the compensation for risk. It is easily calculated as the difference between the redemption yield of the corporate bond and the redemption yield of the benchmark governmental bond. This difference is referred to as the spread S:

$$S_t = Y_{t,c} - Y_{t,b} \tag{4.10}$$

where

$Y_{t,c}$ is the redemption yield of a corporate bond

$Y_{t,b}$ is the redemption yield of a benchmark government bond

4.3.2. Bond Issue Characteristics

To control for the maturity of bonds, daily duration is calculated according to the following formula:

$$d = \frac{1}{B_d} \sum_{i=1} \frac{CF_i}{(1+Y)^{T_i}} T_i \tag{4.11}$$

where

B_d is the dirty bond price (principal + accrued interest)

CF_i is the cash flow in year i

T_i is the time in years to the ith cash flow

The control variable for the size of the bond issue is the natural logarithm of the bond's market price multiplied by the number of outstanding bonds.

4.3.3. Equity Volatility

Equity volatility is calculated at the daily level as described below and annualized by multiplying daily estimates by $\sqrt{255}$.

GARCH

Daily volatility is estimated using a parsimonious GARCH (1,1) model, which was introduced by Bollerslev (1986) as a generalization of Engle (1982) ARCH model. The conditional variance evolves according to the following equation:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 \tag{4.12}$$

where

σ^2 is the variance

ε is the error term from the return model $r_t = \mu + \varepsilon_t \ where\ \varepsilon_t \sim (0, \sigma_t^2)$

EGARCH

In order to take into account the stylized fact that negative and positive news impact upon equity returns in a different manner, equity volatility is also estimated by the exponential GARCH or EGARCH model proposed by Nelson (1991). The EGARCH model allows that positive and negative news impact upon volatility differentially. The model is given by:

$$\log\sigma_t^2 = \omega + \beta \log\sigma_{t-1}^2 + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \eta\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{4.13}$$

4.3.4. Equity Returns

In the first step equity returns are calculated in the usual manner. Define $P_{i,t}$ as the share price of firm i at time t. The rate of return is defined as:

$$r_{i,t} = \ln\frac{P_{i,t} + D_{i,t}}{P_{i,,t\text{-}1}} \tag{4.14}$$

In the second step, equity returns are decomposed into systematic and idiosyncratic returns. A common practice in empirical studies is to consider idiosyncratic returns as the returns in excess of returns of a major equity index (e.g. Campbell and Taksler, 2003; Cremers et al., 2008). This effectively imposes an assumption that the betas of all firms are one which is clearly unrealistic. To avoid this assumption, equity returns in this study are modelled by means of two major models: the CAPM and the Fama and French three factors model. The CAPM is estimated as:

$$r_{i,t} = r_{ft} + \beta_{i,t}(r_{mt} - r_{ft}) + \varepsilon_{i,t} \tag{4.15}$$

where

$r_{i,t}$ is the equity return of firm i at time t

$r_{f,t}$ is the risk-free rate

$r_{m,t}$ is the return on S&P 500 index on time t

$$\beta_{i,t} = \frac{Cov(r_{i,t}, r_{m,t})}{\sigma^2_{m,t}}$$

$\varepsilon_{i,t}$ is the zero-mean idiosyncratic error

The Fama and French three factor model extends the CAPM with two additional factors:

$$r_{i,t} = r_{ft} + \beta_{1,i,t}(r_{m,t} - r_{f,t}) + \beta_{2,i,t} SMB_t + \beta_{3,i,t} HML_t + \varepsilon_{i,t} \tag{4.16}$$

where the additional factors are:

SMB_t is the difference in returns on big and small firms at time t

HML_t is the difference in returns on high and low book-to-market equity firms at time t

Systematic returns are deemed returns implied by the above models, while the difference between the observed and systematic returns (i.e. the residuals) is considered to represent idiosyncratic returns.

In order to take into account the time variation in the risk premium, conditional betas are estimated with bivariate GARCH-in-mean as described in Bollerslev, Engle and Wooldridge (1988). The returns are modelled to be proportional to their conditional variances, which are GARCH (1,1) processes.

Mean equations:

$$\begin{aligned} r_{m,t} &= \alpha_1 + \lambda_1 \sigma^2_{m,t-1} + \varepsilon_{m,t} \\ r_{i,t} &= \alpha_2 + \lambda_2 \sigma^2_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{4.17}$$

Variance equations:

$$\begin{aligned} \sigma^2_{m,t} &= \omega_1^2 + \beta_1^2 \sigma^2_{m,t-1} + \gamma_1^2 \varepsilon^2_{m,t-1} \\ \sigma^2_{i,t} &= \omega_2^2 + \beta_2^2 \sigma^2_{i,t-1} + \gamma_2^2 \varepsilon^2_{i,t-1} \end{aligned} \tag{4.18}$$

Covariance equation:

$$Cov(r_{i,t}, r_{m,t}) = \omega_1 \omega_2 + \beta_1 \beta_2 Cov(r_{i,t}, r_{m,t})_{t-1} + \gamma_1 \gamma_1 \varepsilon^2_{m,t-1} \varepsilon^2_{i,t-1} \tag{4.19}$$

where

r_{mt} is the return on the S&P 500 index or the Fama and French factor on time t

$r_{i,t}$ is the equity return of firm i at time t

The above model can be simply implemented to estimate the covariance between the market and individual stocks returns in the CAPM. Since the Fama and French factor model has three factors, the following auxiliary regressions are run:

$$\begin{aligned} r_{1,i,t} &= \alpha + \beta_{1,i,t} SMB_t + \beta_{2,i,t} HML_t + \varepsilon_{1,i,t} \\ r_{2,i,t} &= \alpha + \beta_{1,i,t} (r_{m,t} - r_t) + \beta_{2,i,t} HML_t + \varepsilon_{2,i,t} \\ r_{3,i,t} &= \alpha + \beta_{1,i,t} (r_{m,t} - r_t) + \beta_{2,i,t} SMB_t + \varepsilon_{3,i,t} \end{aligned} \tag{4.20}$$

Each of the above equations regresses equity returns on two Fama and French model factors. The residuals or returns not explained by the two factors are used in the mean equation of the bivariate GARCH-in-mean model to estimate the correlation of equity returns with a third factor (i.e. the residuals from the first equation with SMB and HML factors as explanatory variables are used for estimation of the conditional correlations with the market factor etc.).

4.3.5. Distance to Default

In the structural model of Merton (1974), debt and equity are considered as derivative securities for the underlying assets of a firm. The value of the firm's assets represents the underlying asset, the strike price is the book value of the firm's debt, and the value of the firm's equity represents the value of the call option. Mathematically, it can be defined as follows:

$$V_E = V_A N(d_1) - X e^{-rT} N(d_2) \tag{4.21}$$

where

$$d_1 = \frac{\ln(\frac{V_A}{X}) + \left(r + \frac{1}{2}\sigma_A^2 \right) T}{\sigma_A \sqrt{T}}$$

$$d_2 = d_1 - \sigma_A \sqrt{T} = \frac{\ln\left(\frac{V_A}{X} \right) + \left(\mathrm{r} - \frac{\sigma_A^2}{2} \right) T}{\sigma_A \sqrt{T}}$$

r is the risk-free rate

N is the cumulative density function of the standard normal distribution

σ_A is the volatility of the market value of the firm's assets

The variable d_2 is a measure of the distance between the market value of assets and the book value of debt relative to the volatility of the market value of assets. It is transformed using the cumulative density function of the standard normal distribution to generate the default probability.

The market value and the volatility of the firm's assets are not observable. The derivative nature of equity can be exploited to estimate the market value and the volatility of assets by simultaneously solving the call pricing formula given in Equation 4.21 and the following hedge equation (Jones, Mason and Rosenfeld, 1984):

$$\sigma_{E,it} = \frac{V_{A,it} N(d_1) \sigma_{A,it}}{V_{E,it}} \tag{4.22}$$

This appears to be the method most frequently used for the estimation of unobservable value of the assets and volatility. It is advocated by major text books (e.g. Hull, 2009; Saunders, 1999), and widely used in academic studies (e.g. Cooper and Davydenko, 2003; Geske and Delianedis, 2001; and Campbell, Hilscher and Szilagyi, 2008).

4.3.6. Panel Data Analysis

The data set consists of equity, bond, accounting and common variables for n different firms over T consecutive time periods. This two-dimensional feature of the dataset implies that the econometric analysis should be undertaken within a panel analysis framework.

The most basic panel data model is given by:

$$y_{it} = \alpha + \beta x_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d.(0,\sigma^2) \qquad (4.23)$$

where

α is the intercept

β is a K x 1 parameter vector

ε is a G x 1 vector of unobserved factors

The subscript i = 1,2…,N denotes firms and t = 1,2,…,T denotes time periods. The disturbance term represents unobserved random factors that affect each firm and vary over time. This basic model assumes that the intercept and slope coefficients are the same for all firms and therefore they have no subscripts, i. In this study, the dependent variable, y_{it}, is a measure of the credit risk and independent variables, x_{it}, are bond issue characteristics, firm-specific risk factors and variables depicting systematic risks.

The error term should satisfy the following assumptions, as stated by $\varepsilon_{it} \sim i.i.d.(0,\sigma^2)$:

- No autocorrelation, i.e. $\mathrm{cov}(\varepsilon_{it}, \varepsilon_{is},) = 0$, for all $t \neq s$
- Group wise homoskedasticity, i.e. $var(\varepsilon_{it}) = \sigma^2$ *for all i*
- Cross-sectional independence, i.e. $\mathrm{cov}(\varepsilon_{it}, \varepsilon_{js},) = 0$, for all $i \neq j$
- No correlation with the regressors, i.e. $\mathrm{cov}(\varepsilon_{it}, x_{it},) = 0$

Under these assumptions, the model is a classical regression model and can be efficiently estimated by the least squares method. If the assumptions do not hold, the appropriate estimation method is the generalized least squares method.

One advantage of a panel regression over a simple cross-section regression is that it provides more flexibility when modelling differences in behaviour across different firms. Consider the following generalized model:

$$y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d.(0,\sigma^2) \qquad (4.24)$$

Where the subscript i in α indicates that the intercept is now allowed to vary across firms or industries. Therefore, this model allows for two types of unobserved factors: 1) factors that are firm or industry specific and constant over time, α, and 2) factors that are firm or industry specific and vary randomly over time, ε.

The above model can easily be expanded to include the time-specific, but common across firms, effect γ_t :

$$y_{it} = \alpha_i + \gamma_t + \beta x_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d.(0, \sigma^2) \tag{4.25}$$

Another point to be considered is whether α_i should be treated as deterministic or randomly distributed across firms. The latter means that unobserved firm-specific factors are orthogonal to the regressors, while in the former case they may be correlated. This may be empirically tested by utilizing the Hausman test, which hypothesizes that the firm-specific factors are correlated with the regressors. Rejection of this hypothesis implies that firm-specific factors should be treated as deterministic rather than random.

Errors in panel data models may be correlated over time for a given firm or contemporaneously correlated in cross section. Petersen (2009) shows that fixed effects in data series bias standard errors downwards. Since the presence of fixed effects in credit spreads is highly likely (e.g. Zhang, Zhou and Zhu 2009), clustered standard errors are used in all models except in models where the dependent variable is the change in the credit spread because the fixed effects are removed by the differencing.

4.4. Data

The study uses the firm-level bond and equity data. Therefore, for a firm to be included in the sample, it must have publicly traded equity and bonds. Furthermore, the estimation of the structural model and the distance-to-default requires accounting values of debt.

As all public firms do not issue bonds, the sample selection process starts from considering all straight corporate bonds issued by non-financial firms in the US market where data is available in the Thomson Reuters Datastream database. There are approximately 4,000 straight corporate bonds, but about 800 individual firms because most of the bond issuers issue multiple bonds. In such cases a bond with the maximum number of observations is considered for the inclusion in the sample. Alternatively, all bonds could be included in the sample as different series. Such an approach would significantly increase the availability of data, but would increase the explanatory power of models without bringing in much new information, as the credit spread of different bonds issued by the same firm are highly correlated. As noted by Eberhart and Siddique (2002), this approach would also bias the standard errors downward. Another alternative would be to average the data for different bonds with a common issuer. This approach would involve taking into account differences between bond issues such as duration and size, and, as already noted, would not significantly improve the information content of the sample. Therefore, the approach of taking one bond issue per issuer appears to be the best given the aim of this study.

Bonds with fewer than 750 observations, asset-backed bonds, bonds with any sort of collateral, or with an average market value of less than USD 10 million are excluded from the sample. Further, data that appears anomalous, such as series with extremely large positive or negative credit spread observations, are removed from the sample. The remaining bonds are carefully linked to the equity and accounting data of the corresponding firms. This selection process results in a sample of 352 firms with linked bond, equity and accounting data.

The sample covers almost 15 years starting on 1/8/1996 and ending 18/2/2011. It should be noted that the sample is an unbalanced panel, as not all series span across the entire sample period.

The total number of daily observations is 729,279 or about 34,300 observations at the monthly level. The number of firms before 2001 is limited when compared to the number of firms in other years, but is still significant when compared to existing studies dealing with the firm-level data (e.g. Cremers at al. (2008) have 69 firms; Norden and Weber (2009) have 58 firms in total). Table 4.1 depicts the number of available firms and the observations per calendar year:

Table 4.1
Number of firms and observations in the sample

Year	Number of firms	Number of observations
1996-97	27	8,956
1998	30	7,239
1999	32	8,171
2000	33	8,538
2001	201	36,621
2002	232	56,696
2003	261	65,026
2004	287	71,279
2005	305	76,138
2006	319	80,755
2007	335	84,537
2008	335	86,852
2009	298	71,271
2010-11	251	67,200
Total		729,279

Table 4.2 depicts descriptive statistics for credit spreads, bond values and four estimated series: equity volatility, distance-to-default, asset volatility and asset value.

Table 4.2
Descriptive statistics of the data series

Statistics	Credit spread	Bond Issue Value	Distance to Default	Equity Volatility	Asset Value	Asset Volatility
Mean	279.07	241.88	5.25	0.37	26,024.51	0.20
Median	185.20	188.38	4.85	0.32	8,963.24	0.18
Maximum	13,352.40	4,606.11	926.18	7.50	1.03E+06	7.49
Minimum	-148.10	2.10	-3.71	0.03	12.95	0.00
Std. Dev.	366.32	270.55	2.88	0.21	61,434.81	0.13
Skewness	10.38	4.79	30.81	3.58	8.35	5.53
Kurtosis	205.23	48.73	9,563.06	32.30	102.48	113.36

Equity volatility is estimated as a GARCH(1,1) process and annualized. Asset values, asset volatilities and the distance-to-default are estimated according to the procedure described in Section 4.3.4. Bond issues and asset values are expressed in US$ millions. Credit spread is expressed in basis points.

Similar to other financial series, all series have excess kurtosis which indicates that their empirical distributions have fatter tails than the normal distribution. The mean of the credit spread series is within the BBB rating category while the median credit spread falls within the BB category according to the mapping of credit spreads with the rating categories presented in Cremers, Driessen and Maenhout (2008). In a few instances the credit spread is negative. As noted above, series with a large negative credit spread observations are excluded from the sample, but series with a few negative credit spread observations at the daily level are technically possible, hence such series are not removed from the sample.

The mean of the distance-to-default series is 5.25 which effectively means that the average default probability implied by the basic structural model is zero. It should be noted that the mean of the series is influenced by a number of very high distance-to-default values which occur when the volatility of assets or leverage is very low. However, the distance to default can be negative when, for example, the volatility of the asset value is high.

The figures 4.1, 4.2 and 4.3 plot the median of the credit spread, equity volatility and distance-to-default series.

Figure 4.1
Median of the credit spread series

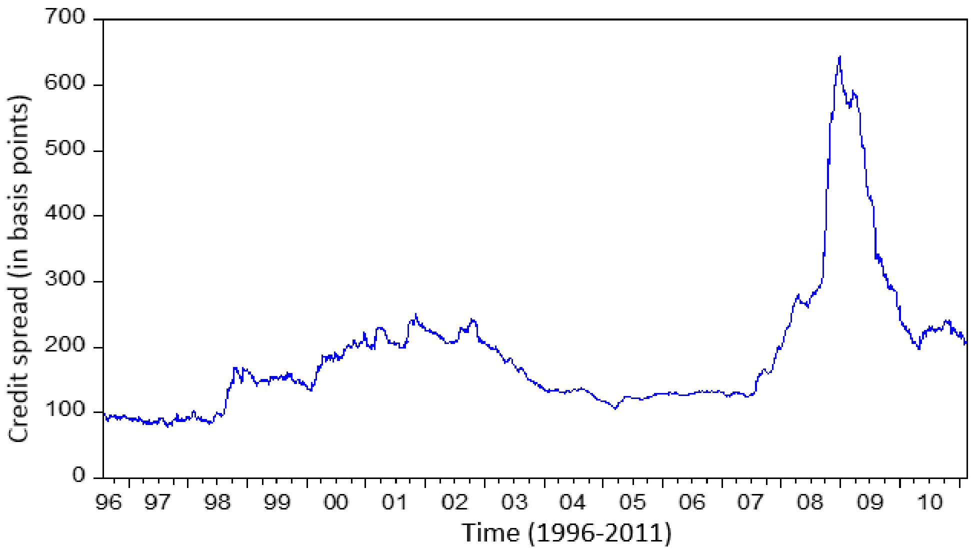


Figure 4.2
Median of the equity volatility series

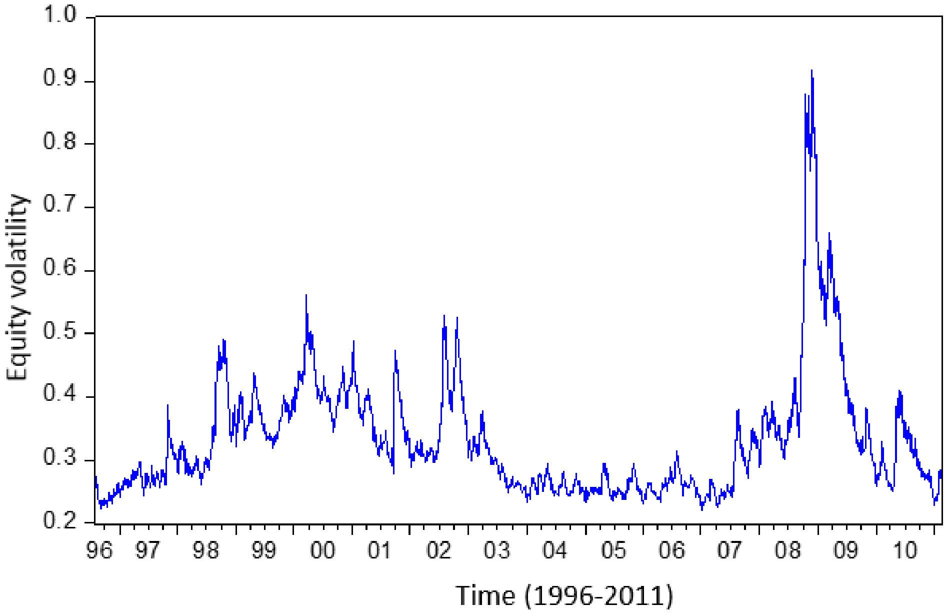
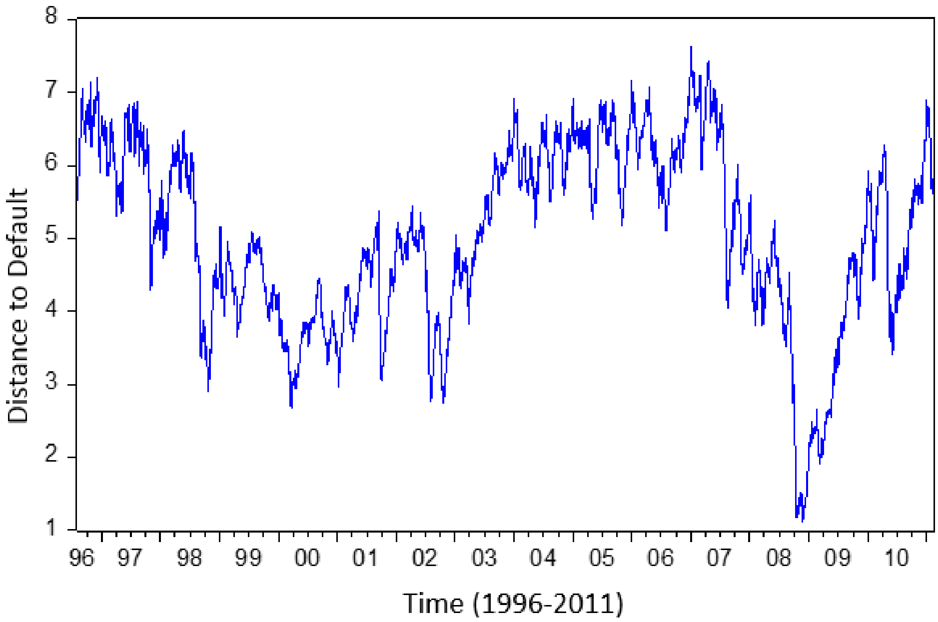


Figure 4.3
Median of the distance to default series



The equity volatility series seem to be more volatile than the credit spread, but both appear to follow the same general pattern. The plot of the distance to default series also generally appears to be consistent with the plots of the other two series as it is low (i.e. high credit risk) when equity volatility and the credit spread are high. It should be noted that, as a risk indicator, the distance-to-default has an inverse interpretation to equity volatility and the credit spread in that a lower distance-to-default implies a higher risk. It is also interesting to observe spikes in the credit spread and equity volatility series and a large drop in the distance-to-default series at the height of the recent financial crisis in 2008.

The equity, bond and interest rate data are collected from the Thomson Reuters Datastream database. Accounting data is sourced from Compustat and the Fama and French factors are obtained from Kenneth R. French's web site. The list of firms, their equity symbols and the corresponding bond codes are presented in the Appendix.

4.5. Summary

Corporate equity and debt securities are essentially different claims on the same assets and therefore their values should be systematically correlated. Merton (1974) provides a framework for empirical analysis of the relationship between the values of different corporate securities. He considers all securities as derivatives written on the value of a firm's assets and applies the option pricing model of Black and Scholes (1973) to derive the analytical solution for the prices of corporate bonds and equities. The model, referred to as the structural model, implies that default occurs when the value of a firm's assets equates the value of debt. The value of a firm's assets is assumed of follow a diffusion process, so the probability that the value of assets will reach the value of debt depends primarily on the volatility of the firm's assets and leverage.

This provides the researcher with a set of predictions. First, equity volatility and credit spread, the latter of which is the yield on corporate bonds in excess of the yield on a government bond with similar maturity, are positively correlated. Second, equity volatility has a larger impact upon default probability as a firm approaches bankruptcy so the strength of the relationship between equity volatility and credit spread depends on the level of credit risk. Third, credit risk depends on total volatility so the systematic and idiosyncratic components of equity return should have the same impact upon the credit spread. Finally, since credit risk is driven by firm-specific information, common risk factors should be less important determinants than firm-specific factors.

Existing studies commonly examine the relationship between equity volatility and the credit spread of investment grade bonds or equity volatility and the credit default swap premia. Following Campbell and Taksler (2003), the idiosyncratic equity volatility is commonly estimated as the volatility of equity returns in excess of those on a major equity index. As predicted by the structural model, idiosyncratic equity volatility is found to be positively correlated with the credit spread and to be a more important determinant of credit spread than market-wide equity volatility. However, Collin-Dufresne, Goldstein and Martin (2001) argue that the credit spread is driven by a common factor and note that S&P 500 index equity returns are more economically significant than firm-level equity returns in explaining the credit spread.

This study aims to extend the existing literature by considering equity volatility as a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) process as well as by examining how the systematic and idiosyncratic components of the firm-level equity volatility impact upon the credit spread. This requires the decomposition of equity returns by the CAPM of the Fama and French three factor model. A bivariate GARCH model is utilized for the estimation of equity betas. Furthermore, the distance to default implied by the structural model is used as an indicator of credit risk rather than accounting based debt measures of credit ratings. The sample consists of merged equity and bond data of 352 firms covering the period from 1/8/1996 to 18/2/2011 (over 700,000 daily observations). Chapter 5 presents the empirical results.

CHAPTER 5

SYSTEMATIC AND IDIOSYNCRATIC EQUITY RISKS AS DETERMINANTS OF THE CREDIT SPREAD: AN EMPIRICAL INVESTIGATION

5.1. Introduction

The aim of this chapter is to assess the statistical validity of the hypotheses proposed in the previous chapter. The empirical investigation starts with the analysis of the univariate relationship between the credit spread and equity volatility which is based on volatility estimated using a GARCH process. This relationship is comprehensively examined in the constant coefficient panel model as well as models with controls for cross-sectional and time variations.

In Section 5.3, the univariate relationship between the credit spread and the distance to default variable of Merton (1974) is examined. Distance to default should reflect all information relevant to credit risk. Besides equity volatility, it incorporates information on a firm's leverage and the risk-free interest rate. Therefore, if the credit spread is primarily driven by credit risk, the distance to default should outperform equity volatility in explaining variations in the credit spread.

Section 5.4 decomposes equity volatility into its systematic and idiosyncratic components and assesses how each component affects the credit spread. The volatility components are estimated as the volatility of expected and unexpected equity returns according to the CAPM and the Fama and French three factor model. The time series of betas are obtained by estimating the bivariate GARCH-in-mean model as described in the previous chapter.

The interaction of equity volatility and the distance to default in determining the credit spread is explored in Section 5.5 by estimating a model of the product of equity volatility and the distance to default, as well as with variables to control for the level of distance to default.

Section 5.6 considers the significance of common risk factors in explaining the credit spread. The significance of the risk-free rate, the slope of the risk-free term structure, S&P 500 index returns, and volatility are evaluated on their own and jointly with firm-level equity volatility and returns.

The analysis in the previous work of this thesis is based on level regressions. Following the literature, Section 5.7 presents the results of regressing changes in the credit spread on changes as well as levels of equity volatility and the distance to default.

The final section examines the robustness of the results to changing the volatility estimation method. Instead of the standard GARCH process, the equity volatility is estimated as an asymmetric EGARCH process to take into account the possibility that negative shocks may have a larger impact upon volatility than corresponding positive shocks. Furthermore, the robustness of the results to controlling for firm size, bond duration and bond issue size is examined.

5.2. The Relationship between the Credit Spread and Equity Volatility

5.2.1. Unit Root Analysis

It is well documented that the credit spread is a long memory process. Pedrosa and Roll (1998) report that the unit root hypothesis can be rejected at the ten per cent level for only one out of sixty credit spread indexes. However, they note that it is implausible that any credit spread is a unit root process and that unit root tests have very low power against near unit root alternatives. Duffee (1999) provides some justification for the level regression by finding that the default intensities implied by credit spreads are stationary with a half-life of less than three years. McCarthy, Pantalone and Li (2009) find that the credit spread is a long memory or fractionally integrated process. As a result, credit spread time series contain time components which may influence any empirical results. However, a significant number of existing empirical studies (e.g. Campbell and Taksler, 2003; Cremers et al., 2008) are based on credit spread levels. The use of credit spread levels in regression analysis is appealing because it enables the analysis of determinants of time series as well as cross-sectional variations in the credit spread. Due to these concerns the empirical analysis of this chapter starts with stationarity tests of the credit spread. Table 5.1 presents probabilities for the presence on a unit root obtained by conducting several specifications for up to five unit root tests.

Table 5.1
Probability values of panel unit-root tests for the credit spread

Test	5 Daily Lags	10 Daily Lags	15 Daily Lags
Panel A: No exogenous regressors			
Levin, Lin & Chu t	0.00	0.00	0.00
ADF - Fisher Chi-square	0.03	0.01	0.00
PP - Fisher Chi-square	0.00	0.00	0.00
Panel B: Intercept as exogenous regressor			
Levin, Lin & Chu t	1.00	1.00	0.99
Im, Pesaran and Shin W-stat	1.00	0.69	0.03
ADF - Fisher Chi-square	0.44	0.06	0.00
PP - Fisher Chi-square	0.00	0.00	0.00
Panel C: Intercept and time trend as exogenous regressors			
Levin, Lin & Chu t	1.00	1.00	1.00
Breitung t-stat	1.00	1.00	1.00
Im, Pesaran and Shin W-stat	1.00	1.00	1.00
ADF - Fisher Chi-square	1.00	1.00	1.00
PP - Fisher Chi-square	0.00	0.00	0.00

Reported results are probability values for the null hypothesis that the series contain a unit-root. Levin, Lin and Chu (2002), and Breitung (2000) test for the presence of common unit root processes while other tests (Im, Pesaran and Shin, 2003; Maddala and Wu,1999; Choi 2001) allow auto regressive coefficients to vary in cross section. Probabilities for the Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

All panel unit root tests without exogenous regressors reject the null of unit root in all of the equations. In the specification with an intercept and five lags, three tests are positive. When the number of lags in increased to 15, only one test remains positive. Finally, four out of five tests with an intercept and trend as exogenous regressors consistently indicate the presence of a unit root regardless of the number of lags included. Unit root tests for equity volatility are not performed because critical values of standard unit root tests are not valid for estimated series. In the following section, the unit root tests are performed on the residuals from regressing the credit spread on equity volatility.

5.2.2. The Constant Coefficient Model

As outlined before, an increase in equity volatility signals an increase in the riskiness of the firm's assets. In the structural framework, an increase in equity volatility increases the volatility of total assets which in turn heightens the probability that the value of total assets will fall to the value of debt and thereby trigger bankruptcy. These arguments imply that the correlation between equity volatility and the credit spread should be significant and positive. In the first step of examining this relationship, the firm-level credit spread at the daily level is regressed on equity volatility estimated as a parsimonious GARCH(1,1) process. Equity volatility is estimated at the daily level and annualized. The results are presented in Table 5.2.

Table 5.2
The relationship between equity volatility and the credit spread: the constant coefficient model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	1,049.14	80.91	12.97	0.00
C	-95.54	24.31	-3.93	0.00
R-squared	0.39	Mean dependent var		276.74
Adjusted R-squared	0.39	S.D. dependent var		360.65
S.E. of regression	280.68	Akaike info criterion		14.11
Sum squared resid	5.75E+10	Schwarz criterion		14.11
Log likelihood	-5.15E+06	Hannan-Quinn criter.		14.11
F-statistic	474,987.50	Durbin-Watson stat		0.03
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected).

The estimated model is $CSit = \alpha + \beta EVit + \varepsilon it$ where CS stands for the credit spread expressed in basis points or 1/100 percentage points. EV is equity volatility and is estimated as a GARCH (1,1) process from daily equity returns and is multiplied by $\sqrt{255}$. The model is estimated without fixed and time effects.

The relationship between equity volatility and the credit spread is positive as hypothesized and the coefficient exhibits very high statistical significance. It is also economically meaningful as an increase in annual equity volatility of one per cent raises the credit spread by 10.49 basis points. The R-squared implies that equity volatility explains about 39 per cent of the variation in the credit spread.

The explained portion of credit spread as measured by the R-squared is high, in line with other studies reporting results of level regressions (e.g. Campbell and Taksler (2003) obtain an R-squared of about 30 per cent; Ericsson, Jacobs and Oviedo (2009) obtain an R-squared of about 60 per cent; and Cremers et al. (2008) obtain an R-squared about

45 per cent). Ericsson, Jacobs and Oviedo note that this result may be obtained because of a high persistence in the credit spread.

The economic significance of equity volatility (ten basis points per one per cent of equity volatility) implied by this parsimonious regression is not directly comparable to other studies. Campbell and Taksler (2003), for example, find that a one per cent increase in annual equity volatility increases the credit spread by 14 basis points. However, they estimate the equity volatility as the volatility of excess equity returns relative to the CRSP value-weighted index, while the model presented in Table 5.2 utilizes volatility of the total equity returns.

To ensure the validity of the statistical inference, the residuals from the regression presented in Table 5.2 are tested for the presence of a unit root. All tests reject the null hypothesis of a unit-root, leading to the conclusion that the residuals are stationary. The test results are presented in Table 5.3.

Table 5.3
A panel unit-root test analysis of the residuals from regressing the credit spread on equity volatility

Test	Statistics	Probability
Panel A: No exogenous regressors		
Levin, Lin & Chu t	-58.29	0.00
ADF - Fisher Chi-square	7,646.74	0.00
PP - Fisher Chi-square	8,507.47	0.00
Panel B: Intercept as exogenous regressor		
Levin, Lin & Chu t	-6.24	0.00
Im, Pesaran and Shin W-stat	-68.94	0.00
ADF - Fisher Chi-square	7,960.54	0.00
PP - Fisher Chi-square	9,284.18	0.00
Panel C: Intercept and time trend as exogenous regressors		
Levin, Lin & Chu t	-10.31	0.00
Breitung t-stat	-30.43	0.00
Im, Pesaran and Shin W-stat	-72.01	0.00
ADF - Fisher Chi-square	8,270.65	0.00
PP - Fisher Chi-square	10,155.80	0.00

The Levin, Lin & Chu and Breitung tests assume common, while other tests assume individual, unit root processes. The probabilities for the Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

The model presented in Table 5.2 assumes that increases and decreases in equity volatility impact the credit spread in the same manner. To allow for an asymmetric response of the credit spread to changes in equity volatility, a variable is added to the model which takes the value of one when equity volatility increases and zero otherwise. The results are presented in Table 5.4.

Table 5.4
Asymmetry in the relationship between equity volatility and the credit spread

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	1,049.99	80.94	12.97	0.00
Δ Equity Volatility > 0	-15.15	1.73	-8.77	0.00
C	-91.47	23.97	-3.82	0.00
R-squared	0.39	Mean dependent var		276.75
Adjusted R-squared	0.39	S.D. dependent var		360.66
S.E. of regression	280.60	Akaike info criterion		14.11
Sum squared resid	5.74E+10	Schwarz criterion		14.11
Log likelihood	-5.15E+06	Hannan-Quinn criter.		14.11
F-statistic	237,849.50	Durbin-Watson stat		0.03
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/02/1996 2/18/2011; Periods included: 3,796; Cross-sections included: 352; Total panel (unbalanced) observations: 729,586; White period standard errors and covariance (d.f. corrected).

The increase in Equity Volatility takes the value of one if the change in equity volatility is positive, i.e. if $EV_t - EV_{t-1} > 0$

The dummy variable coefficient is unexpectedly negative, indicating that a decrease in volatility has a larger positive impact upon the credit spread than an increase of the same magnitude. The estimated coefficients imply that a one percentage point decrease in equity volatility decreases the credit spread by 10.50 basis points, whereas a one percentage point increase in equity volatility increases the credit spread by 10.35 basis points. Although the dummy variable coefficient is statistically significant, it is just 1.4 per cent of the size of the equity volatility coefficient, so its economic significance is limited.

5.2.3. The Cross-sectional Fixed Effects Model

In efficient markets all available information should be reflected in market prices. As a result, all information about the riskiness of the firm's assets should be reflected in the volatility of its equity value. Therefore, cross-sectional differences in the relationship between equity volatility and the credit spread should in general only be influenced by differences in the financial leverage of firms. The model estimated in the previous section imposes the same regression intercept for all firms. In order to examine the presence of firm-specific factors in the credit spread, a fixed effects model is estimated in which the intercept is allowed to vary across firms. This is implemented by augmenting the constant coefficient model with dummy variables which take the value of one if an observation is related to a specific firm and zero otherwise. Fixed effects control for cross-sectional differences in the relationship between equity volatility and the credit spread as well as other variables not included in the model. An examination of the size of the fixed effects can reveal cross-sectional differences in the portion of variations in the credit spread not explained by equity volatility. The fixed effects model is presented in Table 5.5.

Table 5.5
The relationship between equity volatility and the credit spread: the cross-sectional fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	909.15	81.58	11.14	0.00
C	-45.87	28.95	-1.58	0.11
R-squared	0.53	Mean dependent var		276.74
Adjusted R-squared	0.53	S.D. dependent var		360.65
S.E. of regression	246.33	Akaike info criterion		13.85
Sum squared resid	4.43E+10	Schwarz criterion		13.86
Log likelihood	-5.05E+06	Hannan-Quinn criter.		13.85
F-statistic	2,371.49	Durbin-Watson stat		0.03
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,586; White period standard errors and covariance (d.f. corrected).

The estimated model is $CS_{it} = \alpha_i + \beta EV_{it} + \varepsilon_{it}$ where CS stands for the credit spread expressed in basis points or 1/100 percentage points. EV is equity volatility estimated as a GARCH (1,1) process from daily equity returns and multiplied by $\sqrt{255}$. The intercept α_i is allowed to differ where the model is estimated without fixed and time effects.

The fixed effects model fits the data better than its constant-coefficient version presented in Table 5.2. The sum of squared residuals is reduced by 23 per cent. The size of the coefficient of equity volatility decreases from 1,049 to 909, which implies a slight reduction of the economic significance of equity volatility in explaining variations in the credit spread (i.e. from 10.5 to 9.1 basis points per one per cent change in equity volatility). A similar reduction occurs in statistical significance as measured with the coefficient's t-statistics. The inclusion of fixed effects raises the R-squared from 39 per cent to 53 per cent. Formal tests, presented in Table 5.6, strongly reject the hypothesis that fixed effects are redundant.

Table 5.6
Redundant fixed-effects tests

Effects Test	Statistic	d.f.	Prob.
Cross-section F	621.23	-351,729,262.00	0.00
Cross-section Chi-square	190,865.62	351.00	0.00

Redundant Cross-section Fixed Effects Tests for the equation: $CS_{it} = \alpha_i + \beta EV_{it} + \varepsilon_{it}$.

The tests evaluate the joint significance of the fixed effects using sums-of-squares (F-test) and the likelihood function (Chi-square test).

An examination of estimated fixed effects reveals that only one coefficient (out of 351 in total) is more than two standard deviations from the mean on the negative side, whereas 17 coefficients exceed the value of the mean by more than two standard deviations on the positive side.

The fixed effects may be unrelated to equity volatility. In that case it would be more appropriate to treat the intercept as a random variable. Although it is unlikely given the improvement in the model's performance, to examine this possibility a random-effect model is estimated. In this model the intercept is assumed to be random. The results are presented in Table 5.7.

Table 5.7
The relationship between equity volatility and the credit spread: the cross-sectional random effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	909.64	81.54	11.16	0.00
C	-32.93	25.49	-1.29	0.20
Effects Specification			S.D.	Rho
Cross-section random			126.51	0.21
Idiosyncratic random			246.33	0.79
R-squared	0.31	Mean dependent var		12.03
Adjusted R-squared	0.31	S.D. dependent var		296.59
S.E. of regression	246.36	Sum squared resid		4.43E+10
F-statistic	327,633.20	Durbin-Watson stat		0.03
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel EGLS (cross-section random effects); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; Swamy and Arora estimator of component variances.

The estimated coefficient of equity volatility is slightly higher than in the fixed-effects model but the model's explanatory power, as measured by R-squared, is substantially reduced. This model is inconsistent if the random effects are correlated with equity volatility. The Hausman test is used to formally test this hypothesis. The test results are presented in Table 5.8.

Table 5.8
Test of random-effects specification

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	98.47	1.00	0.00

Correlated Random Effects - Hausman Test for the equation Equation: $CS_{it} = \alpha_i + \beta EV_{it} + \varepsilon_{it}$

The test strongly rejects the null hypothesis that individual effects are random and leads to the conclusion that the fixed-effects model is more appropriate.

5.2.4. The Period Fixed Effects Model

The main idea underpinning the joint modelling of the values of bonds and equity securities is that they derive their values from the same underlying assets. A change in the riskiness of the firm's assets should therefore affect the values of both classes of securities, but the relationship between their risk measures should be stable over time. Consistent with this hypothesis, Ericsson, Jacobs and Oviedo (2009), who study the determinants of the credit default swap premia, report that the estimated coefficients of equity volatility are stable in their sample covering the period from 1999 to 2002. It should be noted that due to limitations in the availability of firm-level bond data, existing empirical studies are typically performed on data samples spanning just a few years. As a result, existing empirical evidence of the time series properties of the relationship between the credit spread and equity risk measures is rather limited. The sample used in this study covers a period of almost 15 years starting in 1996 and ending in 2011. It is an unbalanced sample and not all series cover the entire period, so this part of the analysis is also not immune to data limitations. However, the sample does cover well the periods before, during and after the recent western financial crisis in 2007.

Dummy variables which take the value of one if an observation is in a particular year and zero otherwise are added to the model to examine time variations in the relationship between equity volatility and the credit spread. The period dummy variables control for the common time variations in the credit spread. They are the period equivalent of the firm-specific effects estimated in the previous section. Table 5.9 presents the constant coefficient model (i.e. without fixed effects) with a time dummy variable. The first variable covers the years 1996-97 (i.e. from 1/8/1996 to 31/12/1997). The remaining years have respective dummies equal to one for a given year and zero otherwise. The base period or the period with no dummy variable is 1/1/2010 – 18/2/2011.

Table 5.9
The relationship between equity volatility and the credit spread: the period fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	970.03	84.93	11.42	0.00
Year 1996-97	-151.61	14.28	-10.61	0.00
Year 1998	-186.05	17.19	-10.82	0.00
Year 1999	-182.72	19.83	-9.22	0.00
Year 2000	-219.11	23.30	-9.40	0.00
Year 2001	-99.08	13.76	-7.20	0.00
Year 2002	-101.85	13.44	-7.58	0.00
Year 2003	-60.08	11.61	-5.17	0.00
Year 2004	-84.01	10.79	-7.79	0.00
Year 2005	-95.06	9.96	-9.54	0.00
Year 2006	-96.21	9.84	-9.78	0.00
Year 2007	-95.21	9.51	-10.01	0.00
Year 2008	-48.56	14.75	-3.29	0.00
Year 2009	131.10	19.01	6.89	0.00
C	-8.13	27.27	-0.30	0.77
R-squared	0.43	Mean dependent var		276.74
Adjusted R-squared	0.43	S.D. dependent var		360.65
S.E. of regression	271.57	Akaike info criterion		14.05
Sum squared resid	5.38E+10	Schwarz criterion		14.05
Log likelihood	-5.12E+06	Hannan-Quinn criter.		14.05
F-statistic	39,802.67	Durbin-Watson stat		0.03
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected).

These results are comparable with those of the constant coefficient model presented in Table 5.2, which implies that equity volatility remains economically significant (i.e. a one percentage point increase in equity volatility increases the credit spread by 9.7 basis points) after controlling for common time variations in the credit spread. All of the time variables are statistically significant and they raise the model’s explanatory power (R-squared) by four percentage points. This is a relatively modest increase in explanatory power when compared with the simple univariate model, taking into account the large number of observations and the fact that 13 variables are added to the model. Further, the estimated coefficient of equity volatility (970) is relatively close to the coefficient estimated without the time variables (1,049).

The improvement of four percentage points in the model R-squared, achieved by controlling the time variation, pales in comparison with the 14 percentage points improvement obtained by adding firm-specific fixed effects to the model. As implied by the structural framework, this indicates that the strength of the relationship between equity volatility and the credit spread depends primarily on firm-specific factors.

An examination of the size and sign of the time variable coefficients shows that all coefficients are negative except the coefficient for 2009. This implies that, in the aftermath of the financial crisis in 2007, the credit spread increased much more than expected, given the changes in equity volatility. However, the magnitude of the negative coefficients is particularly high in the first few years of the sample (2006-2010), implying lower levels of the credit spread.

The model presented in Table 5.9 does not allow for an inspection of variation in the power of equity volatility in explaining the credit spread. Separate models are estimated on time sub-samples to examine variations in the explanatory power. The sample is divided into five sub-samples covering approximately three years each. Table 5.10 presents the coefficients, the associated probabilities of the coefficients and the overall model R-squared for each sub-sample period.

Table 5.10
The relationship between equity volatility and the credit spread within the time sub-samples

Sub-sample	1/8/1996 - 31/12/1998	1999 - 2001	2002 - 2004	2005 - 2007	1/1/2008 - 2/18/2011
Number of cross-sections	30	201	287	341	339
Number of observations	16,220	53,330	192,974	241,430	225,661
Coefficient	109.45	449.28	813.49	589.00	1,135.13
t-Statistics	4.35	4.22	9.46	8.38	10.11
Probability	0.00	0.00	0.00	0.00	0.00
R-squared	0.08	0.25	0.45	0.28	0.36

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); White period standard errors and covariance (d.f. corrected).

All of the coefficients are statistically significant and positive as expected. The results estimated on the first time-subsample (1/8/1996 – 31/12/1998) stand out in terms of the coefficient size and the model R-squared, with both measures significantly lower than in other time sub-samples. These results should be interpreted with caution, because they are estimated on a sample containing data from only 30 firms.

The relationship between equity volatility and the credit spread appears to be the strongest in the last sub-sample which covers the recent financial crisis. As indicated by the negative coefficients of the time variables in the previous model, the coefficient of equity volatility in the last sub-sample is significantly larger than in the other sub-samples. This indicates that the economic significance of equity volatility increases in financial crises. The robustness of these results to the inclusion of various control variables is examined in subsequent sections.

5.2.5. The Two-way Fixed Effects Model

To complete an examination of the univariate relationship between the credit spread and equity volatility, a model with two-way effect controls (fixed and time) is estimated. The results, which are presented in Table 5.11, reveal that all variables except the time variable for the year 2008 remain significant and that the R-squared has slightly increased to 57 per cent. The estimated coefficient of equity volatility implies that a one percentage point increase in equity volatility widens the credit spread by 7.7 basis points which leads to the conclusion that equity volatility remains economically significant in the two-way fixed effects model. A comparison of all estimated models reveals that about 40 percentage points of the explanatory power may be attributed to equity volatility, about 13 percentage points to the fixed effects, and the remaining 4 percentage points to variations in the relationship between equity volatility and the credit spread through time. This level of explanatory power is larger than that reported by Campbell and Taksler (2003) and in line with that reported by Ericsson, Jacobs and Oviedo (2009).

Table 5.11
The relationship between equity volatility and the credit spread: the two-way fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	770.59	87.54	8.80	0.00
Year 1996-97	-142.40	16.77	-8.49	0.00
Year 1998	-162.54	15.27	-10.65	0.00
Year 1999	-147.49	18.13	-8.13	0.00
Year 2000	-163.75	20.64	-7.93	0.00
Year 2001	-70.76	13.50	-5.24	0.00
Year 2002	-76.63	13.05	-5.87	0.00
Year 2003	-59.14	10.39	-5.69	0.00
Year 2004	-95.16	9.62	-9.89	0.00
Year 2005	-109.01	9.87	-11.04	0.00
Year 2006	-109.01	9.98	-10.92	0.00
Year 2007	-103.25	9.81	-10.52	0.00
Year 2008	-15.53	16.03	-0.97	0.33
Year 2009	155.89	16.94	9.20	0.00
C	56.33	29.85	1.89	0.06
R-squared	0.57	Mean dependent var		276.74
Adjusted R-squared	0.57	S.D. dependent var		360.65
S.E. of regression	235.61	Akaike info criterion		13.76
Sum squared resid	4.05E+10	Schwarz criterion		13.77
Log likelihood	-5.02E+06	Hannan-Quinn criter.		13.76
F-statistic	2,685.78	Durbin-Watson stat		0.03
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (period fixed - dummy variables); Sample: 8/02/1996 2/18/2011; Periods included: 3797; Cross-sections included: 352; Total panel (unbalanced) observations: 729615; White period standard errors & covariance (d.f. corrected).

5.3. The Relationship between the Credit Spread and the Distance to Default of Merton (1974)

5.3.1. The Constant Coefficient Model

The distance to default variable is estimated at the daily level as described in Chapter 4. One minus the distance to default evaluated on the cumulative normal distribution, i.e. N(-D), gives the probability of default in the standard structural model. It should be noted that the probabilities of default derived in this way are typically too low, so in empirical implementation the distance to default estimates are mapped to empirical default probabilities (e.g. Crosbie and Bohn, 2003). Therefore, consistent with Vassalou and Xing (2004) and other studies, the distance to default serves in this study as an indicator of credit risk rather than strictly as a default probability.

The distance to default is a much more comprehensive variable than equity volatility as, besides equity volatility, it incorporates information about the risk-free interest rate and the firm's leverage. Therefore, the distance to default should in theory outperform equity volatility in explaining the credit spread, if it is primarily driven by credit risk. Table 5.12 presents the constant coefficient panel model.

Table 5.12
The relationship between the distance to default and the credit spread: the constant coefficient model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Distance to Default	-58.78	5.10	-11.52	0.00
C	596.33	32.24	18.50	0.00
R-squared	0.21	Mean dependent var		276.78
Adjusted R-squared	0.21	S.D. dependent var		360.72
S.E. of regression	321.04	Akaike info criterion		14.38
Sum squared resid	7.52E+10	Schwarz criterion		14.38
Log likelihood	-5.24E+06	Hannan-Quinn criter.		14.38
F-statistic	191,425.80	Durbin-Watson stat		0.01
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3797; Cross-sections included: 352; Total panel (unbalanced) observations: 729615; White period standard errors & covariance (d.f. corrected); The estimated model is $CS_{it} = \alpha + \beta DD_{it} + \varepsilon_{it}$ where CS stands for the credit spread expressed in basis points or 1/100 percentage points. CS is the distance to default of Merton (1974) estimated over a one year horizon. The value and volatility of the firm's assets are estimated as described in the methodology section.

The distance to default is highly significant with the expected negative coefficient, implying that as a firm moves away from default its credit spread narrows. An improvement in credit quality as measured by one distance to default narrows the credit spread by 58.78 basis points. The variable explains about 20 per cent of the variation in the credit spread. Interestingly, the model R-squared is almost half of the R-squared of the corresponding model for equity volatility, indicating that only a fraction of the credit spread is due to credit risk, as reported by Elton et al. (2001). Equity volatility appears to be a better variable for describing the risks reflected in the credit spread. Because of concern related to the stationarity of the credit spread, unit root tests are performed on residuals from the regression depicted in Table 5.12. The test results are presented in Table 5.13.

Table 5.13 reveals that all of the tests except the common unit root rest of Levin, Lin and Chu in Panel B and in Panel C reject the presence of unit roots.

Table 5.13
Panel unit-root test analysis of residuals from regressing the credit spread on the distance to default

Test	Statistics	Probability
Panel A: No exogenous regressors		
Levin, Lin & Chu t	-39.74	0.00
ADF - Fisher Chi-square	4,766.53	0.00
PP - Fisher Chi-square	5,037.71	0.00
Panel B: Intercept as exogenous regressor		
Levin, Lin & Chu t	1.79	0.96
Im, Pesaran and Shin W-stat	-47.05	0.00
ADF - Fisher Chi-square	5,234.74	0.00
PP - Fisher Chi-square	5,822.35	0.00
Panel C: Intercept and time trend as exogenous regressors		
Levin, Lin & Chu t	1.99	0.98
Breitung t-stat	-15.40	0.00
Im, Pesaran and Shin W-stat	-46.95	0.00
ADF - Fisher Chi-square	5,303.44	0.00
PP - Fisher Chi-square	6,160.34	0.00

All test equations include five lags

5.3.2. The Cross-sectional Fixed Effects Model

In this model specification, each firm in the sample is allowed to have its own intercept or fixed effect. The results are presented in Table 5.14.

The distance to default continues to be highly significant in explaining the credit spread after controlling for fixed effects, and size of the coefficient does not markedly differ from that in the constant coefficient model. This implies that the fixed effects do not substantially reduce the economic significance of the distance to default. After controlling for the fixed effects, an improvement is credit quality as measured by one distance to default narrows the credit spread by 53.33 basis points. An interesting finding is that the fixed effects almost double the R-squared from 21 per cent to 40 per cent, an increase which is significantly larger than the corresponding increase in the models with equity volatility.

Table 5.14
The relationship between the distance to default and the credit spread: the cross-sectional fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Distance to Default	-53.53	4.12	-12.98	0.00
C	567.77	22.42	25.32	0.00

R-squared	0.40	Mean dependent var	276.78
Adjusted R-squared	0.40	S.D. dependent var	360.72
S.E. of regression	278.51	Akaike info criterion	14.10
Sum squared resid	5.65E+10	Schwarz criterion	14.10
Log likelihood	-5.14E+06	Hannan-Quinn criter.	14.10
F-statistic	1,404.56	Durbin-Watson stat	0.01
Prob(F-statistic)	0.00		

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,252; White period standard errors and covariance (d.f. corrected).

Table 5.15 presents the test results of the significance of the fixed effects. The tests strongly rejects null hypothesis that the fixed effects are redundant. Furthermore, the Hausman test rejects the hypothesis that the fixed effects are random, indicating that the distance to default does not capture a large fraction of idiosyncratic movement in the credit spread. However, it should be noted that this model does not include any control variables (these are added in subsequent analysis).

Table 5.15
Redundant fixed-effects tests

Effects Test	Statistic	d.f.	Prob.
Cross-section F	683.92	-3.52E+08	0.00
Cross-section Chi-square	207,606.60	351.00	0.00

The tests evaluate the joint significance of the fixed effects using sums-of-squares (F-test) and the likelihood function (Chi-square test).

5.3.3. The Period Fixed Effects Model

This model examines the strength of the relationship between the distance to default and the credit spread after controlling for the common time variations in the credit spread. As in the estimation of the model with equity volatility as the explanatory variable, this model contains dummy variables taking the value of one if an observation is in a particular year and zero otherwise.

Table 5.16 reveals that all of the dummy variables are statistically significant. Controlling for the common time variations in the credit spread reduces the distance to default coefficient from -58.78 to -48.98 which implies a reduction of the economic significance of a unit change in the distance to default from 58.78 to 48.98 basis points. The time variables jointly raise the explanatory power of the model by seven percentage points, which is significantly less than the improvement of 20 percentage points achieved by including the firm-specific fixed effects. This confirms the theoretical framework prediction that firm-specific factors play a more important role in the credit spread modelling than the time-specific factors.

The dummy variable coefficients for all years up until 2008 are negative, while the coefficient for 2009 is positive and has the largest size. This finding implies that large increases in the credit spread during the recent financial crisis could not be justified by changes in the credit risk of firms. Furthermore, this can be interpreted as the presence of common risk factors in the credit spread as they appear not to be driven by credit risk. Similar to the model with equity volatility as an explanatory variable, the dummy variables for the early years within the sample are more pronounced.

Table 5.16
The relationship between the distance to default and the credit spread: the period fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Distance to Default	-48.98	4.54	-10.78	0.00
Year 1996-97	-175.94	16.45	-10.69	0.00
Year 1998	-195.81	16.23	-12.06	0.00
Year 1999	-187.57	17.00	-11.04	0.00
Year 2000	-204.53	17.38	-11.77	0.00
Year 2001	-85.46	14.58	-5.86	0.00
Year 2002	-78.91	14.74	-5.36	0.00
Year 2003	-76.18	13.20	-5.77	0.00
Year 2004	-91.22	11.29	-8.08	0.00
Year 2005	-94.90	10.30	-9.21	0.00
Year 2006	-90.15	10.07	-8.95	0.00
Year 2007	-83.01	10.02	-8.28	0.00
Year 2008	52.90	12.47	4.24	0.00
Year 2009	213.19	28.69	7.43	0.00
C	580.15	30.09	19.28	0.00
R-squared	0.28	Mean dependent var		276.78
Adjusted R-squared	0.28	S.D. dependent var		360.72
S.E. of regression	306.52	Akaike info criterion		14.29
Sum squared resid	6.85E+10	Schwarz criterion		14.29
Log likelihood	-5.21E+06	Hannan-Quinn criter.		14.29
F-statistic	20,049.71	Durbin-Watson stat		0.01
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,252; White period standard errors & covariance (d.f. corrected).

To complete the time series analysis, five separate models are estimated on time sub-samples, each covering about three years. The main results are presented in Table 5.17.

Table 5.17
The relationship between the distance to default and the credit spread in the time sub-samples

Sub-sample	1/8/1996 - 31/12/1998	1999 - 2001	2002 - 2004	2005 - 2007	1/1/2008 - 2/182011
Number of cross-sections	30	201	287	341	339
Number of observations	16,195	53,330	192,974	241,430	225,323
Coefficient	-6.63	-30.84	-39.32	-24.87	-94.91
t-Statistics	-4.93	-5.13	-7.64	-9.31	-9.74
Probability	0.00	0.00	0.00	0.00	0.00
R-squared	0.10	0.18	0.26	0.26	0.21

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); White period standard errors and covariance (d.f. corrected).

The distance to default has the expected negative sign and is highly statistically significant in all of the time-subsamples. The explanatory power varies from 10 per cent in the first subsample (1996-98) to 26 per cent in the 2005-07 sub-sample. The coefficient size in the 2008-11 subsample, which covers the recent financial crisis, is by far the largest. This implies that a change in credit risk had the largest impact upon the credit spread during the recent financial crisis.

It is interesting to compare the size of coefficients and the explanatory power of the models to the corresponding models with equity volatility. The largest differences can be observed in the last subsample which covers the recent financial crisis. Relative to the preceding subsample (2005-07), the size of the equity volatility coefficient increased by 92 per cent, while the distance to default coefficient increased markedly by 281 per cent. Surprisingly, the R-squared of the equity volatility model increases by 27 per cent, whereas the explanatory power of the distance to default model decreased by 19 per cent. This is another indication that credit risk accounts for just a fraction of the credit spread and that equity volatility outperforms the distance to default in capturing the total risk reflected in the credit spread.

5.3.4. The Two-way Fixed Effects Model

In the last step of the univariate analysis of the relationship between the credit spread and the distance to default, a model with fixed as well as time variables is presented in Table 5.18.

The explanatory power of the model is 47 per cent which implies that controlling for time and cross-sectional differences increases R-squared by 26 percentage points of which about 19 percentage points can be attributed to fixed effects and about seven percentage points to period effects. Interestingly, fixed and period effects jointly appear to outperform the distance to default in terms of explanatory power as measured by the R-squared (the R-squared is 22 per cent without the effects, and the effects add 26 percentage points). Further, fixed and period effects substantially reduce the economic significance of a unit change in the distance to default from 58.78 to 27.18 basis points. It can be argued that this is due to purely statistical reasons as a large increase in explanatory power is expected when 364 dummy variables (351 firm-specific and 13 period-specific) are added to the model. However, it should be noted that the effects have a substantially smaller impact upon the R-squared statistics of the equivalent models with equity volatility. This suggests that this result is not entirely due to statistical reasons.

Table 5.18
The relationship between the distance to default and the credit spread: the two-way fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Distance to Default	-27.18	2.76	-9.83	0.00
Year 1996-97	-145.61	17.93	-8.12	0.00
Year 1998	-143.07	15.05	-9.51	0.00
Year 1999	-119.91	15.75	-7.61	0.00
Year 2000	-108.18	13.89	-7.79	0.00
Year 2001	-41.84	12.69	-3.30	0.00
Year 2002	-40.03	11.85	-3.38	0.00
Year 2003	-66.96	11.55	-5.80	0.00
Year 2004	-107.61	10.66	-10.10	0.00
Year 2005	-117.69	10.82	-10.88	0.00
Year 2006	-114.65	10.77	-10.64	0.00
Year 2007	-101.25	10.46	-9.68	0.00
Year 2008	84.87	11.58	7.33	0.00
Year 2009	242.30	27.53	8.80	0.00
C	454.97	17.28	26.33	0.00
R-squared	0.47	Mean dependent var		276.78
Adjusted R-squared	0.47	S.D. dependent var		360.72
S.E. of regression	262.06	Akaike info criterion		13.98
Sum squared resid	5.01E+10	Schwarz criterion		13.98
Log likelihood	-5.10E+06	Hannan-Quinn criter.		13.98
F-statistic	1,788.56	Durbin-Watson stat		0.01
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected).

5.4. Systematic and Idiosyncratic Equity Volatility as Determinants of the Credit Spread

This section explores how systematic and idiosyncratic volatility affect the credit spread. According to the structural framework, the level of credit risk is influenced by total volatility which implies that all volatility components should have equal statistical and economic significance in explaining the credit spread. In empirical examination of this theoretical prediction, the common approach in the existing literature (e.g. Campbell and Taksler, 2003; Cremers et al., 2008) is to consider the volatility of returns in excess of a major equity index as idiosyncratic volatility. This approach explicitly assumes that all firms have the same exposure to systematic risks. Since the assumption that all firms in the sample have equal betas is not plausible, this study estimates the conditional betas to calculate the equity premiums and expected returns. Idiosyncratic returns are defined as the difference between the observed returns and expected returns. Table 5.19 presents the results of regressing the credit spread on systematic and idiosyncratic volatility in the constant coefficient panel model.

The size of the coefficients of systematic and idiosyncratic equity volatility in the univariate regressions is similar and both variables are highly significant in a statistical as well as in an economic sense. A one percentage point increase in the systematic and the idiosyncratic volatility widens the credit spread by 11.84 and 12.01 basis points respectively. The t-statistics of the systematic volatility coefficients are higher, but the idiosyncratic volatility appears to explain a significantly larger portion of variations in the credit spread than the systematic volatility. The R-squared of the univariate model with idiosyncratic volatility as the explanatory variable is 37 per cent whereas the R-squared of the model with systematic volatility is 24 per cent.

In the multivariate regression, both variables retain the expected positive sign and continue to be highly significant. The coefficient of the idiosyncratic volatility coefficient is significantly larger than the corresponding coefficient of the systematic volatility, which implies that the credit spread responds more strongly to changes in idiosyncratic volatility. The results suggest that a one percentage point increase in the idiosyncratic volatility raises the credit spread by 9.61 basis point, while the corresponding change in the systematic volatility widens the credit spread by 5.01 basis points. A formal test strongly rejects the hypothesis that the coefficients of idiosyncratic and systematic volatility are equal.

A comparison of the R-squared of the univariate models indicates that most of the explanatory power of the multivariate model can be ascribed to idiosyncratic volatility. This finding is generally consistent with King and Khang (2005) who find that systematic factors are less relevant for bond pricing than idiosyncratic factors. They reach this conclusion based on results obtained by regressing the credit spread on the Fama and French (1993) factors (the market, the size and the book-to-market equity factors) and argue in favour of the structural model. Unlike King and Khang who use general common factors, the results presented in Table 5.19 are based on firm-specific exposures to systematic factors. Campbell and Taksler (2003) obtain inconsistent results that average idiosyncratic volatility is a more important determinant of the credit spread for the S&P A-rated bond index, whereas the opposite is obtained for the Moody's index. One possible explanation for this is that the sample used in their study contains non-investment grade bonds which may respond more strongly to changes in idiosyncratic volatility.

Table 5.19
The relationship between the credit spread and systematic/idiosyncratic equity volatility implied by the CAPM: the constant coefficient model

Model	Univariate systematic	Univariate idiosyncratic	Multivariate
Systematic volatility (CAPM)			
Coefficient	1,184.35		501.06
t-Statistics	13.07		11.83
Probability	0.00		0.00
Idiosyncratic equity volatility (CAPM)			
Coefficient		1,200.90	960.53
t-Statistics		11.81	9.13
Probability		0.00	0.00
Adjusted R-squared	0.24	0.37	0.40

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3,795; Cross-sections included: 352; Total panel (unbalanced) observations: 729,573; White period standard errors & covariance (d.f. corrected).

The equity returns are decomposed into systematic and idiosyncratic components as described in Section 4.3.4., and the volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3.

As a check for robustness, the models presented in Table 5.19 are re-estimated with fixed and time effects. Table 5.20 presents the results of the models with fixed effects or different intercepts for each firm in the sample.

The coefficients of both volatility components in the univariate models are lower than the corresponding coefficients in the constant coefficient models presented in Table 5.19. The decrease in the magnitude of coefficients is approximately the same for both components, which implies that the economic significance of the two volatility components remains similar. A one percentage point increase in the systematic and the idiosyncratic volatility widens the credit spread by 10.24 and 10.20 basis points respectively. A comparison of the explanatory power of the univariate models with and without fixed effects reveals an interesting observation. The inclusion of fixed effects increases the R-squared of the idiosyncratic volatility model (increase of 36 per cent, from 37 to 50 per cent) in line with the increase in the total volatility model (observed in Tables 5.2 and 5.5: an increase of 35 per cent, from 39 to 53 percentage points), whereas the R-squared of the systematic volatility model almost doubles, increasing from 24 to 46 per cent. This is expected as the fixed effects capture firm-specific factors, which are by construction not reflected in systematic volatility. The coefficient of idiosyncratic volatility continues to be higher than the systematic volatility coefficient, though the difference between the two coefficients is reduced significantly from 92 per cent in the constant coefficient model to 20 per cent in the fixed effects model. The estimated coefficients imply that a one percentage point increase in the idiosyncratic volatility raises the credit spread by 7.15 basis point, while the corresponding change in the systematic volatility widens the credit spread by 5.94 basis points. This emphasizes the importance of idiosyncratic factors in the modelling of the credit spread.

Table 5.20
The relationship between the credit spread and systematic/idiosyncratic equity volatility implied by the CAPM: the cross-sectional fixed effects model

Model	Univariate systematic	Univariate idiosyncratic	Multivariate
Systematic volatility (CAPM)			
Coefficient	1,024.18		593.68
t-Statistics	12.77		15.02
Probability	0.00		0.00
Idiosyncratic equity volatility (CAPM)			
Coefficient		1,019.57	714.56
t-Statistics		9.32	6.49
Probability		0.00	0.00
Adjusted R-squared	0.47	0.50	0.53

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample: 8/01/1996 2/18/2011; Periods included: 3,795; Cross-sections included: 352; Total panel (unbalanced) observations: 729,573; White period standard errors and covariance (d.f. corrected).

The equity returns are decomposed into systematic and idiosyncratic components as described in Section 4.3.4., and the volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3.

Table 5.21 presents estimates of the models with fixed effects and annual dummy variables. The period dummy variables have the largest effect on the size of the systematic volatility coefficients. In the univariate models, the systematic volatility coefficient drops by 26 per cent while the idiosyncratic volatility coefficient decreases by 15 per cent relative to the corresponding fixed effects models. The difference in the impact of the period control variables upon the coefficients of volatility components is even larger in the multivariate model. While the size of the idiosyncratic volatility coefficient remains virtually the same relative to the fixed effects model, the size of the systematic volatility coefficient is reduced by 37 per cent. This implies a lower economic significance of systematic volatility (i.e. a one percentage point increase in the systematic and idiosyncratic volatility widens the credit spread by 3.7 and 7.07 basis points respectively) in explaining the credit spread, as it can only account for a smaller fraction of the credit spread. This is particularly true during 2009 and thereafter. These results underline the importance of idiosyncratic factors in the modelling of the credit spread, consistent with the structural model. The results also indicate differences in the economic and statistical significance of the systematic and idiosyncratic volatility components.

Table 5.21
The relationship between the credit spread and systematic/idiosyncratic equity volatility implied by the CAPM: the two-way fixed effects model

Model	Univariate systematic	Univariate idiosyncratic	Multivariate
Systematic volatility (CAPM)			
Coefficient	762.79		371.39
t-Statistics	10.06		8.97
Probability	0.00		0.00
Idiosyncratic equity volatility (CAPM)			
Coefficient		862.89	706.51
t-Statistics		7.62	6.13
Probability		0.00	0.00
Adjusted R-squared	0.52	0.56	0.57

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section and period fixed - dummy variables); Sample: 8/01/1996 2/18/2011; Periods included: 3,795; Cross-sections included: 352; Total panel (unbalanced) observations: 729,573; White period standard errors and covariance (d.f. corrected).

The equity returns are decomposed into systematic and idiosyncratic components as described in Section 4.3.4., and the volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3.

As noted above, the decomposition of equity returns for this analysis is based on the CAPM. Since the CAPM’s empirical failing to capture variation in equity returns is well documented, the above analysis is also conducted on the decomposition of equity returns based on the Fama and French (1993) three factor model. Table 5.22 presents the results of regressing the credit spread on the volatility components in the constant coefficient panel model.

The decomposition of equity returns using the Fama and French (1993) model, which is fully described in Section 4.3.4, instead of the CAPM does not significantly change the results. In the univariate regressions, the volatility of idiosyncratic returns continues to explain significantly more variation in the credit spread than the systematic volatility explains, while the economic significance of the two volatility components is similar. In the multivariate regression, idiosyncratic volatility again appears to dominate systematic volatility in terms of the economic significance.

Table 5.22
The relationship between the credit spread and systematic/idiosyncratic equity volatility implied by the Fama and French three factor model: the constant coefficient model

Model	Univariate systematic	Univariate idiosyncratic	Multivariate
Systematic volatility (Fama and French)			
Coefficient	1,097.31		423.49
t-Statistics	12.38		10.04
Probability	0.00		0.00
Idiosyncratic equity volatility (Fama and French)			
Coefficient		1,169.83	919.07
t-Statistics		11.50	8.74
Probability		0.00	0.00
Adjusted R-squared	0.26	0.36	0.39

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected).

The equity returns are decomposed into systematic and idiosyncratic components as described in Section 4.3.4., and the volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3.

Table 5.23 presents estimates of the fixed effects model. These results are not affected by the choice of the equity returns model. As in the CAPM version, the fixed effects substantially increase the explanatory power of the univariate model with systematic volatility. The model's R-squared increases from 26 to 47 per cent. Further, similarly to the model with the decomposition of equity returns based on the CAPM, the difference between the sizes of the estimated coefficients is significantly reduced in the multivariate model. However, the idiosyncratic volatility retains its dominance over the systematic volatility in terms of its economic significance (i.e. a one percentage point increase in the systematic and idiosyncratic volatility widens the credit spread by 5.04 and 6.71 basis points respectively).

Table 5.23
The relationship between the credit spread and systematic/idiosyncratic equity volatility implied by the Fama and French three factor model: the cross-sectional fixed effects model

Model	Univariate systematic	Univariate idiosyncratic	Multivariate
Systematic volatility (Fama and French)			
Coefficient	928.44		503.90
t-Statistics	11.84		12.20
Probability	0.00		0.00
Idiosyncratic equity volatility (Fama and French)			
Coefficient		984.19	670.79
t-Statistics		9.07	6.00
Probability		0.00	0.00
Adjusted R-squared	0.47	0.50	0.52

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected).

The equity returns are decomposed into systematic and idiosyncratic components as described in Section 4.3.4., and the volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3.

Finally, Table 5.24 presents the two-way effect panel model with controls for cross-sectional, as well as period, effects. These results provide further confirmation that the previously reported findings are not affected by the choice of model for decomposing equity returns into systematic and idiosyncratic components. The Fama and French model may give a better estimate of systematic returns than the CAPM, because it has the three systematic factors. However, this does not negate the advantage of idiosyncratic volatility over systematic volatility in terms of economic significance. In fact, the relative difference between the coefficients in the multivariate regression is even larger than that in the corresponding model with the CAPM based decomposition. In the univariate models, a one percentage point increase in the systematic and idiosyncratic volatility widens the credit spread by 7.03 and 8.30 basis points, while in the multivariate model, the economic impact of the idiosyncratic volatility is more than two times the economic impact of the systematic volatility (i.e. 6.54 versus 3.18 basis points).

Table 5.24
The relationship between the credit spread and systematic/idiosyncratic equity volatility implied by the Fama and French three factor model: the two-way fixed effects model

Model	Univariate systematic	Univariate idiosyncratic	Multivariate
Systematic volatility (Fama and French)			
Coefficient	702.61		318.22
t-Statistics	9.39		7.58
Probability	0.00		0.00
Idiosyncratic equity volatility (Fama and French)			
Coefficient		829.93	653.54
t-Statistics		7.34	5.55
Probability		0.00	0.00
Adjusted R-squared	0.53	0.56	0.57

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section and time fixed - dummy variables); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected).

The equity returns are decomposed into systematic and idiosyncratic components as described in Section 4.3.4., and the volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3.

5.5. The Interaction between Equity Volatility and Credit Risk in Explaining Variations in the Credit Spread

The structural model implies that the relationship between equity volatility and the credit spread depends on the level of credit risk. The relationship should be stronger for riskier firms as an increase in the equity volatility of those firms may significantly increase the default probability and hence the potential loss which bondholders face. On the other hand, the potential of equity volatility to meaningfully raise the default probability of high credit quality firms is limited. This implies that it is important to control for the level of credit risk in an analysis of the relationship between the credit spread and equity risk measures. Fixed effects in panel models control for the cross-sectional difference in the level of credit risk to some extent, but since fixed effects are time invariant they cannot capture changes in credit risk over time. A common approach in the literature is to use credit ratings to control for credit risk, which amounts to creating a set of dummy variables taking the value of one if a firm is assigned a particular rating by a major rating agency or zero otherwise. Although appealing on the basis of its simplicity, this approach limits empirical analysis because of the credit ratings are coarse-grained. To overcome this limitation of credit ratings, the level of credit risk is controlled for with an interaction variable (equity volatility times the distance to default), and alternatively with dummy variables for ranges of the distance to default values.

Table 5.25 presents an estimate of the panel model with the equity volatility and the distance to default interaction variable. The coefficient of the interaction variable is negative as expected. It implies that the impact of changes in equity volatility on the credit spread increases with the level of credit risk (i.e. as the distance to default decreases). Equity volatility is virtually economically insignificant in explaining the credit spread on bonds issued by firms five distances away from the default point, and the economic significance of a one percentage point change in equity volatility increases at the rate of 1.68 basis points per unit change in the distance to default. When compared to the univariate model presented in Table 5.2, the coefficient of equity volatility drops from 1,049 to 835 while the R-squared increases from 39 to 42 per cent. This finding is generally consistent with Campbell and Taksler (2003) and Cremers et al. (2008) who use accounting leverage ratios and credit ratings to proxy for the level of credit risk. It is interesting to note that these studies do not evidence a monotonic increase in the importance of equity volatility as credit ratings and the leverage ratio deteriorate. Campbell and Taksler estimate a larger coefficient for firms with long-term debt to assets ratios between 10 and 25 per cent than more leveraged firms with a ratio of between 25 and 66 per cent. Cremers et al. obtain the same inconsistent result for BBB+/BBB- and BB+ and lower rated firms.

Table 5.25
Interaction between equity volatility and the distance to default in explaining variations in the credit spread

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	834.80	59.31	14.07	0.00
Equity Volatility x Distance-to-Default	-168.45	21.96	-7.67	0.00
C	233.48	29.63	7.88	0.00
R-squared	0.42	Mean dependent var		276.78
Adjusted R-squared	0.42	S.D. dependent var		360.72
S.E. of regression	273.97	Akaike info criterion		14.06
Sum squared resid	5.47E+10	Schwarz criterion		14.06
Log likelihood	-5.13E+06	Hannan-Quinn criter.		14.06
F-statistic	267,486.20	Durbin-Watson stat		0.03
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3797; Cross-sections included: 352; Total panel (unbalanced) observations: 729252; White period standard errors & covariance (d.f. corrected).

To further examine this effect, seven dummy variables are created for values of the distance to default variable. The results are presented in Table 5.26. The dummy variable which indicates the lowest credit risk (i.e. distance to default ≥ six) is dropped to avoid the multicollinearity problem (the dummy variable trap). The impact of equity volatility monotonically increases with an increase in credit risk (i.e. a decrease in the distance to default). All control variables are highly statistically significant. This clearly confirms the prediction of the structural model that the credit spread becomes more sensitive to changes in volatility as the default probability increases. Interestingly, the results suggest that equity volatility has a negative impact upon the credit spread on bonds issued by the highest-quality firms (i.e. firms with a distance to default above five). A one percentage point increase in equity volatility widens the credit spread on the highest-risk bonds (i.e. the group with $DD < 1$) by 9.44 basis points, while it narrows the credit spread on the lowest quality bonds by 3.12 basis points (i.e. the group with $DD > 6$).

Table 5.26
The relationship between the credit spread and equity volatility across distance to default groups

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	-312.42	94.75	-3.30	0.00
Equity Volatility x I (DD < 1)	1,256.89	106.15	11.84	0.00
Equity Volatility x I (1 ≤ DD > 2)	950.84	79.86	11.91	0.00
Equity Volatility x I (2 ≤ DD > 3)	731.83	61.94	11.82	0.00
Equity Volatility x I (3 ≤ DD > 4)	532.28	50.15	10.61	0.00
Equity Volatility x I (4 ≤ DD > 5)	356.15	37.00	9.63	0.00
Equity Volatility x I (5 ≤ DD > 6)	208.51	26.02	8.01	0.00
C	213.87	21.45	9.97	0.00

R-squared	0.43	Mean dependent var	276.78
Adjusted R-squared	0.43	S.D. dependent var	360.72
S.E. of regression	272.03	Akaike info criterion	14.05
Sum squared resid	5.40E+10	Schwarz criterion	14.05
Log likelihood	-5.12E+06	Hannan-Quinn criter.	14.05
F-statistic	78,997.99	Durbin-Watson stat	0.04
Prob(F-statistic)	0.00		

Dependent Variable: Credit Spread; Method: Panel Least Squares; Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,252; White period standard errors and covariance (d.f. corrected).

Although the distance to default appears to be successful in grouping observations according to the level of credit risk, it implies zero default probability for the majority of estimates, which is unrealistic. Therefore, the distance to default appears to perform well as a credit risk indicator, but its conversion into probability of default, as envisaged by the structural model, is clearly problematic. This explains the finding of Campbell and Taksler that the impact that equity volatility has on the credit spread is larger than predicted by the structural model, and a weak correlation between the credit spread and the default probability implied by the structural model reported by Bharath and Shumway (2008).

As previously noted, Vassalou and Xing (2004) consider the distance to default as a credit risk indicator, and Crosbie and Bohn (2003) note that Moody's Analytics maps distance to default values to default probabilities according to an empirical default probability distribution.

5.6. The Relationship between the Credit Spread and Common Factors

The structural model predicts a negative correlation between the credit spread and the risk-free rate. An increase in risk-free rate increases a drift or the expected growth rate in the asset value process. As a consequence, the value of assets grows at a faster rate and moves away from the default point. This prediction of the structural model is confirmed by Duffee (1998) and other empirical studies.

The influence that other common risk factors have on the value of the underlying assets is expected to be reflected in equity volatility and returns. Therefore, common factors should be inferior to firm-level risk measures in explaining the credit spread. In a widely cited paper, Collin-Dufresne, Goldstein and Martin (2001) provide the evidence against this argument. They argue that S&P 500 index returns are a more economically significant determinant of the credit spread than firms' own equity returns, which leads them to conclude that equity and bond markets are not integrated. To re-examine this finding, S&P 500 index returns and volatility are included in the analysis and their significance is compared to the significance of the systematic and idiosyncratic components of firm-level equity returns and volatility.

The slope of the risk-free term structure is used as another variable to capture common risk factors. Collin-Dufresne, Goldstein and Martin interpret this slope as an indicator of the health of the overall economy as well as a determinant of the future short-term rate. Following these authors and Campbell and Taksler (2003), this study defines the slope as the difference between 10-year and 2-years Benchmark Treasury yields obtained from the Thomson Reuters Datastream database. Before proceeding with the regression analysis, the strength of the correlation among the variables is considered. Table 5.27 presents the bivariate correlation coefficients between the credit spread, equity volatility, the distance to default and other variables.

The correlation with the credit spread of above +/-20 per cent is observed for total equity volatility (63 per cent) and volatility components, the distance to default (-47 per cent), S&P 500 index volatility (35 per cent), the risk-free rate (-25 per cent) and the slope of risk-free term structure (21 per cent). Total firm-level equity volatility exhibits the strongest correlation with the credit spread, a correlation which is substantially stronger than the correlation between the credit spread and the S&P 500 index volatility. It is also interesting to note that firm-level systematic volatility is more strongly correlated with the credit spread (51 per cent) than S&P 500 index volatility (35 per cent). This indicates the importance of taking into account cross-sectional differences in betas.

These results are in contrast with Collin-Dufresne, Goldstein and Martin (2001) who argue that the credit spread is primarily driven by a common factor rather than firm-specific factors as implied by the structural model. Cremers et al. (2008) also obtain stronger correlation between the credit spread and firm-level equity volatility (86 per cent) than between the credit spread and S&P 500 index volatility (82 per cent). It should be noted that the difference between the two correlation coefficients is much smaller than the correlation reported in this study. This is probably because the data sample used in Cremers et al. (2008) is mostly populated by investment grade bonds.

As confirmed in the previous analysis (in Sections 5.2. and 5.3), equity volatility outperforms the distance to default in terms of the strength of its correlation with the credit spread. The correlation between equity volatility and the distance to default is moderately high at -67 per cent, which is expected as equity volatility is a key variable used in the estimation of the distance to default.

When compared to volatility, equity returns are substantially less correlated with the credit spread. Although the coefficients are small, it is interesting to note that the correlation coefficient between the credit spread and idiosyncratic equity returns is negative, whereas systematic equity returns and the equity premium are positively correlated with the credit spread. Existing empirical studies (e.g. Collin-Dufresne, Goldstein and Martin, 2001; Campbell and Taksler, 2003; Avramov, Jostova and Philipov, 2007) commonly report a negative correlation between the credit spread and total equity returns or returns in excess of a major equity index. The systematic returns and equity premiums in this study are derived from firm-level exposure to systematic risks. Therefore, a higher systematic equity return implies a higher exposure to systematic risks and therefore warrants a higher credit spread.

The correlation between the credit spread and the risk-free rate is as negative as predicted by the structural model and is confirmed by Duffee (1998) and other empirical studies. The slope of the term structure of the risk-free rate is positively correlated with the credit spread. This is an unexpected sign if the slope is interpreted as an indicator of overall economic health or a determinant of the future short-term rate (Collin-Dufresne, Goldstein and Martin, 2001).

Table 5.27
Bivariate correlation coefficients between the credit spread and firm-level and common risk factors

Variable	Credit Spread	Distance-to-Default	Equity Volatility
Credit Spread			
Distance-to-Default	-0.46		
Equity Volatility	0.63	-0.67	
Idiosyncratic Equity Volatility	0.60	-0.61	0.91
Systematic Equity Volatility	0.51	-0.52	0.78
Idiosyncratic Equity Returns	-0.01	0.01	-0.01
Systematic Equity Returns	0.01	-0.01	0.02
Equity Premium	0.01	-0.01	0.02
Risk-free Rate	-0.25	0.05	-0.06
Risk-free Term Structure Slope	0.21	-0.09	0.07
S&P 500 Index Returns	0.00	0.01	0.00
S&P 500 Index Volatility	0.35	-0.39	0.52

The S&P 500 index returns and firm-level equity returns are calculated and decomposed into systematic and idiosyncratic components as described in Section 4.3.4. All volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3.

The risk free rate is the 1-month T-Bill rate (annualized); The Risk-free Term Structure Slope is the difference between annualized yields of 10-year and 2-year Benchmark Treasury Bonds.

The model presented in Table 5.28 examines the importance of common variables in explaining the credit spread variations. The most significant variable is S&P 500 index volatility. The coefficient is positive as expected and is similar in size to the coefficient of firm-level equity volatility (i.e. a one percentage point increase in the S&P 500 index volatility widens the credit spread by 10.46 basis points). However, the S&P 500 index volatility explains a substantially smaller fraction of the credit spread variation than firm-level volatility as the R-squared of the above model is 15 per cent while the R-squared of the univariate model with firm-level equity volatility stands at 39 per cent (Table 5.2).

The S&P 500 index returns are found to be insignificant and the estimated coefficient is unexpectedly positive, a finding which is generally inconsistent with other studies. As noted above, Collin-Dufresne, Goldstein and Martin (2001) find S&P 500 index returns to be significant in explaining changes in the credit spread. Campbell and Taksler (2003) find returns on the CRSP value-weighted index to be negative and statistically as well as economically significant. Hibbert et al. (2011) also find the market premium to be significant across all rating categories. In contrast, Cremers et al. (2008) obtain mixed results, finding mostly insignificant coefficients for the credit spread on short-term bonds and the opposite result for long-term bonds. Ericsson, Jacobs and Oviedo (2009) also get mixed results using the credit default swap premia as the independent variable.

The coefficients of the risk-free rate and the term structure slope are significant and negative, as expected. The risk-free rate indicators appear to be highly significant in a economic sense as well. A one percentage point increase in the risk-free rate lowers the credit spread by 44.99 basis points, while a one percentage point increase in the term structure slope narrows the credit spread by 34.55 basis points. This is consistent with a prediction of the structural model and an interpretation of the slope as an indicator of overall economic health or a determinant of the future short-term rate (Collin-Dufresne, Goldstein and Martin, 2001). The result for the risk-free rate is consistent with other studies (e.g. Duffee, 1998), while existing studies do not produce consistent results for the slope. Campbell and Taksler (2003) obtain a negative and significant coefficient in most regressions, while Collin-Dufresne, Goldstein and Martin get mixed results. Further, Avramov, Jostova and Philipov (2007) obtain a negative coefficient for the 5-2 year slope, whereas the 10-2, 30-2 and 30-10 year slopes all have positive coefficients.

Table 5.28
The relationship between the credit spread and common factors

Variable	Coefficient	Std. Error	t-Statistic	Prob.
S&P 500 Index Volatility	1,045.85	64.17	16.30	0.00
S&P 500 Index Returns	15.48	27.46	0.56	0.57
Risk-free Rate	-4,499.10	478.89	-9.39	0.00
Risk-free Slope	-3,454.80	756.20	-4.57	0.00
C	232.15	18.85	12.31	0.00
R-squared	0.15	Mean dependent var		279.07
Adjusted R-squared	0.15	S.D. dependent var		366.32
S.E. of regression	337.98	Akaike info criterion		14.48
Sum squared resid	8.50E+10	Schwarz criterion		14.48
Log likelihood	-5.39E+06	Hannan-Quinn criter.		14.48
F-statistic	32,505.86	Durbin-Watson stat		0.02
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 743,924; White period standard errors and covariance (d.f. corrected); The S&P 500 index returns and firm-level equity returns are calculated and decomposed into systematic and idiosyncratic components as described in Section 4.3.4. All volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3; The risk free rate is the 1-month T-Bill rate (annualized); The Risk-free Term Structure Slope is the difference between annualized yields of 10-year and 2-year Benchmark Treasury Bonds.

The model in Table 5.29 combines the common and firm-specific variables. Neither the S&P 500 index returns nor both components of the firm-level equity returns are significant. Furthermore, the S&P 500 index volatility is insignificant at the 10 per cent level. However, both components of the firm-level equity volatility are highly significant.

Table 5.29
The performance of firm-level and common factors in explaining the credit spread

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Idiosyncratic Equity Volatility	936.41	104.36	8.97	0.00
Systematic Equity Volatility	291.55	55.24	5.28	0.00
Idiosyncratic Equity Returns	13.20	41.67	0.32	0.75
Systematic Equity Returns	46.60	67.13	0.69	0.49
S&P 500 Index Volatility	112.64	69.64	1.62	0.11
S&P 500 Index Returns	-91.66	65.01	-1.41	0.16
Risk-free Rate	-3,935.16	342.73	-11.48	0.00
Risk-free Slope	-2,665.03	572.36	-4.66	0.00
C	38.23	16.18	2.36	0.02
R-squared	0.41	Mean dependent var		276.74
Adjusted R-squared	0.41	S.D. dependent var		360.65
S.E. of regression	277.46	Akaike info criterion		14.09
Sum squared resid	5.62E+10	Schwarz criterion		14.09
Log likelihood	-5.14E+06	Hannan-Quinn criter.		14.09
F-statistic	62,887.87	Durbin-Watson stat		0.05
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected).

The S&P 500 index returns and firm-level equity returns are calculated and decomposed into systematic and idiosyncratic components as described in Section 4.3.4. All volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3.

The risk free rate is the 1-month T-Bill rate (annualized); The Risk-free Term Structure Slope is the difference between annualized yields of 10-year and 2-year Benchmark Treasury Bonds.

Estimated coefficients of both firm-level volatility components are larger than the coefficient of S&P 500 index volatility. The coefficient of idiosyncratic volatility is similar in size to the corresponding coefficient in the model without common factors (Table 5.22), while the coefficient of firm-level systematic volatility is reduced from 423.5 to 291.5. It is interesting to note that adding firm-level volatility to the model reduces the coefficient of S&P index volatility by 89 per cent, from 1,045.85 to 112.64, and makes it statistically insignificant.

The difference in the significance of S&P 500 volatility index and firm-level systematic volatility indicates that removing the assumption that the betas of all firms are equal to one can affect the results of the analysis focusing of systematic volatility. Campbell and Taksler (2003) conduct their analysis of the relationship between the credit spread and equity volatility assuming that all betas are equal to one, but also note that their results hold after the assumption of equal betas is removed. In addition to confirming the importance of idiosyncratic volatility, the above results point to the importance of firm-level systematic volatility in determining the credit spread.

The coefficients of firm-level returns are surprising as both components of equity returns at the firm-level are insignificant. Further, both estimated coefficients are positive, whereas the coefficient of the S&P 500 index returns is negative as expected. It is interesting to observe that the S&P 500 index returns coefficient is significant at the 20 per cent level. This result is in line with Collin-Dufresne, Goldstein and Martin (2001), but is inconsistent with Campbell and Taksler (2003) who report a significant relationship between the credit spread at the monthly level and excess firm-level equity returns. Hibbert et al. (2011) obtain a significant negative relationship between firm-level (total) equity returns and changes in the credit spread at the daily level.

When considering the importance of firm-level equity returns relative to the importance of equity volatility and market returns, the above results are consistent with other studies. Campbell and Taksler find firm-level equity volatility and market returns to be substantially more significant, both statistically and economically, than firm-level equity returns. Hibbert et al. obtain the same result for aggregate equity volatility as measured by the VIX index.

It should be noted that firm-level systematic equity volatility and returns are by construction correlated with S&P 500 index volatility and returns. The correlation between the volatility measures is 60 per cent, while the strength of correlation between the returns is 70 per cent. Including both measures of systematic volatility and returns in the model, therefore, may be misleading. Therefore, two additional versions of the above model are presented in Table 5.30, one with firm-level measures and the other with S&P 500 index measures of systematic equity volatility and returns.

The results show that all measures of equity returns, including S&P index 500 returns, are insignificant. It is interesting to note that the coefficients of systematic volatility measures are similar in magnitude, but the firm-level measure appears to produce substantially higher t-statistics.

Table 5.30
The difference in the performance of firm-specific and S&P 500 index based measures of systematic risk

Variable	Model with firm-level Variables	Model with S&P 500 Index Variables
Idiosyncratic Equity Volatility	934.93	1,060.14
t-Statistics	[8.92]	[9.65]
Idiosyncratic Equity Returns	-2.25	-0.84
	[-0.06]	[-0.02]
Risk-free Rate	-3,918.14	-4,293.60
	[-11.29]	[-12.23]
Risk-free Slope	-2,403.66	-3,231.16
	[-3.98]	[-5.58]
Systematic Equity Volatility	337.87	
	[7.97]	
Systematic Equity Returns	-29.92	
	[-0.79]	
S&P 500 Index Volatility		310.37
		[5.88]
S&P 500 Index Returns		2.96
		[0.11]
Adjusted R-squared	0.41	0.40

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected).

The S&P 500 index returns and firm-level equity returns are calculated and decomposed into systematic and idiosyncratic components as described in Section 4.3.4. All volatilities of the returns are estimated from a GARCH(1,1) model as described in Section 4.3.3.

The risk free rate is the 1-month T-Bill rate (annualized); The Risk-free Term Structure Slope is the difference between annualized yields of 10-year and 2-year Benchmark Treasury Bonds.

The t-statistics are shown in parentheses.

To summarize, the findings in this study on the importance of equity returns are not easily reconciled with existing studies. However, it is clear that equity volatility is far more important than equity returns in the modelling of the credit spread.

5.7. Changes in the Credit Spread

The existing empirical studies focus on the determinants of credit spread (e.g. Cambell and Taksler, 2003; Cremers et al., 2008; Zhang, Zhou and Zhu, 2009; Cremers et al., 2008; Ericsson, Jacobs and Oviedo, 2009) or changes in the credit spread (e.g. Dufresne, Goldstein and Martin, 2001; Hibbert et al., 2011; Avramov, Jostova and Philipov 2007, Ericsson, Jacobs and Oviedo, 2009). The analysis of changes in the credit spread requires the differencing of all of the variables. As Cremers et al. (2008) note, the differencing removes cross-sectional differences in variables and therefore reduces the scope of the analysis to the time dimension. Furthermore, information on the long-term relationship between the variables is lost if they are cointegrated, as the results of the cointegration tests suggest. On the other hand, as Ericsson, Jacobs and Oviedo (2009) note, although level regressions provide consistent point estimates, the differencing may improve the efficiency of the coefficients. Table 5.31 shows the coefficients and associated t-statistics estimated by regressing changes in the credit spread on changes in equity volatility, changes in the distance to default and the interaction variable.

All of the variables are significant and exhibit the expected signs. However, the R-squared of the models is approaching zero. This confirms the finding of Dufresne, Goldstein and Martin (2001) and others that the theoretically important variables explain just a negligible fraction of changes in the credit spread. However, the estimates of the statistical significance of equity volatility and the distance to default are consistent with those obtained from the level regressions. A comparison of the t-statistics of the coefficients in the change and corresponding level regressions reveal that they are very similar for equity volatility and the distance to default, while the t-statistic of the interaction variable is smaller in the change regression than the level regression. In the corresponding univariate level regression, the coefficient of equity volatility has a t-statistic of 12.97, while the t-statistic associated with the distance to default is 11.52. In the last level model, the t-statistic for equity volatility is 14.01 and the t-statistic for the interaction variable is -7.76.

Table 5.31
The Significance of equity volatility and the distance to default in explaining changes in the credit spread

	Model 1	Model 2	Model 3
Δ Equity Volatility	6.92		7.18
	[10.99]		[11.29]
Δ Distance to Default		-0.37	
		[-5.07]	
Δ Equity Volatility x Distance to Default			-0.75
			[-2.92]
Adjusted R-Squared	0.00	0.00	0.00

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/02/1996 2/18/2011; Periods included: 3,796; Cross-sections included: 352; Total panel (unbalanced) observations: 729,263. The t-statistics are shown in parentheses.

5.8. Robustness of the Results

5.8.1. Equity Volatility Modelled as an Asymmetric EGARCH Process

Existing empirical evidence suggests that the credit spread responds asymmetrically to changes in equity volatility. Collin-Dufresne, Goldstein and Martin (2001), for example, report that the credit spread responds asymmetrically to changes in the VIX index. Therefore, equity volatility modelled as an asymmetric EGARCH process may perform better in explaining the credit spread than the standard GARCH process which does not differentiate between positive and negative (return) innovations in volatility estimation.

Table 5.32 offers a summary of results for all univariate panel models estimated in Section 5.1.

Table 5.32
EGARCH equity volatility and the credit spread

Model	Constant coefficient	Fixed effects	Period effects	Two-way effect
Coefficient	1,068.35	922.31	988.44	776.64
t-Statistics	9.98	7.88	8.48	6.04
Probability	0.00	0.00	0.00	0.00
Adjusted R-squared	0.38	0.52	0.42	0.56

Dependent Variable: Credit Spread; Explanatory Variable: EGARCH Equity Volatility; Method: Panel Least Squares (constant coefficient model); White period standard errors and covariance (d.f. corrected).

The estimated models are 1) $CS_{it} = \alpha + \beta EV_{it} + \varepsilon_{it}$; 2) $CS_{it} = \alpha_i + \beta EV_{it} + \varepsilon_{it}$; 3) $CS_{it} = \alpha + \beta EV_{it} + \sum \beta Y_j + \varepsilon_{it}$; 4) $CS_{it} = \alpha_i + \beta EV_{it} + \sum \beta Y_j + \varepsilon_{it}$ where CS stands for the credit spread expressed in basis points or 1/100 percentage points. EV is equity volatility estimated as an EGARCH (1,1,1) process from daily equity returns and multiplied by $\sqrt{255}$. Y_j are dummy variables taking the value on 1 if an observation occurs in a particular year and zero otherwise.

These results are very similar to the corresponding results of the models with GARCH equity volatility as the explanatory variable. The coefficients of EGARCH volatility are slightly larger than the corresponding coefficients of GARCH volatility, while the opposite is true for model significance in terms of the R-squared. Table 5.33 presents the results of models estimated on the time subsamples as is the case in Table 5.10.

Table 5.33
EGARCH equity volatility and the credit spread in time subsamples

Sub-sample	1/8/1996 - 31/12/1998	1999 - 2001	2002 - 2004	2005 - 2007	1/1/2008 - 2/18/2011
Number of cross-sections	30	201	287	341	339
Number of observations	16,220	53,330	192,974	241,430	225,661
Coefficient	113.61	504.36	889.71	583.45	1,134.51
t-Statistics	3.98	4.09	9.55	7.05	6.83
Probability	0.00	0.00	0.00	0.00	0.00
R-squared	0.08	0.26	0.48	0.28	0.34

Dependent Variable: Credit Spread; Explanatory Variable: EGARCH Equity Volatility; Method: Panel Least Squares (constant coefficient model); White period standard errors and covariance (d.f. corrected).

These results are also similar to those of the corresponding models with GARCH equity volatility. It is interesting to note that the EGARCH models have a slightly higher R-squared than the corresponding GARCH models for the first three subsamples, but in the last two subsamples, which cover the recent financial crisis, the explanatory power is slightly lower. This reason for this is simply that the EGARCH model produces very large volatility estimates when there are large changes in equity prices. This feature of the EGARCH model appears to be very problematic. On a single day, 12 March 2007, the share price of one firm in the sample (Health Management Associates, Inc.) dropped from USD 19.87 to USD 10.29. As a result, the annualized volatility based on the EGARCH model is 1186.05 or 118,605% (whereas the GARCH estimate is 7.5 or 750%). A few observations around this date significantly reduce the R-squared of the model covering the period 2005-2007 in Table 5.33. To avoid this, a few EGARCH estimates of equity volatility (nine in total) are replaced by the GARCH estimates.

5.8.2. Firm Size

Existing empirical studies provide ample evidence that firm size is a significant determinant of the credit spread. Ceteris paribus, larger firms enjoy lower funding costs and higher credit ratings than smaller firms. Demirovic and Thomas (2007) find that measures of firm size are highly correlated with the credit ratings of firms. Furthermore, they report that the market value of assets implied by the structural model outperforms the book value of assets in terms of the strength of correlation with credit ratings. Following this finding, firm size is measured as the logarithm of the structural model implied market value of assets. This variable is estimated as described in the previous chapter. Five dummy variables are created based on the logarithm of asset values. The largest values are the base case and have no dummy variable. Table 5.34 shows the coefficients and associated t-statistics estimated by regressing the credit spread on equity volatility, the distance to default, the interaction variable and the size dummy variables.

The coefficients of the size variables have the expected positive sign, indicating that smaller firms have a wider credit spread. All three of the main variables continue to be significant and retain their expected signs after controlling for firm size. All dummy variables except the one for the largest firms (Dummy 4) are significant at the five per cent level in the equity volatility model. Dummy 3 is insignificant in the models with the distance to default and the interaction variable.

Table 5.34
The significance of equity volatility and the distance to default in explaining changes in the credit spread when controlling for firm size

	Model 1	Model 2	Model 3
Equity Volatility	976.83		794.94
	[12.11]		[13.48]
Distance to Default		-51.27	
		[-10.72]	
Equity Volatility x Distance to Default			-150.74
			[-6.67]
Asset Value Dummy 1 (smallest)	184.96	224.51	157.20
	[6.43]	[5.99]	[5.39]
Asset Value Dummy 2	66.90	42.41	50.76
	[4.23]	[2.10]	[3.32]
Asset Value Dummy 3	37.48	12.65	22.73
	[2.67]	[0.72]	[1.71]
Asset Value Dummy 4 (largest)	9.92	-3.70	2.59
	[0.82]	[-0.25]	[0.23]
C	-112.33	520.47	189.12
	[-4.56]	[15.43]	[5.73]
Adjusted R-Squared	0.42	0.24	0.44

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample (adjusted): 8/02/1996 2/18/2011; Periods included: 3,796; Cross-sections included: 352; Total panel (unbalanced) observations: 729,263; White period standard errors and covariance (d.f. corrected); Asset Value Dummy 1 takes the value of 1 if the firm's asset value is up to 2,322 US$ million (178,674 observations); Dummy 2 is up to 4,915 million (177,819 observations); Dummy 3 is up to 10,405 million (231,074 observations); Dummy 4 is up to 22,026 million (207,485 observations) and Dummy 5, which is dropped from the model as the base case, is above 22,026 million (293,065 observations); The t-statistics are shown in parentheses.

5.8.3. Bond-specific Variables

A longer bond maturity indicates, ceteris paribus, a higher risk and therefore maturity should affect the strength of the relationship between the credit spread and risk measures. As for the level of credit risk, the bond maturity effect is to some degree controlled for by the fixed effects in the panel data analysis. However, since the maturity of bonds is not static but changes over time, a set of dummy variables is created to explicitly control for the maturity of bonds. Following King and Khang (2005), duration is used to control for maturity. Unlike the number in years to maturity, duration incorporates the complete set of cash flows of bonds and takes into account differences in coupon payments as well.

Liquidity is also a bond-specific variable that can influence the empirical results. Elton et al. (2004) report that liquidity is an important factor in corporate bond valuation.

Following Campbell and Taksler (2003), the logarithm of bond issue size is used to control for the cross-sectional differences in bond liquidity. Further, as previously noted, bonds with the smallest issue values are excluded from the sample because of liquidity concerns.

Two sets of four dummy variables are created to control for bond duration and issue size. Table 5.35 depicts the coefficients and associated t-statistics estimated by regressing the credit spread on equity volatility, the distance to default, the interaction variable and the two sets of dummy variables. Bonds with the largest issue size and the longest duration have no dummies in these models.

Table 5.35
The significance of equity volatility and the distance to default in explaining changes in the credit spread when controlling for bond duration and issue size

	Model 1	Model 2	Model 3
Equity Volatility	1,014.24		809.31
	[13.13]		[14.10]
Distance to Default		-55.51	
		[-11.73]	
Equity Volatility x Distance to Default			-163.75
			[-7.41]
Bond Value Dummy 1 (smallest)	54.13	66.78	47.91
	[2.41]	[2.38]	[2.26]
Bond Value Dummy 2	49.32	68.53	48.68
	[2.82]	[3.40]	[3.11]
Bond Value Dummy 3	19.45	40.65	29.66
	[1.45]	[2.60]	[2.52]
Bond Duration Dummy 1 (shortest)	86.60	133.16	88.59
	[3.92]	[4.57]	[4.13]
Bond Duration Dummy 2	39.31	58.28	38.04
	[3.77]	[4.42]	[3.82]
Bond Duration Dummy 3	-17.13	-10.43	-8.04
	[-1.49]	[-0.82]	[-0.70]
C	-132.48	497.85	179.86
	[-4.35]	[17.01]	[5.38]
Adjusted R-Squared	0.41	0.23	0.43

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected); Bond Value Dummy 1 takes the value of 1 if the bond issue value is up to 54.6 US$ million (151,126 observations); Dummy 2 is up to 148.41 million (154,710 observations); Dummy 3 is up to 403.4 million (358,662 observations) and Dummy 4, which is dropped from the model, is above 403.4 million (111,529 observations); Bond Duration Dummy 1 takes the value of 1 if the bond duration is up to 3 years (133,006 observations); Dummy 2 is between 3 and 6 years (239,872 observations); Dummy 3 is between 6 and 9 years (154,815 observations) and Dummy 4, which is dropped from the model, is above 9 years (248,324 observations); The t-statistics are shown in parentheses.

Equity volatility, the distance to default and the interaction variable retain their significance in explaining variations in the credit spread with controls for bond duration and the size of issue. The bond issue dummies are significant in all of the models (except for the one for largest bonds in the first model). As expected, the credit spread and bond issue size are negatively correlated because a larger bond issue is associated with better liquidity. All of the bond duration dummies (except the ones for the longest durations in models 2 and 3) are significant and positive, indicating that a shorter duration is associated with a higher credit spread. This simple interpretation is misleading as only one bond per firm is included in the sample and therefore durations get smaller over time. The coefficients of the bond duration dummies most likely capture a sizeable increase in the credit spread during the recent financial crisis which occurred at the end of the sample period when the average duration was well below its peak value.

5.9. Summary

This chapter empirically examines hypotheses developed in Chapter 4. The main hypotheses are based on the structural model of Merton (1974) and state that equity volatility and credit risk are positively correlated with the credit spread. If the credit spread is primarily driven by the credit risk then the distance to default, which is a theoretically complete measure of credit risk, should outperform equity volatility in explaining variations in the credit spread. Since the structural model implies that the sensitivity of the credit spread to changes in any variable increases as a firm approaches bankruptcy, it is hypothesized that the effect of equity volatility on the credit spread depends on credit risk. Furthermore, the structural model implies that credit risk depends on the firm's total risk exposure, hence it is hypothesised that systematic and idiosyncratic equity volatility are equally important determinants of the credit spread.

These hypotheses are empirically tested on a sample consisting of 352 firms and over 700,000 daily observations. The sample, which includes bonds across the entire quality spectrum, covers a period of almost 15 years, including the recent financial crisis. This provides a richer dataset for empirical analysis when compared to existing studies which are mostly based on data from investment grade firms at the monthly level. Further, this study utilizes a more sophisticated methodology which enables it to obtain a number of novel empirical results. First, while the existing studies focus on the volatility of equity returns in excess of a major index, this study decompose equity volatility into the systematic and the idiosyncratic components and analyse the relationship between the credit spread and each volatility components. Second, since the impact on any variable upon the credit spread depends on the level of credit risk selection of the credit risk control variable is fundamentally important. While the existing studies employ accounting-based indicators or credit ratings this study explicitly estimates the structural model to construct an indicator of credit risk. This enables confirmation of a theoretical prediction on the interaction between equity volatility and credit risk which is unreported by the existing studies. Finally, the study utilizes panel data regression models to obtain more comprehensive and robust empirical results than available in the existing studies.

Equity volatility, which is estimated from a GARCH(1,1) model, is found to be positively correlated with the credit spread, as hypothesized. The relationship is both statistically significant and economically important. The results suggest that a one per cent increase in annual equity volatility raises the credit spread by 10.5 basis points. This is broadly consistent, although not directly comparable, with Campbell and Taksler (2003) who find that a one per cent increase in volatility of excess equity returns raises the credit spread by about 14 basis points. Equity volatility explains about 39 per cent of variations in the credit spread, which is broadly consistent with other studies (e.g. Campbell and Taksler (2003) obtain an R-squared of about 30 per cent; Ericsson, Jacobs and Oviedo (2009) obtain an R-squared of about 60 per cent; and Cremers et al. (2008) obtain an R-squared of about 45 per cent).

Collin-Dufresne, Goldstein and Martin (2001) find that the credit spread responds more strongly to positive changes in the VIX index, which represents a weighted average of eight implied volatilities of near-the-money options on the S&P 100 index. The asymmetric relationship between the credit spread and firm-level volatility is not confirmed in this study. The effect is found to have an unexpected sign and is of limited economic significance. Therefore, the hypothesis that an increase in equity volatility has a bigger impact upon the credit spread than a decrease of a similar magnitude is rejected.

The above results are obtained from a constant coefficient panel model which has unique coefficients in the cross-section. Allowing each firm to have its own intercept in the regression raises the explanatory power of the model from 39 to 53 per cent. The inclusion of period effects (i.e. annual dummy variables) raises the R-squared more modestly from 39 to 43 per cent. This indicates the presence of firm-specific effects which are not captured by equity volatility. The firm-specific effects raise the R-squared substantially, even in presence of control variables for the level of credit risk, firm size, bond issue size and duration. Ericsson, Jacobs and Oviedo (2009) also obtain the same results for the credit default swap premia and note that the theoretical variables perform better in time-series than in cross-sectional analyses.

Equity volatility does not, at least explicitly, contain information on leverage which is the most important variable form a credit risk perspective. According to the structural model, a complete measure of credit risk is the distance to default or the difference between the value of assets and the value of debt relative to the volatility of the value of the firm's assets. As hypothesized, the relationship between the distance to default and the credit spread is found to be consistently negative, i.e. a higher distance to default implies a lower credit risk and therefore a narrower credit spread. A unit increase in the distance to default on average narrows the credit spread by six basis points. A comparison of this result with the economic impact of equity volatility leads to the rejection of the hypothesis that the distance to default is an economically more significant determinant of the credit spread than equity volatility.

Furthermore, the distance to default explains 20 per cent of the variation in the credit spread which is just half of the explanatory power of the corresponding model with equity volatility. Further, the fixed effects have a substantially larger impact upon the explanatory power of the distance to default model. This result is robust to controlling for firm size and bond characteristics. A possible explanation is that only a fraction of the credit spread is related to credit risk as Elton et al. (2001) report. The distance to default may only be related to the credit component, while equity volatility is related to all components of the credit spread. Further support for this argument is provided with the finding that the explanatory power of equity volatility increases during the recent financial crisis, whereas the distance to default ability to explain variations in the credit spread decreases.

The distance to default is used as an indicator of credit risk to examine how the level of credit risk influences the relationship between equity volatility and the credit spread. The interaction variable (equity volatility x the distance to default) is found to consistently have a significant and negative coefficient. As hypothesized, this result implies that the economic significance of equity volatility in determining the credit spread diminishes as firms move away from the default point. Furthermore, the economic significance of equity volatility is found to monotonically increase as the distance to default narrows. Campbell and Taksler (2003) and Cremers at al. (2008) obtain mixed results when using an accounting-based leverage measure and credit ratings as indicators of credit risk. Therefore, this result, which is obtained by including six control variables in the model, indicates that the distance to default is useful as an indicator of credit risk.

In a further exploration of the relationship between equity volatility and the credit spread, equity volatility is decomposed into its systematic and idiosyncratic components using the CAPM and the Fama and French three factor model. The magnitude of the volatility components coefficients are statistically equal in the univariate regressions which indicates that changes in the systematic and the idiosyncratic volatility have approximately the same impact on the credit spread. However, the idiosyncratic volatility explains a substantially larger fraction of variations in the credit spread. Furthermore, the economic significance of idiosyncratic volatility consistently exceeds the significance of systematic volatility, which clearly indicates that the dominant drivers of the credit spread are firm-specific. This finding leads to a rejection of the hypothesis that idiosyncratic and systematic equity risks are equally important as determinants of the credit spread.

The finding on the importance of idiosyncratic factors is inconsistent with Collin-Dufresne, Goldstein and Martin (2001) who argue that the credit spread is driven by a common factor. To further explore the role of common risk factors, S&P 500 index volatility and returns are considered and a significant positive correlation is found between credit spread and S&P 500 index volatility, though S&P index returns are found to be insignificant determinants.

Common factors (S&P 500 index volatility and returns, the risk-free rate and the slope of the risk-free rate) jointly explain about 15 per cent of the variation in the credit spread, which is substantially lower than the explanatory power of equity volatility (40 per cent) and the distance to default (20 per cent). When firm-level systematic equity volatility (implied by the Fama and French three factor model) and the S&P 500 index volatility are jointly evaluated, the latter variable becomes insignificant. This finding supports the acceptance of the hypothesis that firm-specific risk measures are more important determinants of the credit spread than the aggregate risk factors. It should be noted that existing empirical studies (e.g. Campbell and Taksler, 2003; Cremers et al., 2008) commonly assume that the betas of all firms in the market model are equal to one. The results presented in this chapter indicate that taking into account differences in betas is important.

The results of all previous studies are based on level regressions. The statistical significance of the relationship between the credit spread and equity volatility, the distance to default and the interaction between the two variables is also confirmed in the change regressions. Furthermore, the results are robust to changes in the volatility estimation model and the inclusion of controls for the firm size, bond issue value and bond duration.

The next chapter reviews the existing literature, develops hypotheses and presents the research methodology for the empirical study of the correlation between equity and bond returns.

CHAPTER 6

CORRELATION BETWEEN THE EQUITY AND BOND RETURNS

6.1. Introduction

The equity and debt issued by a firm are generally exposed to the same risks. Despite significant differences between the equity and debt securities, stakeholders and debt investors essentially have different claims on the same assets. Since both classes of securities are exposed to the same risk inherent in firm's assets, their values must be systematically correlated in complete markets. The theoretical foundation for the analysis of the relationship between the values of different classes of securities is provided by Merton (1974). In this framework, the value of equity is treated as a call option written on the value of firm's assets, whereas the difference between the values of risky and risk-free debt is the value of a put option on firm's assets.

Merton (1974) referred to this as the structural model because it depends on the firm's capital structure. His model points to drivers of the correlation between equity and bond returns. The first driver is the firm's earnings potential which is a major determinant of the value of its assets. A drop in the firm's earnings potential negatively impacts on its equity value. It also has negative implications on the value of firm's bonds as the lower earnings potential implies potential problems with bond repayment. As the values of both securities should move in the same direction, the contemporaneous correlation is expected to be positive and significant. Furthermore, the correlation should be stronger for riskier firms with a greater possibility of default.

A change in the volatility does not affect the overall firm value but exerts different effects on the value of equity and debt. In this zero-sum game, the equity holders benefit from an increase in volatility while corresponding losses are inflicted on debt holders. Therefore, opposite to a change in the asset value, a change in the volatility of firm's assets induces a negative contemporaneous correlation between the values of equity and debt securities.

Section 2 of this chapter reviews the existing literature concerning the correlation between the equity and bond returns. The literature review leads to hypotheses which are tested empirically on a firm-level dataset consisting of more than 33,000 firm-month observations. The research methodology is presented in Section 3 and the dataset is described in Section 4, while the empirical results are presented in the subsequent Chapter 7.

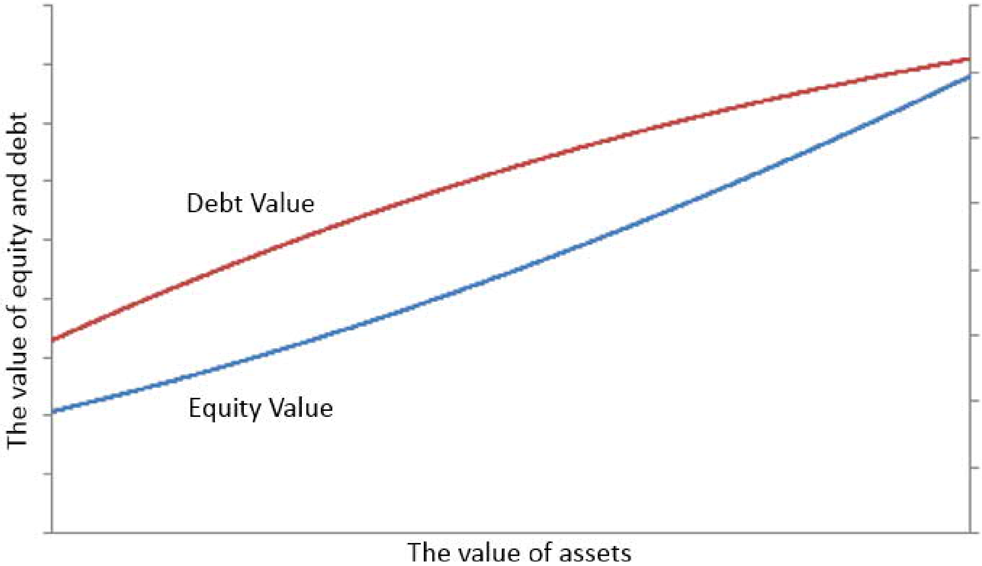
Most existing empirical studies (e.g. Kwan, 1996; Campbell and Taksler, 2003; Cremers et al., 2008) focus on examining the unconditional correlation between the credit spread or the bond yield and the variables included in the structural model of Merton (1974). This study takes a different methodological approach to enable a more thorough analysis. Instead of simply regressing bond returns on equity returns and other variables, this study utilizes a bivariate GARCH model to estimate the conditional correlation between the equity and bond returns, and then examines the determinants of this correlation in the second step.

6.2. Literature Review and Development of Hypotheses

The structural model of Merton (1974) describes the theoretical relationship between the values of firm's assets and the values of the securities issued by a firm. Merton shows that the value of equity equals the value of a call option and the value of debt is equal to the value of risk-free debt less the put option written on the value of the firm's assets. The strike price of both options is the value of debt.

The structural model implies that a change in the value of firm's assets causes a positive correlation between the returns on equity and debt. A change in the value of assets, ceteris paribus, affects the value of equity and debt in the same manner. An increase in the value of assets, for instance, is beneficial to equity holders as the growth in the underlying stock price is beneficial for an investor who purchased a call option. An increase in the value of assets also supports the value of debt by lowering the firm's leverage and, by extension, the probability of default. This causes a positive correlation between equity and debt returns as illustrated in Figure 6.1.

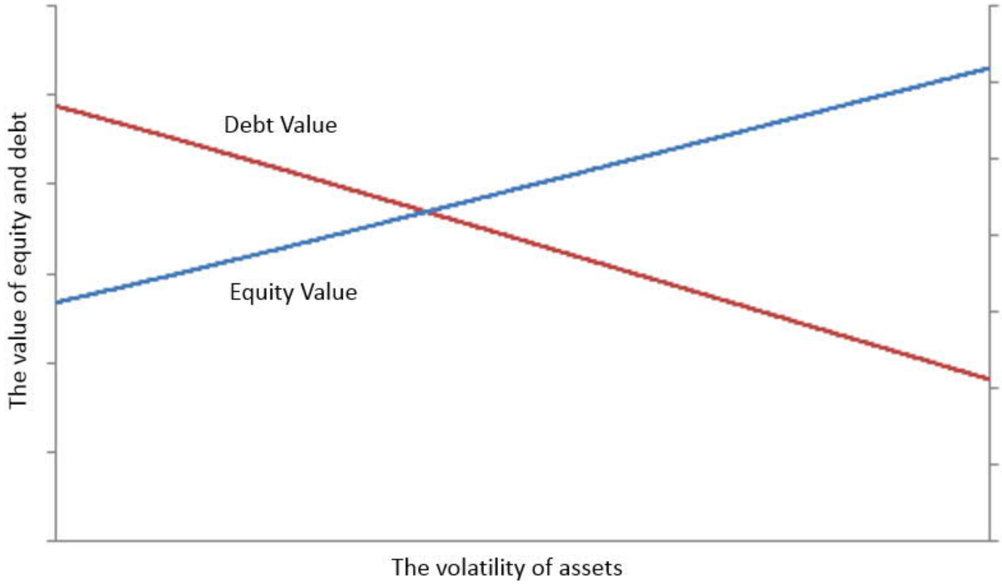
Figure 6.1[3]
Sensitivity of the values of equity and debt to changes in the value of the firm's assets



A contrasting argument is that a change in the volatility of firm's assets has an opposite effect on the values on equity and debt because equity holders stand to benefit from the upside potential of more volatile assets, whereas debt holders face an increased default probability as more volatile assets are more likely to fall to the value of debt and trigger bankruptcy. Therefore, a change in the volatility of assets induces a negative correlation between the values of equity and debt as illustrated in Figure 6.2.

[3] The graph is based on the structural model of Merton (1974) with the following parameters: the value of assets: 90-110; the volatility of the asset value: 20%; the book value of debt: 100; the risk-free rate: 2.00%; and the time horizon is 1 year.

Figure 6.2[4]
Sensitivity of the values of equity and debt to changes in the volatility of firm's assets



6.2.1. Correlation between Equity and Bond Returns

As discussed in Section 6.2, the correlation between equity and bond returns may be positive or negative depending on whether new information about a firm primarily affects the value of assets or the volatility of assets. In an early study, Kwan (1996) examines the bond yields and equity returns of 327 firms from 1986 to 1990. He reports a negative correlation between the firm-level equity returns and the bond yields. Since the bond yields and bond returns move in opposite directions, this finding may be interpreted as a positive correlation between equity and bond returns. Hotchkiss and Ronen (2002) examine returns on 55 high-yield bonds and corresponding firm equities. They find equity returns to be significant in explaining only the returns on the lowest rated bonds (i.e. B- and lower) in their sample. Norden and Weber (2009) analyse the intertemporal relationship between credit default swaps, equities and bonds. They analyse data of 58 firms from 2000 to 2002 and report that the relationship

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[4] The graph is based on the structural model of Merton (1974) with the following parameters: the volatility of assets: 20% - 60%; the value of assets: 110; the book value of debt: 100; the risk-free rate: 2.00%; and the time horizon is 1 year.

between equity returns and bond spreads (bond returns) to be significant and negative (positive).

A negative correlation is generally found to be caused by an agency conflict whereby managers take actions that increase the equity value at the expense of debt value. An example of such action is share repurchases. Maxwell and Stephens (2003) find that around share repurchase announcements, equity returns are abnormally positive while bond returns are negative. Alexander, Edwards and Ferri (2000) also confirm that the correlation between equity and bond returns occasionally turns negative around events which are beneficial to equity holders (e.g. issuing debt, adopting risky projects etc.) or debt holders (e.g. paying down debt, diversifying assets etc.). Since the takeovers, particularly if they are funded by debt negatively affect the value of the existing debt, Bhanot, Mansi and Wald (2010) find that takeover risk also has a negative effect on the correlation between equity and bond returns.

Most empirical evidence point out that the correlation between equity and bond returns is positive, but it turns negative around wealth-transferring events such as leveraged buyouts. Since the wealth-transferring events are relatively infrequent their effect upon the correlation between equity and bond returns should not be dominant in medium and long-term periods. Therefore, the following hypothesis is put forward:

H1: The correlation between equity and bond returns is positive.

In contrast to previous studies which typically conduct the empirical testing by regressing bond yields on equity returns, this study proceeds with empirical testing in two steps. First, the conditional correlation between equity and bond returns is estimated in a bivariate GARCH model. Second, the statistical significance of the coefficients in the covariance equations is examined, and the hypothesis is formally tested that the mean of the conditional correlation series is positive and different from zero.

6.2.2. Equity Volatility and the Correlation between Equity and Bond Returns

The correlation between the values of debt and equity should depend on the riskiness of firm's assets. A higher volatility implies a higher default probability. Furthermore, the sensitivity of the default probability increases as a firm approaches bankruptcy. This is confirmed by a number of empirical studies. Kwan (1996) finds that the returns on AAA-bonds approach the risk-free rate, while the returns on non-investment grade bonds are highly correlated with the returns on the corresponding firm equities. Hotchkiss and Ronen (2002) and Cheyette and Tomaich (2003) confirm this finding.

Employing a similar methodological approach to that in this study, Scheicher (2009) analyses the determinants of conditional correlations between stock returns and changes in credit default swap (CDS) premiums for a sample of 129 firms in the US market. As expected, equity volatility is reported to have a negative impact upon the correlation between equity returns and credit default swap premiums.

This discussion leads to the following hypothesis:

H2: Equity volatility has a positive impact upon the correlation between equity and bond returns.

This hypothesis is tested by regressing the conditional correlation between equity and bond returns on the corresponding (conditional) equity volatility obtained from a GARCH process. Let V_t be the estimated volatility and $CORR_t$ be the conditional correlation between equity and bond returns at time t. Then the hypothesis is tested by assessing the coefficient b in the following regression:

$$CORR_t = a + bV_t + \varepsilon_t \tag{6.1}$$

6.2.3. Credit Risk and the Correlation between Equity and Bond Returns

The structural model implies that the level of credit risk is the most important determinant of the strength of the correlation between equity and bond returns. As previously discussed, a small change in the value of the equity or equity volatility of high-quality firms has a limited impact upon the firm's default probability. However, as the default probability increases, its sensitivity to changes in any theoretical variable also increases. This is generally confirmed by the existing empirical studies which commonly use credit ratings to control for credit risk. Hotchkiss and Ronen (2002) find that the correlation between equity and bond returns is not statistically significant without controlling for credit risk. Similarly, Cheyette and Tomaich (2003) report that the bond yields of high quality issuers are primarily explained by changes in the risk-free rate, while the bond yields of firms with a lesser credit quality are determined by equity returns. Surprisingly, the bond yields of firms with intermediate credit quality are not related to either interest rate factors or equity returns.

Scheicher (2009) finds leverage (the accounting-based ratio of total debt to total assets) to be an insignificant determinant of conditional correlations between equity returns and changes in the credit default swap premium. Campbell and Taksler (2003) also use accounting leverage ratios to control for credit risk in their analysis of the determinants of credit spreads. They fail to confirm the prediction of the structural model that the importance of equity volatility in determining the credit spreads increases with the credit risk. Similarly, Cremers et al. (2008) obtain inconsistent results with this prediction of the structural model by using credit ratings to control for the credit risk.

As implied by the structural model, the following hypothesis is formulated:

H3: The strength of correlation between the equity and bond returns depends on credit risk. Specifically, the correlation is expected to be highly positive for high risk firms and low or no correlation for low risk firms.

The third hypothesis (H3) is tested empirically by regressing the conditional correlation between equity and bond returns on the distance to default of Merton (1974). The distance to default can be updated frequently and is in this regard superior to credit ratings. Let DD_t be the estimated distance to default and let $CORR_t$ be the conditional correlation between equity and bond returns at time t. The hypothesis is tested by assessing if the coefficient b is statistically different from zero in the following regression:

$$CORR_t = a + bDD_t + \varepsilon_t \tag{6.2}$$

The coefficient b indicates how, on average, across sample firms a change in the distance to default impacts upon the correlation between equity and bond returns. As discussed above, it is expected that the impact of a change in the distance to default strongly depends on the level of credit risk. In other words, a small change in a high distance to default should have a limited impact upon the correlation between equity and bond returns, though the magnitude of impact should grow as the distance to default shrinks. To take this effect into account, Equation 6.2 is extended as follows:

$$CORR_t = a + bDD_t + \sum_{i=1}^{k} c_i DD_t^i + \varepsilon_t \tag{6.3}$$

where $DD_t^i = I(x_i \leq DD_t < x_{i+1})$ and $I()$ is the indicator function which equals 1 if the distance to default is within a predefined range, and zero otherwise. The x_i are pre-selected thresholds, and k is the number of risk classes in the sample. The coefficient b now represents the average effect after controlling for level of the distance to default, while c_i captures the additional effect of the distance to default for predefined risk classes. If Hypothesis 3 holds, the coefficients c_i should be statistically significant and monotonically increasing in size as the predefined thresholds of the distance to default decrease (i.e. as the level of credit risk increases).

6.2.4. Interaction between Equity Volatility and the Distance to Default

Hypothesis 2 states that equity volatility positively impacts upon the correlation between equity and bond returns. Instead of being linear, this relationship is expected to strengthen as credit risk increases. Therefore, there should be a significant interaction effect between equity volatility and the distance to default. A change in equity volatility should have a disproportionate effect upon the correlation between equity and bond returns for firms on the brink of bankruptcy, and almost no impact upon the correlation of returns for very safe firms. Campbell and Taksler (2003) and Cremers et al. (2008) provide some evidence of this effect but do not obtain a monotonic relationship between the level of credit risk and the effect of equity volatility on the credit spread. These inconclusive results are likely to be caused by weak proxies of credit risk (an accounting based ratio and firm credit ratings) and data samples populated mostly by investment grade firms.

Consistent with theory, the results presented in Chapter 5 (Table 5.26) show that the economic impact of equity volatility on the credit spread grows monotonically as the distance to default shrinks. Therefore, it is hypothesized that the same effect holds for the correlation between equity and bond returns.

H4: The positive impact of equity volatility on the correlation between the equity and bond returns increases as the distance to default shrinks.

This hypothesis is examined by regressing the conditional correlation between the equity and bond returns on equity volatility and a variable capturing the interaction between the equity volatility and the distance to default. Let V_t be the estimated volatility, DD_t be the distance to default, and $CORR_t$ be the conditional correlation between equity and bond returns at time t. Then the hypothesis is tested by assessing the statistical significance of coefficient c in the following regression:

$$CORR_t = a + bV_t + c\, V_t\, DD_t + \varepsilon_t \tag{6.4}$$

Additionally, the interaction effect is examined by estimating a discrete version of the above model:

$$CORR_t = a + bV_t + \sum_{i=1}^{k} c_i V_t^i + \varepsilon_t \tag{6.5}$$

where $V_t^i = V_t\ I\,(x_i \leq DD_t < x_{i+1})$ and $I()$ is the indicator function which equals one if the distance to default is within a predefined range and zero otherwise. The x_i are pre-selected thresholds, and k is the number of risk classes in the sample.

6.2.5. Common Factors and the Correlation between the Equity and Bond Returns

Common factors are generally expected to influence the correlation between asset returns. Longin and Solnik (2001), and Ang and Bekaert (2002) find that the correlation between the returns in international equity markets tends to increase in turbulent times. In a recent study, Bartram and Bodnar (2009) document a sharp increase in the correlation between international equity markets during the recent financial crisis in 2008. Ben-David, Franzoni and Moussawi (2012) report that hedge funds rushed to exit equity markets during the 2007-2009 crisis which implies that the average correlation between the returns on equities increased during the crisis.

These studies suggest that common factors influence the correlation between equities and that their importance increases in turbulent times when investors tend to decrease their exposure to equity markets in general. If investors attempt to cut their risk exposure in all markets then prices in equity and bond markets will be subject to downward pressure. As a result, the correlation between equity and bond returns will increase. Belke and Gokus (2011) provide some evidence that this effect is present in the returns of different securities issued by the same firm. They examine the volatility patterns of the credit default swap spreads, the bond yield spreads and the equity returns of four large banks, and report that the correlations strongly vary over time and increase in absolute values after the outbreak of the recent financial crisis in 2007. The conditional correlations between the values of equity and debt were negative before the crisis and turned positive during the crisis.

Scheicher (2009) documents a significant increase in the conditional correlation between the equity and credit default swap markets during the market turmoil of May 2005 caused by the S&P's decision to downgrade General Motors and Ford to the speculative status. Besides the firm-level equity volatility, the slope of the swap curve (defined as the 10 year swap rate minus the three-month money market rate) is reported to be a significant determinant of the correlation. Therefore, the author concludes that the correlation is determined by both firm-level and common factors.

The impact of common factors on the correlation between equity and bond returns can also be analysed at the micro level. The structural model implies that the equity and bond returns are both the functions of the value of firm's assets. Campello, Chen and Zhang (2008) show that the equity premium equals the bond risk premium multiplied by the unobservable elasticity of the equity value with respect to the bond value. Since the equity premium depends on the exposure to systematic risks, it follows that the bond premium also depends on systematic factors. Elton et al. (2001) show that the common equity pricing factors of Fama and French (1993) are significant in explaining the bond credit spread. Campbell and Taksler (2003) report that both excess equity market return and market volatility are significant determinants of the credit spread.

The risk-free rate is the only common variable in the structural model. It is assumed that the value of firm's assets grows at the risk-free rate. Therefore, an increase in the risk-free rate leads to an increase in the value of assets which positively affects the value of equity. On the other hand, a higher risk-free interest rate implies a higher discount rate for the future coupon and principal payments and therefore a lower bond value. This induces a negative correlation between the equity and bond returns. Furthermore, if considered as an indicator of the health of the overall economy, the risk free-rate should have a negative impact upon the correlation between equity and bond returns as a higher risk-free rate is associated with better macroeconomic conditions.

Based on the above discussion, the following hypotheses are put forward:

H5: Systematic risk has a positive impact upon the correlation between the equity and bond returns.

The empirical testing is conducted by regressing the conditional correlation between the equity and bond returns on the risk-free rate, the S&P 500 index returns and volatility. Let $CORR_t$ be the conditional correlation between the equity and bond returns at time t, V_t^m be the estimated volatility of the S&P 500 index, and R_t^m be the return of the same index at time t. Then Hypothesis 5 is tested by assessing the statistical significance of coefficients b and c in the following regression:

$$CORR_t = a + bV_t^m + cR_t^m + \varepsilon_t \tag{6.6}$$

The above model ignores different exposures of firms to systematic risks (i.e. different firm betas) and therefore may bias the importance of systematic risks downward. To examine this, the returns and volatility of the S&P 500 index are replaced by firm-level measures of systematic equity returns and the volatility of systematic equity returns, which are estimated by the three factor model of Fama and French (1993) [5].

$$CORR_t = a + bV_t^{sys} + cR_t^{sys} + \varepsilon_t \tag{6.7}$$

H6: The risk-free rate has a negative impact upon the correlation between the equity and bond returns.

[5] The Estimation procedure is described in Section 6.3.5.

To test this hypothesis empirically, Model 6.6 is extended as follows.

$$CORR_t = a + bV_t^m + cR^m + dR_t^f + eS_t^f + \varepsilon_t \tag{6.8}$$

where R_t^f is the risk-free rate and S_t^f is the difference between the redemption yields on 10-year and 2-year Treasury bonds. Significantly negative coefficients d and e lead to the acceptance or rejection of Hypothesis 6.

6.3. Methodology

6.3.1. Equity and Bond Returns

The equity returns are calculated in the usual manner. Define $P_{i,t}^E$ as the share price of firm i at time t, and $D_{i,t}$ as dividends paid from time t-1 to time t. The rate of return is defined as:

$$R_{i,t}^E = \ln \frac{P_{i,t}^E + D_{i,t}}{P_{i,t\text{-}1}^E} \tag{6.9}$$

The holding-period returns for the bonds are calculated in a similar manner. Define $P_{i,t}^B$ as the bond price of firm i at time t, $C_{i,t}$ as the coupon payments, and $AC_{i,t}$ as the accrued interest on bond i from time t-1 to time t. The rate of return is defined as:

$$R_{i,t}^B = \ln \frac{P_{i,t}^E + C_{i,t} + AC_{i,t}}{P_{i,t\text{-}1}^B + AC_{i,t-1}} \tag{6.10}$$

6.3.2. Conditional Correlation between the Equity and Bond Returns

The conditional correlation between the equity and bond returns can be modelled as a bivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) process. The mean equations are set as:

$$R_{i,t}^{E} = c_1$$
$$R_{i,t}^{B} = c_2 \tag{6.11}$$

where $R_{i,t}^{E}$ and $R_{i,t}^{B}$ are the equity and bond returns of firm i at time t. The theoretical literature offers several specifications for the conditional variance-covariance matrix. Bollerslev, Engle and Wooldridge (1988) proposes the general VECH(p,q) model which models the variances and the covariance as linear functions of all lagged variances, covariances and errors as well as the cross-product of lagged errors. The VECH (p,q) model is given by:

$$VECH(H_t) = C + AVECH(\varepsilon_{t-j}\varepsilon_{t-j}^{'}) + BVECH(H_{t-j})$$
$$\varepsilon_t | \psi_{t-1} \sim N(0, H_t) \tag{6.12}$$

where

H_t is the conditional variance matrix of R_t, i.e. $H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{bmatrix}$,

VECH(·) is the column-stacking operator applied to the upper portion of the symmetric matrix,

A and B are 3 x 3 parameter matrices,

ε is the error term from the mean equations in 6.11.

The variance and covariance equations in the full form of the most parsimonious VECH(1,1) model are as follows:

$$\begin{aligned} h_{E,t} &= c_{11} + a_{11}\varepsilon_{E,t-1}^{2} + a_{12}\varepsilon_{B,t-1}^{2} + a_{13}\varepsilon_{E,t-1}^{2}\varepsilon_{B,t-1}^{2} + \\ &\quad b_{11}h_{E,t-1} + b_{12}h_{B,t-1} + b_{13}h_{EB,t-1} \\ h_{B,t} &= c_{21} + a_{21}\varepsilon_{E,t-1}^{2} + a_{22}\varepsilon_{B,t-1}^{2} + a_{23}\varepsilon_{E,t-1}^{2}\varepsilon_{B,t-1}^{2} + \\ &\quad b_{21}h_{E,t-1} + b_{22}h_{B,t-1} + b_{23}h_{EB,t-1} \\ h_{EB,t} &= c_{31} + a_{31}\varepsilon_{E,t-1}^{2} + a_{32}\varepsilon_{B,t-1}^{2} + a_{33}\varepsilon_{E,t-1}^{2}\varepsilon_{B,t-1}^{2} + \\ &\quad b_{31}h_{E,t-1} + b_{32}h_{B,t-1} + b_{33}h_{EB,t-1} \end{aligned} \tag{6.13}$$

As can be seen from the above equations, the bivariate VECH(1,1) model requires the estimation of 21 coefficients, which makes it difficult to estimate. Imposing the diagonal restriction on the matrices a and b reduces the number of coefficients to 9. The resulting model is referred to as the Diagonal VECH(1,1):

$$
\begin{aligned}
h_{E,t} &= c_1 + a_1 \varepsilon^2_{E,t-1} + b_1 h_{E,t-1} \\
h_{B,t} &= c_2 + a_2 \varepsilon^2_{E,t-1} + b_2 h_{B,t-1} \\
h_{EB,t} &= c_3 + a_3 \varepsilon^2_{E,t-1} \varepsilon^2_{B,t-1} + b_3 h_{EB,t-1}
\end{aligned} \tag{6.14}
$$

The Diagonal VECH does not guarantee that the conditional covariance matrix is positive semi-definite. In other words, it does not ensure that all elements of the covariance matrix are non-negative and the covariance is the same regardless of the order of the equations in the model. As noted by Ding and Engle (2001), one way to achieve these desirable properties is to restrict the coefficient matrices to Rank 1 matrices. This reduces the number of coefficients in the variance/covariance equations to 6:

$$
\begin{aligned}
h_{E,t} &= c_1 + a_1 \varepsilon^2_{E,t-1} + b_1 h_{E,t-1} \\
h_{B,t} &= c_2 + a_2 \varepsilon^2_{E,t-1} + b_2 h_{B,t-1} \\
h_{EB,t} &= c_1 c_2 + a_1 a_2 \varepsilon^2_{E,t-1} \varepsilon^2_{B,t-1} + b_1 b_2 h_{EB,t-1}
\end{aligned} \tag{6.15}
$$

This specification is the same as the Diagonal BEKK model of Engle and Kroner (1995) and is widely utilized in empirical studies (e.g. Belke and Gokus, 2011; Ang and Chen, 2002; Bekaert and Wu, 2000).

The above specification assumes that the variances and the covariance respond symmetrically to positive and negative news. This assumption can be relaxed by extending the variance equations with an addition term which takes a positive value only if a shock is negative and zero otherwise (i.e. $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, and zero otherwise).

$$
\begin{aligned}
h_{E,t} &= c_1 + a_1 \varepsilon^2_{E,t-1} + b_1 h_{E,t-1} + d_1 \varepsilon^2_{E,t-1} I_{E,t-1} \\
h_{B,t} &= c_2 + a_2 \varepsilon^2_{E,t-1} + b_2 h_{B,t-1} + d_2 \varepsilon^2_{B,t-1} I_{B,t-1} \\
h_{EB,t} &= c_1 c_2 + a_1 a_2 \varepsilon^2_{E,t-1} \varepsilon^2_{B,t-1} + b_1 b_2 h_{EB,t-1} + d_1 d_2 \varepsilon^2_{E,t-1} I_{E,t-1} \varepsilon^2_{B,t-1} I_{B,t-1}
\end{aligned} \tag{6.16}
$$

6.3.3. Equity Volatility

The equity volatility is estimated using the parsimonious GARCH (1,1) model, which was introduced by Bollerslev (1986) as a generalization of Engle (1982). The conditional variance evolves according to the following equation:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 \tag{6.17}$$

where

σ is the volatility

ε is the error term from the return model $r_t = \mu + \varepsilon_t \; where \; \varepsilon_t \sim (0, \sigma_t^2)$

6.3.4. Distance to Default

As described in Section 4.3.4, the Distance to Default is given by:

$$DD = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \tag{6.18}$$

where

V_A is the market value of the firm's assets,

σ_A is the volatility of the market value of the firm's assets,

X is the book value of the firm's debt,

r is the risk-free rate,

N is the cumulative density function of the standard normal distribution,

T is the time horizon in years

The Distance to Default is the difference between the market value of the assets and the book value of debt relative to the volatility of the market value of the assets. The unobservable market value and volatility of the firm's assets are estimated by simultaneously solving the call option pricing equation (Black and Scholes, 1973) and the hedge equation (Jones, Mason and Rosenfeld, 1984) as described in Section 4.3.4.

6.3.5. Equity Systematic Returns and Volatility

The market-wide returns and volatility are proxied by the S&P 500 index returns and volatility and are calculated as described in sections 6.3.1. and 6.3.3.

To take into account differences in exposure to systematic risk, the systematic equity returns and volatility are also estimated at the firm level. According to the widely used model of Fama and French (1993), the systematic or expected equity return is given by:

$$r_{i,t} = r_{ft} + \beta_{1,i,t}(r_{m,t} - r_{f,t}) + \beta_{2,i,t} SMB_t + \beta_{3,i,t} HML_t \tag{6.19}$$

where

$r_{i,t}$ is the equity return of firm i at time t

$r_{f,t}$ is the risk-free rate

r_{mt} is the return on the S&P 500 index at time t

SMB_t is the difference in the returns of big and small firms at time t

HML_t is the difference in the returns of high and low book-to-market equity firms at time t

As described in Section 4.3.4, the conditional betas are estimated with bivariate GARCH-in-mean as proposed by Bollerslev, Engle and Wooldridge (1988). Once the conditional betas are estimated, the systematic equity returns are calculated in a fairly straightforward manner according to Equation 6.19. Finally, it is assumed that the volatility of systematic returns follows the GARCH(1,1) process given in Equation 6.17.

6.3.6. Bond Issue Characteristics

To control for the maturity of bonds, daily duration is calculated according to the following formula:

$$d = \frac{1}{B_d} \sum_{i=1} \frac{CF_i}{(1+Y)^{T_i}} T_i \tag{6.20}$$

where

B_d is the dirty bond price (principal + accrued interest)

CF_i is the cash flow in year i

T_i is the time in years to the i th cash flow

The control variable for the size of the bond issue is the natural logarithm of the bond's market price multiplied by the number of outstanding bonds.

6.3.7. Panel Data Analysis

The data set consists of the conditional correlation between the equity and bond returns, and a set of independent variables for n firms over T consecutive time periods. The simplest model for analysis of this two-dimensional data set is given by:

$$CORR_{it} = \alpha + \beta x_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d.(0, \sigma^2) \tag{6.21}$$

where

$CORR_{it}$ is the conditional correlation between the equity and bond returns of firm i at time t

α is the intercept

β is a k x 1 parameter vector

x_{it} is a vector of k explanatory variables

ε_{it} is a disturbance term

This model is referred to as the constant coefficient model because it imposes the same coefficient for all firms in the sample. This is the most parsimonious panel data model but is severely restricted. Most importantly, by imposing the same intercept for all firms it effectively assumes that other firm-specific determinants of the correlation between the equity and bond returns are the same for all firms. Other firm-specific effects can be taken into account by allowing the intercept to vary in the cross-section. Consider the following model:

$$CORR_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d.(0, \sigma^2) \tag{6.22}$$

The subscript i for α indicates that each firm has its own intercept or fixed effect. This feature of the model controls for time invariant firm characteristics and therefore provides the basis for the analysis of the effect of controlled variables that vary over time.

The correlation between the equity and bond returns may vary across time. As with cross-sectional fixed effects, the constant coefficient panel data model can be extended to control for time effects. Consider the following model:

$$CORR_{it} = \alpha + \gamma_t + \beta x_{it} + \varepsilon_{it,} \quad \varepsilon_{it} \sim i.i.d.(0,\sigma^2) \tag{6.23}$$

where γ_t is time-specific, effect. This effect is common in the cross-section so it captures all time-varying variables that affect the correlation between the equity and bond returns but are constant in the cross-section.

Following Petersen (2009), and Zhang, Zhou and Zhu (2009) clustered standard errors are used in all models to account for the serial correlation of errors (i.e. cross-sectional clustering).

6.4. Data

This study requires the firm-level equity and bond data. Since bond data points are relatively scarce compared to the equity data, the sample selection starts with all straight corporate bonds issued by non-financial companies in the US market available in the Thomson Reuters Datastream database. When multiple bonds are available from the same issuer, the bond with the maximum number of observations in considered. This is preferred to averaging the data of different bonds with a common issuer because all bonds have different characteristics such as duration and issue size. Bonds with less than 36 monthly observations, asset-backed bonds, bonds with any sort of collateral, or with an average market value of less than USD 10 million are excluded from the sample. Once the bond data is collected, it is matched with the equity data, also obtained from the Thomson Reuters Datastream database. The matched sample consists of 351 firms and 33,870 observations at the monthly level.

The sample covers the period from August 1996 to February 2011. Not all series cover the entire sample period, so the sample is unbalanced. It should be noted that the number of observations available at the beginning of the sample period (1996-2000) is much lower than later in the sample period (2001-2011). However, the beginning sample dataset is still large (1,519 observations for 33 firms) when compared to other studies which deal with bond data.

The accounting data required for the estimation of the distance-to-default is obtained from Compustat. The Fama and French factors are obtained from Kenneth R. French's web site, and the risk-free interest rate and the S&P 500 index data are downloaded from the Thomson Reuters Datastream database.

6.5. Summary

The structural model of Merton (1974) shows that the equity and debt securities issued by a firm can be considered as contingent claims on firm's assets with the book value of debt as the strike price. The value of equity resembles a call option, while the risk premium on a bond is modelled as a put option. As the option pricing theory of Black and Scholes (1973) suggests, the values of both equity and debt primarily depend on the value and the underlying assets volatility.

Factors affecting the value of the assets push the values of equity and bonds in the same direction and therefore induce a positive correlation between the returns of these two asset classes. On the other hand, an increase in the volatility of firm's assets augments the value of equity and depresses the value of bonds, which clearly induces a negative correlation between the returns. The empirical literature generally finds that the correlation between equity and debt returns is positive, which implies that changes in the values of equity and debt are mostly caused by a change in the value of firm's assets. The volatility of assets is found to be the major determinant of the correlation between the equity and bond returns around specific events such as share repurchases and leveraged buyouts when the correlation turns negative.

Another important theoretical prediction arising from the literature is that the strength of correlation between the returns depends on the riskiness of firm's assets. Information from the equity market has a limited impact upon the value of bonds issued by firms which are stable and with little debt. The sensitivity of the value of debt to changes in the value of equity increases with the riskiness of the assets and therefore the correlation between the returns strengthens. Hotchkiss and Ronen (2002) find that the correlation between the equity and bond returns is not statistically significant without controlling for the credit risk. Scheicher (2009) finds the equity volatility to be a significant determinant of the correlation between equity returns and the credit default swap premium. Other studies generally confirm that credit risk and equity volatility are important determinants of the relationship between equity and bond returns.

The empirical literature emphasizes that the correlation between returns increases in turbulent times. The structural model does not distinguish between idiosyncratic and systematic risks. Systematic risks, therefore, should be as important as idiosyncratic risks in determining the correlation between equity and bond returns. The only common variable that is explicitly included in the structural model is the risk-free rate. In the risk-neutral framework of the structural model, the value of assets grows at the risk-free rate. As a result, an increase in the risk-free rate increases the value of equity. On the other hand, bonds prices decrease as all future cash flows are discounted at a higher rate. A change in the risk free rate, therefore, negatively affects the correlation between the equity and bond returns.

The overwhelming majority of the existing empirical studies (e.g. Kwan, 1996; Campbell and Taksler, 2003; Cremers et al., 2008) focuses on examining the unconditional correlation between the credit spread or the bond yield and the variables deriving from the structural model of Merton (1974). This study aims to extend the existing literature by examining the time properties of the correlation between the equity and bond returns. This is achieved by estimating the conditional correlation between the equity and bond returns, and then regressing this on a measure of credit risk, on equity volatility and on other variables of interest.

The conditional correlation between the equity and bond returns is estimated by means of a bivariate GARCH model. The data sample consists of the merged equity and bond data sets of 351 firms covering the period from 1/8/1996 to 18/2/2011 (over 33,000 monthly observations).

The next chapter presents the empirical results.

CHAPTER 7

CORRELATION BETWEEN THE EQUITY AND BOND RETURNS:

AN EMPIRICAL INVESTIGATION

7.1. Introduction

This chapter empirically examines the correlation between equity and bond returns. The statistical validity of hypotheses proposed in Chapter 6 is assessed by regressing the conditional correlation between the equity and bond returns on measures of equity, credit and systematic risks. The empirical analysis commences with the calculation of equity and bond returns. As described in Section 6.3.1, equity returns are calculated as the natural logarithm of the share price at the time t plus the dividends paid out during the period t over the share price at the time t-1, while bond returns are calculated as the exponential bond price returns plus the interest accrued during the observation period. The conditional correlation between the equity and bond returns, estimated by a bivariate Diagonal VECH, is comprehensively examined in a set of panel data models. Section 7.2 evaluates the conditional correlation between the equity and bond returns estimated by the bivariate Diagonal VECH(1,1) model, as well as the asymmetric Diagonal VECH(1,1,1) model. Section 7.3 presents an analysis of the effect of equity volatility on the correlation between the equity and bond returns. The analysis proceeds by regressing the correlation on equity volatility in the constant coefficient panel model. In the second stage, panel data models with cross-sectional and time fixed effects are estimated.

Section 7.4 examines the impact of credit risk upon the correlation between the equity and bond returns. The distance to default measure of Merton (1974) is utilized as an indicator of credit risk. As in the previous section, a set of panel data models is estimated with the correlation as the dependent variable and the distance to default and fixed effects as regressors. Section 7.5 considers the interaction between equity volatility and the distance to default. The analysis is conducted by regressing the correlation on equity volatility and the interaction variable (equity volatility x the distance to default). The discrete version of this model is also estimated, whereby the interaction variable is replaced with a set of dummy variables taking the value of one if the distance to default is within a predefined range, and zero otherwise.

Section 7.6 examines the relationship between common factors and the correlation between equity and bond returns. The common factors considered are: the S&P 500 index returns, the S&P 500 index volatility, the risk-free rate, and the slope of the risk-free term structure. To take into account differences in firm exposure to systematic risks, firm-level systematic returns are considered instead of the S&P 500 index returns. The Fama and French (1993) model is employed to estimate firm-level systematic returns or expected returns. The final section examines the robustness of the results to changing the conditional correlation estimation model. The base case bivariate Diagonal VECH(1,1) model is expanded to allow for an asymmetric response of the conditional correlation to positive and negative shocks to equity and bond returns. Furthermore, the robustness of the results to controlling for firm size, bond duration and bond issue size is examined.

7.2. The Conditional Correlation between the Equity and Bond Returns

The conditional correlation between the equity and bond returns is estimated by means of a symmetric and an asymmetric bivariate Diagonal VECH/Diagonal BEKK model, as described in the previous chapter. Following Scruggs and Glabadanidis (2003) the correlation is estimated at the monthly level as noise in the returns at higher frequencies makes it difficult to determine the true relationship between the returns. Table 7.1 summarises the main results from the two bivariate models employed in this study. The statistics shown are based on pooled data (across both firm and time dimensions).

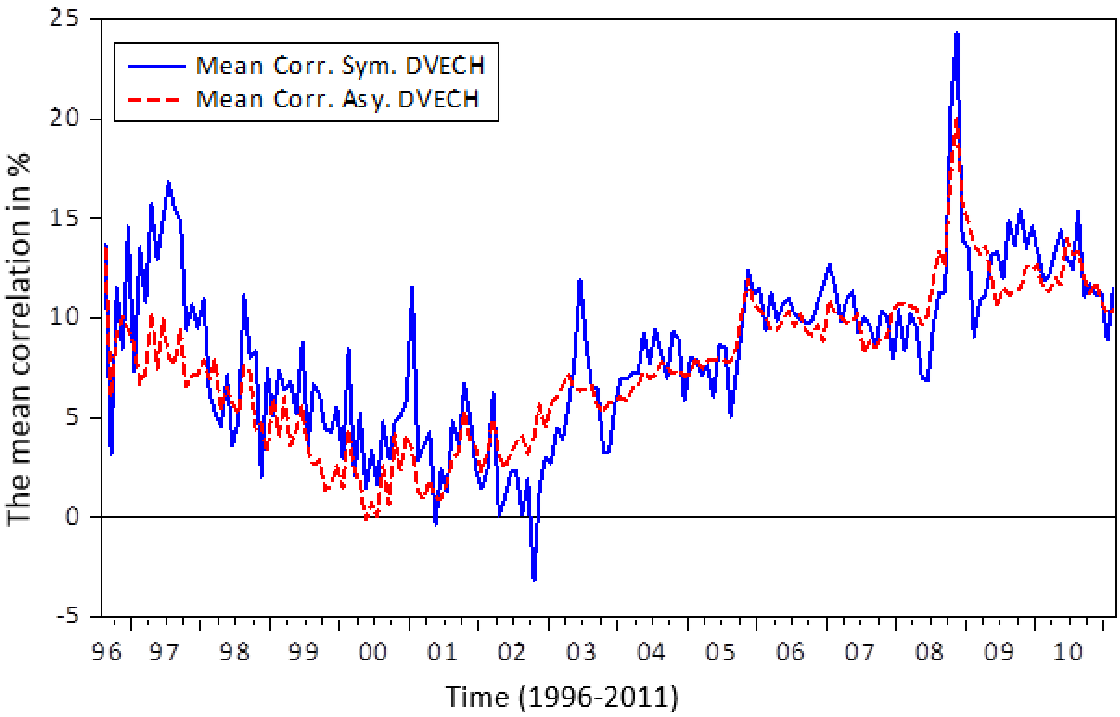
Table 7.1
Descriptive statistics of the correlation series

	Symmetric DVECH(1,1)	Asymmetric DVECH(1,1,1)
Mean	0.09	0.09
Median	0.06	0.07
Maximum	1.00	0.99
Minimum	-0.93	-0.80
Std. Dev.	0.28	0.26
Skewness	0.24	0.38
Kurtosis	3.20	3.17

The number of observations is 33,870

The mean correlations are positive which implies that on average equity and bond prices move in the same direction. It should be noted that the correlation is weakly positive hence agency conflicts (e.g. share repurchases) which induce a negative correlation and thus lowers the series mean are important determinants of the correlation between the equity and bond returns. On a prima facie basis, the descriptive statistics of the correlation series estimated by two models are very similar. However, Figure 7.1 shows that the conditional correlations estimated by the symmetric and the asymmetric models are substantially different. The correlations shown in the graph are based on cross-sectional averages. The symmetric model produces more volatile time series of correlations, while the asymmetric model gives a smoother pattern.

Figure 7.1
The mean correlation between the equity and bond returns estimated by the symmetric and asymmetric Diagonal VECH models



The econometric models are described in detail in Chapter 6. The correlation equations are reproduced below:

$$h_{EB,t} = c_1 c_2 + a_1 a_2 \varepsilon^2_{E,t-1} \varepsilon^2_{B,t-1} + b_1 b_2 h_{EB,t-1}$$
$$h_{EB,t} = c_1 c_2 + a_1 a_2 \varepsilon^2_{E,t-1} \varepsilon^2_{B,t-1} + b_1 b_2 h_{EB,t-1} + d_1 d_2 \varepsilon^2_{E,t-1} I_{E,t-1} \varepsilon^2_{B,t-1} I_{B,t-1}$$

Besides the intercept, the correlation equations consist of ARCH (i.e. $a_1 a_2 \varepsilon^2_{E,t-1} \varepsilon^2_{B,t-1}$), GARCH (i.e. $b_1 b_2 h_{EB,t-1}$), and, in the case of the asymmetric model, a TARCH (i.e. $d_1 d_2 \varepsilon^2_{E,t-1} I_{E,t-1} \varepsilon^2_{B,t-1} I_{B,t-1}$) component. The statistical significance of the estimated coefficients is reviewed to examine the importance of these components in determining the correlation between equity and bond returns. Table 7.2 depicts the percentage of estimated coefficients that are significant at the five per cent level.

The GARCH coefficient is significant in 274 symmetric and 257 asymmetric models out of a total of 351 models. The low percentage of significant TARCH coefficients indicates that allowing for an asymmetric response in the correlation to positive and negative news does not substantially improve the basic symmetric model. It indicates that negative and positive returns affect the correlation between equity and bond returns in a similar manner. An evaluation of model selection criteria provides a mixed result – the Akaike criterion favours the asymmetric model 53 per cent of the time, whereas the Schwartz criterion indicates that the symmetrical model is preferred in 66 per cent of cases.

Table 7.2
Percentage of significant coefficients at the 5% level in the correlation equations of Diagonal VECH models

	Symmetric model	Asymmetric model
ARCH	47%	6%
GARCH	78%	73%
TARCH		16%

The coefficient is considered significant if the probability associated with its z-statistic is less than 5 per cent. There are 351 models in total.

Since there is no clear evidence that the asymmetric model performs better, the correlation between the equity and bond returns estimated by the symmetric version of the Diagonal VECH model is used in the base case regressions.

7.3. The Relationship between Equity Volatility and the Correlation between the Equity and Bond Returns

It is expected that equity volatility has a positive impact upon the conditional correlation between the equity and bond returns. This expectation is inconsistent with the prediction of the structural model that a change in volatility of the value of firm's assets has an opposite effect on the values of equity and debt. As holders of a call option on firm's assets, equity holders stand to benefit from the upside potential associated with higher volatility, whereas debt holders face only a higher default probability caused by an increase in volatility. Therefore, a change in asset volatility should give rise to a negative correlation between equity and bond returns. This result is derived under an assumption that the value of the underlying assets remains the same. In this case, a change in asset volatility causes a redistribution of value between equity and debt holders.

In the empirical data it is hard to find an observation when the asset volatility changes while the asset value remains unchanged. In the sample used in this study, the volatility of underlying assets is negatively correlated with equity and bond returns. This indicates that an increase in volatility is accompanied by a decrease in the values of debt and equity.

7.3.1. The Constant Coefficient Model

In the first step, the relationship between the equity volatility and the conditional correlation between equity and bond returns is examined in a constant coefficient panel data model which estimates unique coefficients for all firms in the sample. The results are presented in Table 7.3.

The relationship between equity volatility and the correlation between the equity and bond returns is positive as expected. The coefficient is statistically significant and its size implies that a percentage point increase in annual equity volatility raises the correlation by 0.3 per cent. Equity volatility explains about six per cent of variations in the correlation.

This result is generally consistent with Scheicher (2009) who reports that an increase in equity volatility negatively impacts upon the correlation between the equity returns and credit default swap premia. A negative coefficient of equity volatility in the Scheicher study is equivalent to a positive coefficient in this study because bond returns and credit default swap premia are negatively correlated.

Table 7.3
The impact of equity volatility upon the correlation between the equity and bond returns: the constant coefficient model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	0.33	0.03	10.14	0.00
C	-0.03	0.01	-1.76	0.08
R-squared	0.06	Mean dependent var		0.09
Adjusted R-squared	0.06	S.D. dependent var		0.28
S.E. of regression	0.27	Akaike info criterion		0.20
Sum squared resid	2,428.70	Schwarz criterion		0.20
Log likelihood	-3,432.80	Hannan-Quinn criter.		0.20
F-statistic	2,128.31	Durbin-Watson stat		0.35
Prob(F-statistic)	0.00			

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,870; White period standard errors & covariance (d.f. corrected); Equity volatility is annualized.

7.3.2. The Cross-sectional Fixed Effects Model

The constant coefficient model by construction does not allow cross-sectional differences in a relationship. In this case it is too restrictive as the correlation between equity and bond returns should be, in addition to equity volatility, influenced by bond maturity, credit risk and other factors. To account for those other factors, each firm in the sample is allowed to have its own intercept or fixed effect.

The results, which are presented in Table 7.4, indicate large cross-sectional differences in the correlation between the equity and bond returns. The relationship between equity volatility and the correlation remains positive and significant as in the constant coefficient model presented in Table 7.3, but the economic and the statistical significance of equity volatility is substantially reduced. The results imply that a one percentage point increase in equity volatility raises the correlation by 0.1 percentage point. Further, the fixed effects increase the R-squared of the model from six per cent to 61 per cent.

Table 7.4
The impact of equity volatility upon the correlation between the equity and bond returns: the cross-sectional fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	0.06	0.02	2.77	0.01
C	0.07	0.01	9.36	0.00
R-squared	0.61	Mean dependent var		0.09
Adjusted R-squared	0.61	S.D. dependent var		0.28
S.E. of regression	0.17	Akaike info criterion		-0.67
Sum squared resid	996.51	Schwarz criterion		-0.58
Log likelihood	11,653.73	Hannan-Quinn criter.		-0.64
F-statistic	151.87	Durbin-Watson stat		0.83
Prob(F-statistic)	0.00			

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,870; White period standard errors & covariance (d.f. corrected).

Formal tests strongly reject the hypothesis that fixed effects are redundant. As shown in Table 7.5, the F-test and the χ^2 test assign zero probability to a hypothesis that the fixed effects are redundant.

Table 7.5
The test for the redundancy of the fixed-effects

Test cross-section fixed effects	Statistic	d.f.	Prob.
Cross-section F	137.63	-3.50E+07	0.00
Cross-section Chi-square	30173.04	350.00	0.00

The tests evaluate the joint significance of the fixed effects using sums-of-squares (F-test) and the likelihood function (Chi-square test).

It is noted that the fixed effects are substantially more important in the analysis of the correlation between the equity and bond returns than in the analysis of the credit spread, as presented in Chapter 5. In the latter analysis, the fixed effects improve the model's R-squared by 14 percentage points and do not substantially reduce the size of the coefficient of equity volatility.

7.3.3. The Period Fixed Effects Model

The constant correlation panel model is augmented with period fixed effects to control for time variations in the relationship between equity volatility and the correlation.

Similar to cross-sectional fixed effects, which capture firm specific factors, period fixed effects are dummy variables which take the value of one if an observation is in a particular month, and zero otherwise. The results are presented in Table 7.6.

The relationship between equity volatility and the correlation between the equity and bond returns remains positive and statistically significant after controlling for the period effects. The economic significance of equity volatility (the magnitude of the coefficient) is increased by 43 percentage points relative to the coefficient in the constant coefficient model presented in Table 7.3. The estimated coefficient implies that a one percentage point increase in equity volatility raises the correlation by 0.5 percentage point. The period fixed effects improve the model's adjusted R-squared from six per cent to nine per cent. Formal tests strongly reject the hypothesis that the period effects are redundant. It should be noted that the improvement in explanatory power is modest in comparison to the improvement associated with the cross-sectional fixed effects. Consistent with the results presented in Chapter 5 and other studies (e.g. Ericsson, Jacobs and Oviedo, 2009), this result highlights the challenges in explaining the correlation between the equity and bond returns in cross-section.

Table 7.6
The impact of equity volatility upon the correlation between the equity and bond returns: the period fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	0.47	0.05	9.66	0.00
C	-0.08	0.02	-4.16	0.00

R-squared	0.10	Mean dependent var	0.09
Adjusted R-squared	0.09	S.D. dependent var	0.28
S.E. of regression	0.26	Akaike info criterion	0.17
Sum squared resid	2,330.59	Schwarz criterion	0.22
Log likelihood	-2,734.45	Hannan-Quinn criter.	0.19
F-statistic	20.71	Durbin-Watson stat	0.36
Prob(F-statistic)	0.00		

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (period fixed - dummy variables); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,870; White period standard errors & covariance (d.f. corrected).

7.4. The Relationship between the Distance to Default of Merton (1974) and the Correlation between the Equity and Bond Returns

The structural model implies that the strength of correlation between the returns on firm's equity and debt depend on the level of credit risk. High quality firms are very unlikely to default hence new information from equity markets has limited importance for the holders of their debt. Therefore, the returns on high quality bonds behave like the returns on government bonds. However, a change in the value of equity becomes increasingly relevant for bond pricing as the level of credit risk increases. At the brink of bankruptcy, bond returns are expected to be highly and positively correlated to equity returns.

The level of credit risk is proxied by the distance to default of Merton (1974). A higher distance to default implies a lower credit risk. Therefore, it is expected that the distance to default has a negative impact upon the correlation between the equity and bond returns.

7.4.1. The Constant Coefficient model

The starting point of the analysis is a constant coefficient panel model. The conditional correlation between the equity and bond returns is regressed on the distance to default, and unique coefficients are estimated for all firms in the sample. The results are presented in Table 7.7.

The coefficient of the distance to default is negative and significant as expected. The effect is significant in an economic sense as well. An improvement in credit quality as measured by one distance to default lowers the correlation by two percentage points. This implies that the equity and bond returns of risky firms (i.e. firms with a lower distance to default) are more positively correlated than for less risky firms. The distance to default explains about six per cent of the variation in the correlation, which is similar to the explanatory power of equity volatility.

Table 7.7
The impact of the distance to default upon the correlation between the equity and bond returns: the constant coefficient model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Distance to Default	-0.02	0.00	-7.01	0.00
C	0.22	0.02	9.35	0.00
R-squared	0.06	Mean dependent var		0.09
Adjusted R-squared	0.06	S.D. dependent var		0.28
S.E. of regression	0.27	Akaike info criterion		0.20
Sum squared resid	2,426.22	Schwarz criterion		0.20
Log likelihood	-3,421.46	Hannan-Quinn criter.		0.20
F-statistic	2,141.28	Durbin-Watson stat		0.35
Prob(F-statistic)	0.00			

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,855; White period standard errors & covariance (d.f. corrected).

7.4.2. The Cross-sectional Fixed Effects Model

Table 7.8 presents an estimate of the fixed effects panel data model in which each firm in the sample has its own intercept.

Table 7.8
The impact of the distance to default and the correlation between the equity and bond returns: the cross-sectional fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Distance to Default	0.00	0.00	-1.59	0.11
C	0.10	0.01	11.17	0.00
R-squared	0.61	Mean dependent var		0.09
Adjusted R-squared	0.61	S.D. dependent var		0.28
S.E. of regression	0.17	Akaike info criterion		-0.66
Sum squared resid	998.77	Schwarz criterion		-0.58
Log likelihood	11,602.71	Hannan-Quinn criter.		-0.64
F-statistic	151.08	Durbin-Watson stat		0.83
Prob(F-statistic)	0.00			

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,855; White period standard errors & covariance (d.f. corrected).

After allowing for fixed effects, the distance to default becomes statistically insignificant. The t-statistic is reduced from 7.01 in the constant coefficient model presented in Table 7.7 to 1.59 which makes it statistically insignificant at the ten per cent level. Further, the coefficient size approaches zero which indicates a low economic significance. This unexpected result is also obtained by Scheicher (2009) who reports that a simple leverage ratio (total debt / total assets) is not a significant determinant of the correlation between the equity returns and the credit default swap premia. As in this study, Scheicher uses a panel model with fixed effects and a White period covariance matrix. The author notes that this finding may be due to a limited data sample which includes only three years of quarterly observations. The above results are based on a data sample with 33,855 observations hence they cannot be explained by a limited sample. Since the distance to default becomes insignificant after the fixed effects are added to the model, an alternative explanation is that the cross-sectional differences in credit risk are captured by the fixed effects. To examine this hypothesis, a constant coefficient model is augmented with dummy variables taking the value of one is the distance to default is within a certain range and zero otherwise, instead of the fixed effects.

Seven dummy variables are created for values of the distance to default variable. The dummy variable which indicates the lowest credit risk (i.e. the distance to default ≥ 6) is dropped to avoid the multicollinearity problem (the dummy variable trap). As shown in Table 7.9, after controlling for the level of the distance to default, changes in that distance are not significant in explaining the correlation between the equity and bond returns. As suspected, it seems that the fixed effects in the panel model presented in Table 7.8 capture this effect. The dummy variables are statistically significant for values of the distance to default up to a value of four. The magnitude of coefficients emphasizes the economic significance of credit risk in determining the correlation. The correlation between equity and bond returns of the lowest-risk firms is virtually zero, while the correlation between the returns of the highest-risk firms is 31 per cent.

Table 7.9
The impact of the distance to default upon the correlation between the equity and bond returns, after controlling for the level of distance to default

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Distance to Default	0.00	0.00	-0.43	0.67
Distance to Default < 1	0.31	0.04	7.74	0.00
1 ≤ Distance to Default < 2	0.25	0.04	6.64	0.00
2 ≤ Distance to Default < 3	0.18	0.03	6.10	0.00
3 ≤ Distance to Default < 4	0.10	0.02	4.49	0.00
4 ≤ Distance to Default < 5	0.03	0.02	1.65	0.10
5 ≤ Distance to Default < 6	0.00	0.01	0.26	0.80
C	0.04	0.03	1.29	0.20
R-squared	0.10	Mean dependent var		0.09
Adjusted R-squared	0.10	S.D. dependent var		0.28
S.E. of regression	0.26	Akaike info criterion		0.16
Sum squared resid	2,321.86	Schwarz criterion		0.16
Log likelihood	-2,677.26	Hannan-Quinn criter.		0.16
F-statistic	536.91	Durbin-Watson stat		0.37
Prob(F-statistic)	0.00			

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,855 - Distance-to-Default < 1 (800), 1 ≤ Distance-to-Default > 2 (1811), 2 ≤ Distance-to-Default > 3 (3,430), 3 ≤ Distance-to-Default > 4 (4,615), 4 ≤ Distance-to-Default > 5 (5,611), 5 ≤ Distance-to-Default > 6 (5,387), Distance-to-Default ≥ 6 (12,201); White period standard errors & covariance (d.f. corrected).

The results presented in Table 7.9 indicates that the correlation between the equity and bond returns monotonically decreases with the credit risk up to a certain point after which further changes in the credit risk do not impact upon the correlation.

To further examine this issue, Table 7.10 presents a panel model with fixed effects for observations with a value of distance to default of less than four. The coefficient of the distance to default is negative and significant at the five per cent level. An improvement in credit quality as measured by one distance to default lowers the correlation by one percentage point. This confirms that the statistical insignificance of the distance to default in the model presented in Table 7.8 is explained by the fixed effects capturing cross-sectional differences in credit risk.

Table 7.10
The impact of the distance to default (for observations with the value less than 4) upon the correlation between the equity and bond returns: the cross-sectional fixed model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Distance to Default	-0.01	0.01	-2.30	0.02
C	0.24	0.02	14.64	0.00
R-squared	0.59	Mean dependent var		0.20
Adjusted R-squared	0.57	S.D. dependent var		0.31
S.E. of regression	0.20	Akaike info criterion		-0.33
Sum squared resid	421.84	Schwarz criterion		-0.10
Log likelihood	2,085.28	Hannan-Quinn criter.		-0.25
F-statistic	43.23	Durbin-Watson stat		0.97
Prob(F-statistic)	0.00			

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample: 1996M08 2011M02 IF Distance to Default<4; Periods included: 164; Cross-sections included: 339; Total panel (unbalanced) observations: 10,656; White period standard errors & covariance (d.f. corrected).

7.4.3. The Period Fixed Effects Model

To control for the common time variations in the correlation between the equity and bond returns, the model is augmented with a dummy variable for each period (i.e. month) in the sample. The results are presented in Table 7.11.

After controlling for the time variations, the relationship between the distance to default and the correlation between the equity and bond returns remains negative and significant. Relative to the constant coefficient model presented in Table 7.7, the size of the coefficient increased in the absolute value from -0.02 to -0.03 with no substantial change in statistical significance. This implies that an improvement in credit quality as measured by one distance to default lowers the correlation by three percentage points. The results are similar to the results obtained in the model with equity volatility as an independent variable, and are expected because equity volatility and the distance to default are highly correlated. The significance of period fixed effects indicates the influence of common factors on the relationship between the equity and bond returns.

Table 7.11
The impact of the distance to default upon the correlation between the equity and bond returns: the period fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Distance to Default	-0.03	0.00	-6.63	0.00
C	0.26	0.03	8.74	0.00
R-squared	0.10	Mean dependent var		0.09
Adjusted R-squared	0.09	S.D. dependent var		0.28
S.E. of regression	0.26	Akaike info criterion		0.17
Sum squared resid	2,334.35	Schwarz criterion		0.22
Log likelihood	-2,768.06	Hannan-Quinn criter.		0.19
F-statistic	20.23	Durbin-Watson stat		0.36
Prob(F-statistic)	0.00			

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (period fixed - dummy variables); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,855; White period standard errors & covariance (d.f. corrected).

7.5. The Interaction between the Equity Volatility and Credit Risk in Explaining Variations in the Correlation between the Equity and Bond Returns

The structural model implies that the importance of equity volatility as a determinant of the value of corporate debt increases with credit risk. In Chapter 5 it is shown that the economic and the statistical significance of equity volatility in determining the credit spread increases monotonically as the distance to default shrinks (i.e. the credit risk increases). This prediction of structural model is generally confirmed by a number of existing studies (e.g. Campbell and Taksler, 2003; Cremers et al., 2008). To examine if the relationship between the equity volatility and the correlation between the equity and bond returns depends on the level of credit risk, the constant coefficient model is augmented with the equity volatility multiplied by the distance to default as an interaction variable. The results are presented in Table 7.12.

The interaction variable is statistically significant as expected. A negative coefficient implies a lower correlation of the equity and bond returns for stronger firms (i.e. firms with a high value for the distance to default). The interaction effect appears to be very high in magnitude. The coefficient of the interaction variable is 77 per cent of the equity volatility coefficient, whereas in the corresponding model with the credit spread as a dependent variable it stands at 20 per cent of the equity volatility coefficient.

The results imply that the interaction effect is highly economically significant in explaining the correlation between equity and bond returns. The magnitude of the interaction coefficient reveals that the effect of equity volatility on the correlation between the equity and bond returns is not always positive. While an increase in credit risk (i.e. a decrease in the distance to default) always has a positive impact upon the correlation, an increase in equity volatility only heightens the correlation between the equity and bond returns of firms with the highest credit risk exposure (i.e. firms with the distance of default up to 1.3). A one percentage point increase in equity volatility raises the correlation by 0.17 percentage point, and that effect decreases at the rate of 0.13 percentage point per improvement in credit quality as measured by one distance to default. In other words, after controlling for the credit risk, the effect of equity volatility on the correlation turns negative.

Table 7.12
The interaction between the equity volatility and the distance to default in explaining variations in the correlation between equity and bond returns

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	0.17	0.04	4.32	0.00
Equity Volatility x Distance to Default	-0.13	0.03	-5.07	0.00
C	0.23	0.05	4.44	0.00

R-squared	0.09	Mean dependent var	0.09
Adjusted R-squared	0.09	S.D. dependent var	0.28
S.E. of regression	0.26	Akaike info criterion	0.17
Sum squared resid	2,351.22	Schwarz criterion	0.17
Log likelihood	-2,889.97	Hannan-Quinn criter.	0.17
F-statistic	1,644.63	Durbin-Watson stat	0.36
Prob(F-statistic)	0.00		

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,855; White period standard errors & covariance (d.f. corrected).

The coefficient of the interaction variable shows how the effect of equity volatility changes with a unit change in the distance to default. It should be noted that the interaction coefficient shows the average change in the effect of equity volatility. By construction, it cannot take into account the non-linearity in the relationship between the distance to default and the effect of equity volatility (i.e. a change in the effect of equity volatility is expected to be different when the distance to default increases from, for example, one to two than when the distance to default increases from four to five). To take into account this feature of the interaction, the interaction variable in Table 7.12 is replaced with a set of discreet interaction variables, i.e. dummy variables controlling for the differences in the distance to default multiplied by equity volatility. As in Chapter 5, seven dummy variables are created and the dummy variable which indicates the lowest credit risk (i.e. the distance to default ≥ 6) is dropped to avoid the dummy variable trap. The results are presented in Table 7.13.

The total effect of equity volatility in Table 7.13 is the sum of the equity volatility coefficient and an interaction variable coefficient. It is clear that an increase in equity volatility positively impacts the correlation between the equity and bond returns of the firms with the distance to default up to three, whereas the impact is negative for the firms further away from the default point. The difference in the total effect between the highest and the lowest credit risk groups is highly significant in an economic sense. A one percentage point increase in equity volatility of the lowest-risk firms (DD>6) lowers the correlation by 0.78 percentage point, while the equivalent change in equity volatility increases the correlation between equity and bond returns of the highest-risk firms (DD<1) by 0.12 percentage point.

The results presented in tables 7.12 and 7.13 clearly leads to acceptance of the hypothesis that the effect of equity volatility upon the correlation between the equity and bond returns depends on the level of credit risk.

Table 7.13
The relationship between equity volatility and the correlation between the equity and bond returns across distance to default groups

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Equity Volatility	-0.78	0.04	-4.34	0.00
Equity Volatility x I (Distance to Default < 1)	0.90	0.03	5.70	0.00
Equity Volatility x I (1 ≤ Distance to Default < 2)	0.89	0.03	6.24	0.00
Equity Volatility x I (2 ≤ Distance to Default < 3)	0.79	0.04	6.48	0.00
Equity Volatility x I (3 ≤ Distance to Default < 4)	0.61	0.04	6.03	0.00
Equity Volatility x I (4 ≤ Distance to Default < 5)	0.36	0.03	4.54	0.00
Equity Volatility x I (5 ≤ Distance to Default < 6)	0.20	0.02	3.41	0.00
C	0.20	0.01	5.12	0.00

R-squared	0.10	Mean dependent var	0.09
Adjusted R-squared	0.10	S.D. dependent var	0.28
S.E. of regression	0.26	Akaike info criterion	0.15
Sum squared resid	2,309.34	Schwarz criterion	0.16
Log likelihood	-2,585.75	Hannan-Quinn criter.	0.15
F-statistic	566.03	Durbin-Watson stat	0.38
Prob(F-statistic)	0.00		

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33855; White period standard errors & covariance (d.f. corrected).

$I(\cdot)$ is the indicator function which equals one if the distance to default is within a predefined range and zero otherwise

7.6. The Relationship between Common Factors and the Correlation between the Equity and Bond Returns

It is commonly accepted that the correlation between asset returns increases in volatile times. Bartram and Bodnar (2009) document an increase in the correlation between equity markets during the recent financial crises in 2008. Longin and Solnik (2001) find that the conditional correlation strongly increases only in bear markets. In line with these findings, Belke and Gokus (2011) report that the correlation between equity returns and credit spreads of four major financial institutions increased during the recent financial crises in 2008. These findings suggest that market-wide volatility and returns are important determinants of the correlation between the equity and bond returns. On the other hand, the structural model implies that the correlation is primarily determined by idiosyncratic factors such as firm's leverage and its asset volatility.

The risk-free rate is expected to have a negative impact upon the correlation between the equity and bond returns because an increase in the risk-free rate gives rise in equity prices while depressing bond prices through higher discounting of promised coupon and principal payments.

As discussed in Chapter 5, common factors considered are the S&P 500 index return and volatility, the risk-free rate, and the slope of the risk-free term structure measured as the difference in the redemption yields of government bonds with a maturity of ten and two years. The relationship between the common factors and the correlation between the equity and bond returns is examined in a constant coefficient panel model. The results are presented in Table 7.14.

The risk-free rate and the slope of the risk-free term structure are statistically significant in explaining the variations in the correlation between the equity and bond returns. As expected, the estimated coefficients are negative in both cases. It should be highlighted that the economic significance of the risk-free rate by far exceeds the economic significance of all of the firm-level variables considered (i.e. the equity volatility and the distance to default) as well as market-wide equity volatility. A one percentage point increase in the risk-free rate and the slope decreases the correlation by 2.07 and 3.88 percentage points respectively. The S&P 500 index returns are found to be insignificant, while the S&P 500 index volatility is significant. As expected, an increase in the S&P index volatility leads to an increase in the correlation between the equity and bond returns. However, the economic significance of the S&P 500 index volatility is low as a one percentage point increase in the volatility raises the correlation by 0.11 percentage point, which is substantially less than the increase of 0.3 percentage point caused by the same increase in firm-level equity volatility in the corresponding model presented in Table 7.3. Although the three variables considered are found to be statistically significant in explaining variations in the correlation between the equity and bond returns, the model's explanatory power is low. At less than one per cent its power is just a fraction of that for an univariate model with the firm-level equity volatility or the distance to default as explanatory variables.

Table 7.14
The relationship between common factors and the correlation between the equity and bond returns

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Risk-free Rate	-2.07	0.46	-4.45	0.00
Risk-free Term Structure Slope	-3.88	0.83	-4.65	0.00
S&P 500 Index Returns	0.01	0.03	0.26	0.80
S&P 500 Index Volatility	0.11	0.03	4.01	0.00
C	0.17	0.03	6.39	0.00
R-squared	0.00	Mean dependent var		0.09
Adjusted R-squared	0.00	S.D. dependent var		0.28
S.E. of regression	0.28	Akaike info criterion		0.26
Sum squared resid	2,570.35	Schwarz criterion		0.26
Log likelihood	-4,392.75	Hannan-Quinn criter.		0.26
F-statistic	36.15	Durbin-Watson stat		0.32
Prob(F-statistic)	0.00			

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,870; White period standard errors & covariance (d.f. corrected).

Not accounting for cross-sectional differences in exposure to systematic risks may be one cause for the low explanatory power of the model. This is examined by regressing the correlation between the equity and bond returns on the expected equity returns and the volatility of expected equity returns implied by the Fama and French three factor model instead of the S&P 500 index returns and volatility. The expected equity returns, which take into account firm-level exposure to systematic risks, are estimated according to the procedure described in Section 4.3.4. The results are presented in Table 7.15.

Taking into account cross-sectional differences in betas appears to improve the model. Unlike the S&P 500 index returns, the Fama and French three factor model implied systematic returns are found to be statistically significant. The positive coefficient implies that an increase in the expected returns heightens the correlation between the equity and bond returns. However, the economical significance appears to be limited.

The results imply that a one per cent increase in the systematic returns raise the correlation by 0.07 percentage point. Since the systematic returns are determined by the risk premiums and sensitivities of firm-level returns to changes in the risk premiums, an increase in systematic returns may be interpreted as an increase in the exposure to systematic risks. Therefore, this result is consistent with the hypothesis that an increase in firm's risk exposure strengthens the correlation between bond and equity returns. The volatility of expected returns outperforms the S&P 500 index volatility in terms of statistical significance. A one percentage point increase in volatility of the expected returns raises the correlation by 0.28 percentage point, while, as presented in Table 7.14, the corresponding increase in the S&P Index volatility rises the correlation by 0.11 percentage point. As a consequence the R-squared of the model is substantially improved relative to the model presented in Table 7.14. However, at three per cent it still does not approach the level of a univariate model with the firm-level equity volatility or the distance to default as an explanatory variable. This suggests that idiosyncratic factors are more important determinants of the correlation between the equity and bond returns than common factors.

Table 7.15
The relationship between the firm's exposure to systematic risks and the correlation between the equity and bond returns

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Risk-free Rate	-1.12	0.46	-2.42	0.02
Risk-free Term Structure Slope	-2.87	0.82	-3.49	0.00
Systematic Equity Returns	0.07	0.03	2.15	0.03
Systematic Equity Volatility	0.28	0.04	6.94	0.00
C	0.10	0.03	3.78	0.00
R-squared	0.03	Mean dependent var		0.09
Adjusted R-squared	0.03	S.D. dependent var		0.28
S.E. of regression	0.27	Akaike info criterion		0.24
Sum squared resid	2,516.14	Schwarz criterion		0.24
Log likelihood	-4,031.76	Hannan-Quinn criter.		0.24
F-statistic	219.34	Durbin-Watson stat		0.34
Prob(F-statistic)	0.00			

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02Periods included: 175Cross-sections included: 351Total panel (unbalanced) observations: 33,870; White period standard errors & covariance (d.f. corrected).

7.7. Robustness of the Results

7.7.1. The Correlation between the Equity and Bond Returns Modelled as an Asymmetric Diagonal VECH Process

The empirical results presented in this chapter may be influenced by the choice of method for estimation of the conditional correlation between the equity and bond returns. Based on the analysis in Section 7.2, a bivariate Diagonal VECH (1,1) model is utilised to estimate the correlation. This model does not allow that positive and negative news have a different impact upon equity and bond volatility. Although this feature is arguably unrealistic, an extended version of the model allowing for the asymmetric impact of positive and negative news on the volatilities is not found to be clearly superior relative to the Diagonal VECH (1,1) model.

To examine if a different specification of the model might change the main results, the correlation between the equity and bond returns is estimated by an asymmetric Diagonal VECH (1,1,1) model, and regressed on equity volatility, the distance to default and the interaction variable. The regression results are presented in Table 7.16.

The statistical and economic significance of all of the model coefficients is very similar to those previously presented in Tables 7.3, 7.7 and 7.11. Allowing for the asymmetry appears to slightly improve the explanatory power of the models. The largest improvement in R-squared of about one percentage point can be observed in the univariate model with equity volatility as an explanatory variable (Model 1). Therefore, it can be concluded that the results obtained are robust to a change in the method for estimating the correlation between the equity and bond returns.

Table 7.16
Robustness check: modelling the correlation between the equity and bond returns as an Asymmetric Diagonal VECH process

Variable	Model 1	Model 2	Model 3
Equity Volatility	0.33		0.20
	[10.00]		[5.05]
Distance to Default		-0.02	
		[-6.61]	
Equity Volatility x Distance to Default			-0.11
			[-4.55]
C	-0.03	0.22	0.19
	[-1.88]	[8.89]	[3.75]
Adjusted R-Squared	0.07	0.06	0.09

Dependent Variable: Equity-Bond Returns Correlation (Asymmetric); Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,870; White period standard errors & covariance (d.f. corrected). The t-statistics are shown in parentheses.

7.7.2. The Firm Size

The firm size is also an important risk indicator. The results presented in Chapter 5 indicate that small firms have a wider credit spread than large firms. To examine if the results obtained hold after controlling for the size of firms in the sample, the regression models are augmented with a set of four dummy variables which take the value of one if firm's asset value is in a certain range, and zero otherwise. The fifth dummy variable, which represents the largest firms, is dropped to avoid the multicollinearity problem or the dummy variable trap. The results are presented in Table 7.17.

The results are not substantially changed after controlling for size. The coefficients of all three variables (the equity volatility, the distance to default and the interaction variable) retain their statistical and economic significance in determining the correlation between the equity and bond returns.

Table 7.17
Robustness check: controlling for the firm size

Variable	Model 1	Model 2	Model 3
Equity Volatility	0.29		0.15
	[8.10]		[3.69]
Distance to Default		-0.02	
		[-6.23]	
Equity Volatility x Distance to Default			-0.13
			[-4.91]
Asset Value Dummy 1 (smallest)	0.07	0.06	0.05
	[2.30]	[1.83]	[1.53]
Asset Value Dummy 2	-0.04	-0.06	-0.06
	[-1.48]	[-2.08]	[-1.99]
Asset Value Dummy 3	-0.03	-0.04	-0.04
	[-0.92]	[-1.48]	[-1.42]
Asset Value Dummy 4 (largest)	-0.03	-0.04	-0.04
	[-1.20]	[-1.58]	[-1.51]
C	0.00	0.24	0.26
	[-0.17]	[6.99]	[4.54]
Adjusted R-Squared	0.07	0.08	0.10

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33'855; White period standard errors & covariance (d.f. corrected). The t-statistics are shown in parentheses.

7.7.3. Bond-specific Variables

Bond duration and bond issue size are important characteristics which might potentially influence the correlation between the equity and bond returns. The relationship between the duration and risks inherent in a bond is straightforward. A longer duration indicates a higher risk, ceteris paribus. Therefore, the returns on long-term bonds should behave more like the equity returns than the returns on short-term bonds.

The size of a bond issue may affect the correlation between the equity and bond returns through the liquidity mechanism. Large bond issues are more liquid, and therefore, their values should react more quickly to shocks in the value of the issuing firm's equity.

To examine if the obtained results are sensitive to changes in the maturity and liquidity of bonds in the sample, the models are augmented with two sets of four dummy variables to control for bond duration and the issue size. Bonds with the largest issue size and the longest duration have no dummies in these models. The results are presented in Table 7.18.

Controlling for the bond characteristics does not change the results presented earlier in this chapter. The magnitude and t-statistics of the coefficients of the equity volatility, the distance to default and the interaction variable are almost the same as previously presented in Tables 7.3, 7.7 and 7.11. Interestingly, none of the control variables is statistically significant.

Table 7.18
Robustness check: controlling for the bond duration and the bond issue size

Variable	Model 1	Model 2	Model 3
	0.33		0.18
Equity Volatility	[10.85]		[4.71]
Distance to Default		-0.03	
		[-7.33]	
Equity Volatility x Distance to Default			-0.13
			[-5.10]
Bond Value Dummy 1 (smallest)	-0.04	-0.04	-0.04
	[-1.01]	[-1.12]	[-1.21]
Bond Value Dummy 2	-0.05	-0.05	-0.05
	[-1.37]	[-1.48]	[-1.50]
Bond Value Dummy 3	-0.04	-0.04	-0.03
	[-1.27]	[-1.19]	[-1.09]
Bond Duration Dummy 1 (shortest)	-0.02	-0.02	-0.03
	[-0.82]	[-0.65]	[-1.15]
Bond Duration Dummy 2	0.04	0.03	0.03
	[1.60]	[1.50]	[1.19]
Bond Duration Dummy 3	0.01	0.00	0.00
	[0.42]	[0.01]	[0.04]
C	0.00	0.25	0.25
	[-0.11]	[6.91]	[4.41]
Adjusted R-Squared	0.07	0.07	0.10

Dependent Variable: Equity-Bond Returns Correlation; Method: Panel Least Squares (constant coefficient model); Sample: 1996M08 2011M02; Periods included: 175; Cross-sections included: 351; Total panel (unbalanced) observations: 33,870; White period standard errors & covariance (d.f. corrected).

7.8. Summary

This chapter empirically examines the hypotheses formulated in Chapter 6. The structural model of Merton (1974) implies that the information affecting the value of firm's assets induces a positive correlation between the equity and bond returns, whereas the information related to the volatility of underlying assets causes a wealth transfer between the equity and debt holders, hence inducing a negative correlation between the returns. Since the wealth-transferring events (e.g. leveraged buyouts) are relatively rare, Hypothesis 1 states that the correlation between the equity and bond returns is positive on average.

Signals from the equity market become increasingly relevant to bond holders as a firm's risk exposure grows and therefore the default becomes more probable. The existing empirical evidence (e.g. Cheyette and Tomaich, 2003) points out that the returns on bonds issued by highly rated firms can be primarily explained by the returns on government bonds. The relevance of equity returns in explaining the bond returns increase as firm's credit rating deteriorates. Therefore, hypotheses 2 and 3 state that the equity volatility and credit risk have a positive impact upon the correlation between the equity and bond return. Following the same argument, there should be a significant interaction between the equity volatility and credit risk in explaining the correlation between the equity and bond returns, hence Hypothesis 4 states that the effect of equity volatility depends on the credit risk.

Common factors are generally expected to influence the correlation between asset returns. The existing empirical studies focus on the correlation between international equity markets and generally report that the correlation increases in turbulent times. In line with this, the hypotheses 5 and 6 state that the systematic risks (the risk-free rate) have a positive (negative) impact upon the correlation between the equity and bond returns.

These hypotheses are empirically tested on a sample consisting of 351 firms, including over 33,000 monthly observations. This study contributes to the existing literature in a number of ways. While most of existing studies examines the unconditional correlation between the credit spread and risk indicators, this study utilizes the bivariate Diagonal

VECH(1,1) model to estimate the conditional correlation between the equity and bond returns, and then comprehensively examines how equity and credit risks impact upon the correlation. Scheicher (2009), and Belke and Gokus (2011) use a similar methodology, but Scheicher (2009) analyses the relationship between the equity and credit default swap markets, and the Belke and Gokus (2011) study is based on a limited sample consisting of four large banks. Further, this study explicitly estimates to structural model to derive an indicator of credit risk, while the mentioned studies use an accounting-based leverage ratio (Scheicher, 2009) or omit analysis of determinants of the correlation (Belke and Gokus, 2011).

In line with Scheicher (2009) and Belke and Gokus (2011), the conditional correlation is found to vary over time, peaking during the recent 2007 financial crisis. The bond and equity returns are found to be positively correlated on average, which leads to the acceptance of Hypothesis 1.

Equity volatility, which is estimated from a GARCH(1,1) model, is found to have a positive effect on the correlation between the equity and bond returns. In the constant coefficient panel model, the equity volatility is statistically significant and explains about six per cent of the variation in the correlation. The magnitude of the coefficient implies that it is also economically significant. An increase in equity volatility of one per cent raises the correlation by 0.3 per cent.

Factually, the sensitivity of the correlation to changes in equity volatility depends on the level of credit risk, bond characteristics and other factors. As a result, allowing for cross-sectional fixed effects reduces the size and the significance of the equity volatility coefficient, but equity volatility remains statistically significant at the level of one per cent. Furthermore, the fixed effects increase the R-squared ratio from six per cent to 61 per cent. These results are consistent with those reported by Scheicher (2009) and highlight challenges in explaining the correlation between the equity and bond returns in the cross-section. A strong presence of these cross-sectional fixed effects is also found in Chapter 5 and in other existing empirical studies of the relationship between the equity volatility and the credit spread (e.g. Ericsson, Jacobs and Oviedo, 2009). On the other hand, allowing for the period fixed effects increases the size of the coefficient, but does not significantly change the coefficient's significance and the model's R-squared ratio. These results lead to the acceptance of Hypothesis 2 stating that equity volatility has a positive impact upon the correlation between the equity and bond returns.

The impact of credit risk upon the correlation between the equity and bond returns is assessed by regressing the correlation on the distance to default by Merton (1974). As the feedback from the equity markets becomes increasingly important when a firm approaches bankruptcy, Hypothesis 3 states that the strength of the correlation between the equity and bond returns depends on the credit risk. The results from the constant coefficient panel model leads to the acceptance of this hypothesis. The coefficient of the distance to default is statistically significant and negative, indicating that the returns of firms with a lower distance to default (i.e. higher credit risk) are more positively correlated. The distance to default does not appear to be a better explanatory variable than the equity volatility in terms of statistical significance and explanatory power. This comes as a surprise as the distance to default is a much more comprehensive indicator of credit risk than equity volatility. In addition to equity volatility, the distance to default incorporates the information on firm leverage and the risk-free rate. Therefore, the distance to default should clearly outperform the equity volatility as a determinant of the correlation between the returns.

The impact of credit risk upon the correlation is highly nonlinear. In other words, the sensitivity of the correlation to changes in the distance to default depends on the level of distance to default. As a result, the distance to default is insignificant in a panel model with cross-sectional fixed effects. However, in contrast, the dummy variables which control for the level of distance to default are highly significant. The magnitude of the coefficients increases monotonically as the distance to default approaches zero (i.e. as the credit risk increases). This clearly confirms that the cross-sectional fixed effects capture the differences in the level of the distance to default.

Consistent with Hypothesis 4, the sensitivity of the correlation between the equity and bond returns to changes in equity volatility is found to strongly depend on the level of credit risk. In fact, the interaction between the equity volatility and credit risk is crucial to understanding how the equity volatility influences the correlation between the equity and bond returns. As noted above, an increase in equity volatility strengthens the correlation on average. After controlling for the credit risk, the effect of equity volatility becomes negative. In other words, the effect is positive only if the firm's credit risk is high. Theoretically, this implies that a change in equity volatility of high-quality firms primarily affects the volatility, rather than the value of firms' underlying assets. Practically, a same hedging strategy involving corporate equities and bonds may be profitable for portfolios consisted of high-quality firms and produce a loss for portfolios consisting of high-risk firms.

The structural model implies that the correlation between the equity and bond returns is primarily driven by the firm-level variables. In contrast to this, a growing body of empirical literature emphasizes the importance of common factors in determining the correlation between asset returns. As set out in Hypothesis 5, the market-wide equity volatility is found to be a significant determinant of the correlation between the equity and bond returns. However, there is no evidence suggesting that the correlation between the equity and bond returns is primarily driven by the common factors. The statistical and economic significance of the market-wide volatility pales in comparison to the significance of the firm-level volatility. Furthermore, the explanatory power of the market-wide volatility is just a fraction of the one for the firm-level equity volatility. These results hold even when the differences in the firm exposure to systematic risks (i.e. betas) are taken into account.

The risk-free interest rate is the only common variable which is explicitly incorporated into the structural model. The value of assets is assumed to be growing at the risk-free rate. An increase in the risk-free rate, therefore, has a positive effect on the value of equity. On the other hand, it depresses the value of debt through a higher discount rate. A change in the risk-free rate, therefore, clearly induces a negative correlation between the equity and bond returns. The empirical results support this empirical prediction. In accordance with Hypothesis 6, the coefficients of the risk-free rate and the slope of risk-free term structure are negative and statistically significant. The economic significance of the risk-free rate by far exceeds the economic significance of any other variable including the firm-level equity volatility and the distance to default. This implies that hedging strategies involving corporate equities and bonds will be significantly less effective in a high risk-free rate environment.

The results are robust to changes in the conditional correlation estimation model and the inclusion of controls for the firm size, the bond issue value and the bond duration.

The next chapter reviews the existing literature, develops hypotheses and presents the research methodology for the empirical study of the relevance of accounting data in explaining the credit spread.

CHAPTER 8

EXPLAINING THE CREDIT SPREAD: THE RELEVANCE OF ACCOUNTING DATA

8.1. Introduction

Financial accounting data have traditionally played a major role in credit risk analysis. In an early paper, Beaver (1966) found that the leverage and cash flow ratios of non-defaulted firms differed significantly from the ratios of defaulted firms, well in advance and leading up to the default date. This research inspired a number of studies which attempt to extract credit sensitive information from financial accounting data. As a result, a number of summary accounting measures, which combine multiple accounting ratios, have been proposed to group firms into different credit risk categories.

The major limitation of using accounting data to assess credit risk stems from the fact that such data are by definition backward looking. Accounting indicators reflect only past performance and in general do not capture expectations about future performance. They are very different in nature from the measures of credit risk and credit spread which are forward looking. Furthermore, accounting data do not contain all of the relevant information required for the measurement of credit risk, hence any accounting-based measures cannot provide a complete picture for the credit risk.

A forward looking measure of credit risk that incorporates all available information is proposed by Merton (1974). By considering debt and equity as derivative securities written on the value of the firm's assets, Merton employs the option pricing theory to derive a measure of credit risk that theoretically reflects all available information contained in the market prices of securities. This market-based measure of credit risk should therefore reflect all relevant information contained within accounting data, making such data redundant in the measurement of credit risk.

The purpose of this chapter is to review the existing studies of the relevance of accounting data in the measurement of credit risk. The literature review guides the formulation of hypotheses on the relevance of accounting data and the incremental relevance of accounting variables when considered jointly with market-based measures of credit risk. This chapter goes on to present the research methodology and the dataset. The hypotheses are tested empirically on a substantial sample of firm-level data in Chapter 9.

The existing literature focuses on examining the relevance of accounting data to equity market investors (e.g. Amir, Harris and Venuti, 1993; Collins, Maydew and Weiss, 1997; Lev and Zarowin, 1999; Brown, Lo and Lys, 1999). A limited number of existing studies that focus on the relevance of accounting data in credit markets examine the incremental information value of financial accounting data in explaining bankruptcies, credit ratings or credit default swap premiums. This study extends the existing literature by considering the relevance of accounting data in explaining variations in the credit spread on corporate bonds. Furthermore, this study focuses on a panel data analysis and thus enables a more thorough analysis of the cross-sectional and time effects when testing the relevance of accounting data.

8.2. Literature Review and Development of Hypotheses

8.2.1. Accounting-based Indicators of Credit Risk

Traditionally, accounting data have been used in credit risk analysis. The earliest studies use discriminant analysis to classify firms depending on their accounting characteristics. In his pioneering research, Beaver (1966) examines 14 individual accounting ratios for their significance when predicting a firm default. He reports that leverage and cash flow ratios of non-defaulted firms significantly differ from those of defaulted companies. Furthermore, he finds that these ratios are significant predictors of a firm's failure to service its contractual obligations. A subsequent study of Deakin (1972) utilises the same ratios within a series of multivariate discriminant models rather than studying the ratios individually.

Altman (1968) employs a multiple discriminant analysis to test for the difference between groups of defaulted and non-defaulted companies. From his initial list of 22 variables, five are included in the final discriminant function, known as the Z-score model (Working Capital / Total Assets, Retained Earnings / Total Assets, EBIT / Total Assets, Shareholders Equity / Total Liabilities and Sales / Total Assets). All of these variables except for sales to total assets are found to be significant at the one per cent level, with the most significant variable being retained earnings to total assets. Discriminant analysis emerged as one of the most popular statistical techniques used to analyse accounting variables in the context of credit risk. Importantly, studies using the discriminant analysis methodology are in general able to achieve a high level of classification accuracy.

However, discriminant analysis is criticized because of restrictive statistical assumptions such as the requirement for the normal distribution of independent variables. This issue led to the introduction of binary choice models such as probit and logit. Conducting a logit analysis, Ohlson (1980) finds that the variables significantly affecting credit risk are firm size, measures of leverage, profitability and liquidity. Zmijewski (1984) warns that bankruptcy prediction studies are exposed to sample selection bias, which arises from a low bankruptcy rate and the lack of a complete set of accounting data across firms. More recently, Shumway (2001) proposes a hazard model which considers the length of time firms spend in the non-default group as a dependent variable and thus, unlike previously mentioned models, explicitly accounts for time.

Wu, Gaunt and Gray (2010) study a sample of firms listed in the US to examine the performance of these bankruptcy prediction models, and report that the most important accounting variables are those which gauge profitability, liquidity and leverage. Khurana and Raman (2003) find a composite financial accounting-based measure to be a significant determinant of the yields on newly issued bonds by US firms. As discussed in Abarbanell and Bushee (1998), the authors employ nine variables to estimate a measure which they interpret as a proxy for expected future earnings. Consistent with expectations, they find a negative correlation between bond yields and this accounting measure. In line with this finding, Callen, Livnat and Segal (2009) find that earnings are significantly negatively correlated with credit default swap premia.

Bhojraj and Swaminathan (2009) find that operating accruals, defined as the change in non-cash working capital less depreciation, have a significant impact upon the performance of corporate bonds, as those issued by firms with high operating accruals underperform the bonds of firms with low accruals, thus emphasising the importance of cash flow in the measurement of credit risk. Beaver, McNichols and Rhie (2005) examine the performance of accounting variables in the prediction of bankruptcies in the US over time and find that a parsimonious model with only three variables has a consistently good performance in explaining bankruptcies over a 40 year period. They use the return on total assets, the ratio of earnings to total liabilities, and the leverage ratio as explanatory variables, and note that the precise combination of accounting variables depicting profitability, cash flow generation and leverage is of minor importance as variables are correlated.

Consistent with these studies, it is hypothesised that accounting variables are significant in explaining the variations in the credit spread on corporate bonds. Specifically, the following hypothesis is formulated:

H1: Accounting-based indicators are associated with the credit spread as follows:

Indicator	Relation with the credit spread
Profitability	Negative
Liquidity	Negative
Efficiency	Negative
Cash flow	Negative
Leverage	Positive
Firm size	Negative

The hypothesis states that a greater profitability, liquidity, efficiency and cash flow generation narrows the credit spread, whilst a higher leverage widens the credit spread. Further, the existing empirical evidence suggests that larger firms, ceteris paribus, pay a lower spread, and the hypothesis tests if an accounting-based firm size measure captures this effect.

8.2.2. Comparing the Impact of Accounting and Market based Measures on the Credit Spread

Merton (1974) proposes a method for the measurement of credit risk which relies on the information reflected in the market prices of securities. A firm's equity and debt are considered as derivatives written on the value of the firm's assets, and the option pricing theory of Black and Scholes (1973) is applied to price those claims. Default occurs when the market value of the firm's assets reaches the value of its debt. Under the assumption that the value of assets follows a geometric Brownian motion, both the firm leverage and the volatility of the value of assets are major determinants of default probability.

In contrast to the use of accounting data, Merton's measure of credit risk is forward-looking and takes into account all information reflected in the market price of securities, including the relevant economic information contained in the accounting data. It explicitly accounts for leverage while other aspects of firm's performance are taken into account less directly through equity value. An improvement in the firm's prospects leads to an increase in the value of equity, thereby leading to a decrease in leverage and credit risk.

It should be emphasised that the information content of the market prices of securities exceeds the information content of financial accounting data by a wide margin, as evidenced in the empirical literature. Shivakumar et al. (2011), for instance, report that the credit default swap spread responds to management earnings forecasts. But the latter are not reflected in backward looking accounting data. Lok and Richardson (2011) note that this finding is expected, since it has already been determined (e.g. Collins and Kothari, 1989) that management earnings forecasts are significantly related to equity returns. Therefore it is not surprising that the existing empirical studies find Merton's measure of credit risk, referred to as the distance to default, to be a significant factor in explaining variations in the values of credit sensitive securities (e.g. Avramov, Jostova, Philipov, 2005; Bharat and Shumway, 2008). The empirical results presented in Chapter 5 of this thesis show that the distance to default and the credit spread on corporate bonds are negatively correlated. A strong positive relationship between the credit spread and equity volatility is also reported, and equity volatility appears to perform better than the distance to default in explaining variations in the credit spread. The significance of equity volatility is not surprising, as it is a major determinant of the distance to default. However, it should not outperform the distance to default, which in addition to volatility, reflects information on leverage. A plausible explanation is that only a fraction of the credit spread is related to credit risk (e.g. Elton et al., 2001; Longstaff, Mithal and Neis, 2005), and equity volatility performs better in capturing variations in other factors influencing the credit spread such as the overall market conditions.

Therefore it is expected that market based measures outperform financial accounting based measures in explaining variations in the credit spread. Therefore, the following hypothesis is proposed:

H2: Market based information has more relevance than accounting based information in explaining variations in the credit spread.

This hypothesis is examined by comparing the statistical significance of individual variables and the explanatory power of models employing accounting variables and models using market-based measures as explanatory variables.

8.2.3. The Incremental Information Value of Financial Accounting Data

The acceptance of Hypothesis 2 above does not imply that accounting variables have no role in the measurement of credit risk. If accounting variables contain any relevant information not reflected in the market based measures - then a hybrid model, which combines both variable types, will outperform a model utilizing only the market based measures. Therefore, the relevance of accounting variables depends on their incremental information value when considered along with the market based measures.

Hillegeist et al. (2004) report that the distance-to-default variable outperforms the accounting based models of Altman (1968) and Ohlson (1980) in explaining corporate bankruptcies. However, they also note that the distance-to-default fails to capture all the information related to the probability of default contained within the accounting variables. Demirovic and Thomas (2007) find that accounting variables are incrementally informative in explaining changes in the credit ratings of UK firms. Das, Hanouna and Sarin (2009) report that the accounting variables of US firms improve the explanatory power of market based variables in explaining variations in the credit default swap spread. In line with this finding, Batta (2011) finds that accounting measures of profitability and leverage retain their statistical significance when the distance to default is included in models of the credit default swap premium.

These findings on the incremental information value of accounting variables are surprising as they imply that accounting variables are not fully reflected in equity market values. Several explanations for the incremental information value of accounting variables are presented in the literature. Core and Schrand (1999) examine the effect of accounting-based debt covenants on equity valuation, arguing that the information that does not affect the cash flow will affect equity valuation if it affects the probability of violating accounting-based debt covenants. Such information is even more relevant for debt securities as it directly affects default probability. Demerjian (2007) finds that coverage, liquidity, leverage and net worth are commonly used accounting measures in debt covenants.

Duffie and Lando (2001) also suggest that accounting information can be incrementally informative. They find that any accounting variable, which is correlated with the market value of a firm's assets, will have incremental information value if investors cannot observe the market value of the firm's assets, and have instead access only to periodic and imperfect accounting reports. Yu (2005) argues that the perceived transparency of a firm's accounting information disclosure can affect the level and the slope of the term structure of the credit spread, and finds that firms with higher disclosure tend to have lower credit spreads, implying that the relevant information contained within accounting data may not be fully reflected in the market prices of securities.

Bharath and Shumway (2008) point out that, while useful in bankruptcy prediction, the distance to default of US firms should not be considered as an all-encompassing credit risk measure, hence other variables can be incrementally informative. Campbell, Hilscher and Szilagyi (2008) show that a combination of accounting and market-based variables substantially outperform the distance to default alone in predicting bankruptcies in the US. Du and Suo (2007) argue that distance to default does not reflect all information available in equity values. They reach this conclusion based on the finding that equity value improves the performance of models with the distance-to-default as an explanatory variable, implying that the structural model of Merton (1974) does not fully utilize the information contained within the market price of equity. Du and Suo utilize the credit rating as an indicator of credit risk, hence their results may reflect the shortcomings of the credit rating an indicator of credit risk rather than weaknesses of the structural model. Similarly, in a study based on a sample of the UK firms, Agarwal and Taffler (2008) find that the distance to default and a composite accounting measure based on the Z-score model of Altman (1968) do not fully match in terms of information content and that neither of them is a sufficient measure of credit risk.

The above discussion leads to the following hypothesis:

H3: Accounting variables are incrementally informative in explaining variations in the credit spread.

This hypothesis is examined by comparing the explanatory power and the information criteria of models using market based measures only and hybrid models, which combine market-based measures and accounting variables.

8.3. Methodology

8.3.1. Credit Spread and Bond Characteristics

The general bond pricing equation can be defined as follows:

$$B = \sum_{i=1}^{n} \frac{CF_t}{(1+y)^t} \tag{8.1}$$

where

CF_t is the cash flow in year t

y is the discount rate

The redemption yield or yield to maturity is the discount rate y which equates all future cash flows due to bond holders to the market price of the bond. As described in Section

4.3.1., the credit spread CS is obtained as the difference between the redemption yield of the corporate bond and the redemption yield of the benchmark government bond.

To control for the maturity of bonds, the bond duration is calculated according to the following formula:

$$d = \frac{1}{B_d} \sum_{i=1} \frac{CF_i}{(1+Y)^{T_i}} T_i \qquad (8.2)$$

where

B_d is the dirty bond price (principal + accrued interest)

CF_i is the cash flow in year i

T_i is the time in years to the i th cash flow

The control variable for the size of the bond issue is the natural logarithm of the bond's market price multiplied by the number of outstanding bonds.

8.3.2. Accounting Variables

The aim of the financial accounting variables selected is to identify variables that extract the most credit risk related information from the financial statements. Based on the extant literature review, the variables depicting the following aspects of a firm's performance and characteristics are selected: profitability, liquidity, leverage, cash flow generation, efficiency and firm size.

The variables presented in Table 8.1 are initially considered for inclusion in models as explanatory variables.

Table 8.1
Accounting variable definitions

PROFITABILITY INDICATORS
Annual Net Income / Annual Revenues ; Quarterly Net Income / Quarterly Revenues
Annual Net Income / Total Assets ; Quarterly Net Income / Total Assets
Annual Net Income / Shareholders Equity ; Quarterly Net Income / Shareholders Equity
Annual EBIT / Annual Revenues ; Quarterly EBIT / Quarterly Revenues
Annual EBIT / Total Assets; Quarterly EBIT / Total Assets
Annual EBIT / Shareholders Equity ; Quarterly EBIT / Shareholders Equity
Retained Earnings / Total Assets
Annual EBIT / Interest Expenses
LIQUIDITY INDICATORS
Current Assets / Current Liabilities
Cash and Short term Investments / Total Assets
Cash and Short term Investments / Short term Debt
Cash and Short term Investments / Current Liabilities
Current Assets less Inventory / Current Liability
LEVERAGE INDICATORS
Total Liabilities / Total Assets
Total Liabilities / Shareholders Equity
Total Debt / Total Assets
Total Debt / Shareholders Equity
CASH FLOW GENERATION INDICATORS
Annual Operating Net Cash Flow / Annual Revenue
Annual Operating Net Cash Flow / Total Assets
Annual Operating Net Cash Flow / Short term Debt
Annual Operating Net Cash Flow / Total Debt
Annual Operating Net Cash Flow / Total Liabilities
EFFICIENCY INDICATORS
Quarterly Revenue / Total Assets
Annual Revenue / Total Assets
FIRM SIZE INDICATOR
Natural Logarithm of Total Assets

The accounting variables, especially those within the same variable grouping, are expected to be correlated and thus Beaver, McNichols and Rhie (2005) note that the precise combination of variables is not important. Hillegeist et al. (2004) use the composite measures of Altman's (1968) and Ohlson's (1980) models. This approach is sufficient to test the joint relevance of accounting variables, but does not provide an insight into the significance of individual variables. Therefore, the use of individual variables is preferred in the modelling of this thesis. The final list of model variables, consisting of at least one variable from each grouping, is selected based on the strength of their correlation with the credit spread.

8.3.3. Market-based Variables

The distance to default of Merton (1974) is widely employed in the literature as an indicator of credit risk (e.g. Vassalou and Xing, 2004; Hillegeist et al., 2004). It represents the difference between the market value of assets and the book value of debt relative to the volatility of the market value of assets. Therefore, the distance to default combines information on both leverage and the volatility of assets. The scaling of leverage using asset volatility implies that given the same leverage ratio, more stable (i.e. less volatile) firms are less likely to default on their obligations. As described in Section 4.3.4, the distance to default is given by:

$$DD = \frac{\ln\left(\frac{V_A}{X}\right) + \left(\mathrm{r} - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \tag{8.3}$$

where

V_A is the market value of firm's assets,

σ_A is the volatility of the market value of the firm's assets,

X is the book value of firm's debt,

r is the risk-free rate,

N is the cumulative density function of the standard normal distribution,

T is the time horizon in years

The unobservable market value and the volatility of firm's assets are estimated by simultaneously solving the call option pricing equation (Black and Scholes, 1973) and the hedge equation (Jones, Mason and Rosenfeld, 1984) as described in Section 4.3.4.

Equity volatility is the main input for the estimation of asset volatility reflected in the distance to default. Equity volatility does not explicitly incorporate information on leverage and is in this regard a less comprehensive variable than the distance to default. However, Campbell and Taksler (2003) find that equity volatility affects the credit spread to a significantly greater degree than predicted by the structural model.

Consistent with this finding, the results presented in Chapter 5 show that equity volatility is more statistically and economically significant than the distance to default in explaining variations in the credit spread. Therefore, equity volatility is considered as a market-based indicator. It is estimated using a parsimonious GARCH (1,1) model, introduced by Bollerslev (1986) as a generalization of Engle (1982). The conditional variance is assumed to evolve according to the following equation:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 \tag{8.4}$$

where

σ is the volatility

ε is the error term from the returns model $r_t = \mu + \varepsilon_t$ *where* $\varepsilon_t \sim (0, \sigma_t^2)$

Finally, the natural logarithm of the estimated market value of a firm's assets is considered as a market-based indicator of firm size.

8.3.4. Panel Data Analysis

The data set consists of the credit spread and two sets of explanatory variables (accounting variables and market-based variables). The relationship between the credit spread and the explanatory variables is examined in a set of panel data models. The most parsimonious panel data model, referred to as the constant coefficient model, imposes the same intercept for all firms in the sample. It is defined as follows:

$$CS_{it} = \alpha + \beta' x_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d.(0, \sigma^2) \tag{8.5}$$

where

CS_{it} is the credit spread of corporate bond i at time t

x_{it} is a K x 1 vector of independent (explanatory) variables for firm i at time t.

α is the intercept

β is a K x 1 parameter vector

ε_{it} is the usual disturbance term

The constant coefficient model does not allow uncontrolled variables to vary in the cross-section, thereby greatly increasing the risk of bias introduced by the correlation between the explanatory variables and uncontrolled effects. Other firm-specific effects can be taken into account by allowing the intercept to vary in cross-section. Consider the following model:

$$CS_{it} = \alpha_i + \beta' x_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d.(0,\sigma^2) \tag{8.6}$$

The subscript i in α indicates that each firm has its own intercept or fixed effect which captures time invariant firm characteristics, hence removing the potential bias resulting from the correlation between the fixed effects and the explanatory variables. As with cross-sectional fixed effects, the constant coefficient panel data model can be extended to control for time effects. Consider the following model:

$$CS_{it} = \alpha + \gamma_t + \beta' x_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d.(0,\sigma^2) \tag{8.7}$$

where γ_t is the time-specific effect. This effect is common in the cross-section, so it captures all uncontrolled time-varying variables that commonly affect the correlation between the equity and bond returns for all firms in the sample. Following Petersen (2009), and Zhang, Zhou and Zhu (2009), the clustered standard errors are employed in all models to account for the serial correlation of errors.

8.4. Data

The data set consists of matched firm-level equity, bond and accounting data. The bond data and equity data are obtained from the Thomson Reuters Datastream database, while the accounting data is sourced from Compustat. Sample selection commences with all available straight corporate bonds issued by non-financial companies in the US market. When multiple bonds are available from the same issuer, the bond with the maximum number of observations is selected. This is preferred to averaging the data of different bonds with a common issuer as all bonds have different characteristics such as duration and issue size. Bonds with less than 12 quarterly observations, asset-backed bonds, bonds with any form of collateral, or with an average market value of less than

$10 million are excluded from the sample. Once the bond data is collected it is matched with the equity and accounting data.

The matched sample consists of 349 firms and 11,632 quarterly observations. Financial accounting data for current assets and current liabilities is not available for all data points, so the regression analysis involving the current ratio (Current Assets / Current Liabilities) is slightly reduced to 338 firms and 11,224 quarterly observations. The sample covers the period from August 1996 to February 2011. The dates of release for the accounting data are obtained from Compustat. In the case when the dates are not available (less than two per cent of observations), as in Demirovic and Thomas (2007), it is assumed that the accounting data is released 60 days after the end of the financial quarter.

Table 8.2 depicts the mean values of the market-based indicators and selected accounting variables for ranges of the credit spread. Most of observations (62 per cent) are associated with a credit spread of between 50 and 250 basis points. About 36 per cent of the observations are linked to a credit spread larger than 250 basis points, whereas about two per cent of observations are related to a credit spread of less than 50 basis points.

Table 8.2
Mean values of explanatory variables conditioned on the credit spread

CS	EV	DD	NI/TA	RE/TA	CA/CL	TL/TA	CF/TA	R/TA	TABV	TAMV
<50	0.24	8.63	0.02	0.45	1.61	0.57	0.14	0.26	9.65	10.44
50-100	0.26	7.31	0.02	0.33	1.44	0.60	0.11	0.26	9.22	9.82
100-150	0.29	6.40	0.02	0.30	1.53	0.61	0.11	0.25	9.13	9.67
150-200	0.32	5.53	0.02	0.26	1.52	0.62	0.10	0.24	9.08	9.50
200-250	0.34	5.07	0.01	0.23	1.52	0.63	0.10	0.23	8.95	9.33
250-300	0.37	4.60	0.01	0.21	1.58	0.63	0.10	0.23	8.75	9.09
300-350	0.39	4.03	0.01	0.17	1.64	0.66	0.08	0.24	8.62	8.91
350-400	0.44	3.64	0.01	0.15	1.55	0.68	0.08	0.24	8.65	8.92
400-450	0.46	3.49	0.01	0.12	1.78	0.65	0.08	0.22	8.36	8.57
450-500	0.49	3.20	0.00	0.15	1.65	0.68	0.08	0.25	8.60	8.82
500-550	0.51	2.98	0.00	0.15	1.83	0.66	0.09	0.23	8.52	8.70
550-600	0.56	2.77	0.01	0.12	1.68	0.65	0.08	0.24	8.60	8.72
600-650	0.57	2.58	0.00	0.11	1.80	0.68	0.08	0.22	8.31	8.45
650-700	0.59	2.49	0.01	0.05	1.67	0.71	0.07	0.26	8.23	8.42
700-750	0.62	2.33	-0.01	0.02	1.81	0.70	0.07	0.25	8.03	8.19
750-800	0.66	2.09	0.00	0.01	1.64	0.71	0.07	0.23	8.16	8.24
>800	0.90	1.20	-0.02	-0.03	1.72	0.79	0.06	0.25	8.09	8.06

Credit Spread <50 (266 observations, hereafter shown in parentheses); 50-100 (1,914); 100-150 (2,338); 150-200 (1,757); 200-250 (1,249); 250-300 (864); 300-350 (676); 350-400 (476); 400-450 (367); 450-500 (294); 500-550 (247); 550-600 (212); 600-650 (188); 650-700 (157); 700-750 (118); 750-800 (87); >800 (474).

CS = Credit Spread (in basis points); EV = Equity Volatility; DD = Distance to Default; NI/TA = Net Quarterly Income/Total Assets; RE/TA = Retained Earnings/Total Assets; CA/CL = Current Assets / Current Liabilities; TL/TA = Total Liabilities / Total Assets; CF/TA = Net Operating Cash Flow / Total Assets; R/TA = Quarterly Revenue / Total Assets; TABV=Log of Total Book Value Assets; TAMV = Log of Total Market Value of Assets.

The data reveal monotonically consistent relationships between the credit spread and the market-based measures, i.e. the distance to default and equity volatility. As expected, on average the credit spread monotonically widens as the distance to default (equity volatility) decreases (increases). Although not as monotonic and pronounced as in the case of the market-based variables, the relationship between the credit spread and the accounting variables appears as expected from theory, excluding the current ratio (Current Assets / Current Liabilities) which improves rather than worsens as the credit spread widens.

8.5. Summary

Financial accounting data has traditionally been used in credit risk analysis. Indeed, a large body of literature indicates that accounting variables are significant indicators of credit risk. Beaver, McNichols and Rhie (2005) show that a parsimonious model with only three accounting variables performs consistently well in explaining corporate bankruptcies over a 40 year period. The accounting variables that contain the most credit sensitive information are those which gauge profitability, leverage and cash flow generation.

However, accounting data is not entirely forward-looking and by definition reflects only past performance. Further, such data may not reflect historic events that have a significant impact upon future performance as any business change takes time to be reflected in the accounting figures. This limits the usefulness of accounting data in the measurement of credit risk. However, the market prices of securities should reflect all available public information including expectations about future performance. The structural model of Merton (1974) builds on option pricing theory to extract all relevant information from the market prices of securities and therefore provides a theoretically complete measure of credit risk.

A limited number of studies examine the incremental information value of financial accounting variables in credit markets. The existing studies focus on the incremental information value of accounting variables in predicting corporate bankruptcy (Hillegeist et al., 2004; Agarwal and Taffler, 2008), credit ratings (Demirovic and Thomas, 2007; Du and Suo, 2007) and, more recently, the credit default swap premium (Das, Hanouna and Sarin, 2009; Batta, 2011). These studies in general indicate that the structural model outperforms accounting variables in the measurement of credit risk, but they fail to provide evidence that the structural model is an encompassing or complete measure of credit risk. Accounting variables are found to be incrementally informative when considered in conjunction with the distance to default or the leverage ratio scaled by asset volatility, which, according to the structural model, is a sufficient measure of credit risk.

The evidence on the incremental information value of accounting data is not easily reconciled with the efficient market hypothesis, which states that all available information, including the information that is contained within accounting data, is reflected in the market price of securities. The literature offers a few plausible explanations for the incremental information value of accounting data. Core and

Schrand (1999) point out that debt covenants are typically expressed in terms of accounting ratios, hence directly linking accounting variables to default probability. Duffie and Lando (2001) argue that additional information about credit risk can be derived from any accounting variable that is correlated with the underlying ratio of the market value of assets to the market value of liabilities. A growing body of literature indicates that the structural model neither provides a sufficient measure of credit risk nor even fully utilizes the information available in the variables used to make the estimate.

This study examines the incremental information value of financial accounting data in explaining variations in the credit spread of corporate bonds. The data sample consists of matched equity, bond and accounting data for 349 firms and over 11,000 quarterly observations, covering the period from 1/8/1996 to 1/2/2011.

Chapter 9 presents the empirical results.

CHAPTER 9

ACCOUNTING DATA AND THE CREDIT SPREAD:

AN EMPIRICAL INVESTIGATION

9.1. Introduction

This chapter tests the statistical validity of the hypotheses proposed in the previous chapter. The empirical analysis commences with the selection of the accounting variables that capture firm profitability, liquidity, leverage, cash flow generation, efficiency and size. As the accounting variables are highly correlated, seven variables are selected, based on the strength of their correlation with the credit spread. Section 9.2 presents the variable correlation matrix and discusses the correlation between the credit spread and each of the accounting variables.

Section 9.3 presents an analysis of the relationship between the credit spread and the accounting variables by means of a set of univariate and multivariate panel models. The results provide evidence on the relevance of financial accounting variables to the measurement of the credit spread.

Section 9.4 examines the relationship between the credit spread and market-based measures of credit risk, i.e. the distance to default of Merton (1974), equity volatility, and a market-based indicator of firm size. The same panel data models discussed in the previous section are estimated, so that the performance of the market-based indicators can be directly compared with the performance of the accounting-based indicators.

Section 9.5 examines whether the accounting variables are already subsumed within the market-based indicators, as finance theory suggests, by estimating a set of hybrid panel data models with the market-based indicators as well as the accounting variables as explanatory variables. The results indicate which accounting indicators are incrementally informative in explaining the credit spread and the extent to which the inclusion of the accounting variables improves the explanatory power of the market based models.

The final section examines whether the results are robust to controlling for bond duration and bond issue size.

9.2. The Correlation between the Financial Accounting Ratios and the Credit Spread

As discussed in Chapter 8, the accounting ratios are grouped into six categories: profitability, liquidity, leverage, cash flow generation, efficiency and size. All ratios within a given variable group indicate a common characteristic of the firm's performance or position and are, therefore, highly correlated. Beaver, McNichols and Rhie (2005) note that a high correlation between accounting variables makes the precise selection of a measure for inclusion in credit risk models less important. The selection of ratios for further analysis is based on the correlation with the credit spread. The descriptive statistics of the selected ratios is presented in Table 9.1, while the correlation matrix is presented in Table 9.2.

All of the considered correlation coefficients are statistically significant at the five per cent level except the coefficient depicting the correlation between leverage (TL/TA) and firm size (TA). The indicators of profitability (NI/TA and RE/TA), leverage and firm size are highly correlated with the credit spread (CS). However, liquidity (CA/CL), cash flow (CF/TA) and efficiency (R/TA) exhibit a low correlation with the credit spread. Interestingly, the current asset to the current liabilities ratio (CA/CL), which is an indicator of liquidity, is positively correlated with the credit spread. This indicates that firms with better liquidity pay a higher premium on their debt, which is at first glance counterintuitive. It could also imply that a firm has poor working capital management, or it might be a signal of hoarding cash or near-cash as the firm knows it may encounter working capital problems in the near term. A similar result is obtained by Demirovic and Thomas (2007) who analyse the relationship between accounting variables and credit ratings. The signs of the other correlation coefficients are consistent with expectations. A higher current and past profitability is associated with a lower credit spread, while a higher total leverage indicates a higher credit spread. Also consistent with expectations is the finding that total assets is negatively correlated with the credit spread.

The correlations between the accounting ratios reveal some interesting relationships. Since the total assets equals the total liabilities plus equity (TA=TL+E), the leverage indicator (TL/TA) is negatively correlated with the indicator of past profitability (RE/TA; r=-0.486). Furthermore, the leverage indicator is negatively correlated with the indicators of liquidity (CA/CL; r=-0.302) and cash flow (CF/TA; r=-0.371). The correlations are highly significant in all three cases, and in the case of retained earnings the correlation approaches 0.50 in absolute value. This indicates that the leverage ratio captures, or proxies for, multiple aspects of a firms' performance. Interestingly, firm size, as measured by the natural logarithm of total assets, is negatively correlated with the liquidity indicator, and thus it can be interpreted that larger firms maintain lower liquidity. Large firms have easier access to longer term financing and, as a result, do not require as much working capital as small firms. This may explain the positive correlation between the credit spread and the liquidity indicator.

Table 9.1
Descriptive statistics of the financial accounting ratios

Statistics	NI/TA	RE/TA	CA/CL	TL/TA	CF/TA	R/TA	TA
Mean	0.01	0.23	1.56	0.63	0.10	0.25	8.91
Median	0.01	0.23	1.39	0.62	0.07	0.22	8.86
Maximum	0.40	1.73	9.01	1.89	1.36	1.20	13.58
Minimum	-1.72	-2.19	0.00	0.00	-0.51	0.00	4.58
Std. Dev.	0.03	0.29	0.81	0.17	0.12	0.17	1.22
Skewness	-19.42	-1.00	1.85	0.76	1.98	1.88	0.11
Kurtosis	952.48	10.78	9.98	5.81	12.86	8.07	2.94

NI/TA=Net Quarterly Income/Total Assets; RE/TA=Retained Earnings/Total Assets; CA/CL=Current Assets / Current Liabilities; TL/TA=Total Liabilities / Total Assets; CF/TA=Net Operating Cash Flow / Total Assets; R/TA= Quarterly Revenue / Total Assets; TA=Log of Total Assets

Table 9.2
The correlation matrix between the credit spread and the financial accounting ratios

	CS	NI/TA	RE/TA	CA/CL	TL/TA	CF/TA	R/TA
CS	1.000						
NI/TA	-0.347 (-39.87)	1.000					
RE/TA	-0.295 (-33.24)	0.263 (38.42)	1.000				
CA/CL	0.055 (5.79)	0.038 (5.31)	0.099 (13.71)	1.000			
TL/TA	0.243 (27.00)	-0.151 (-21.51)	-0.486 (-78.43)	-0.302 (-43.82)	1.000		
CF/TA	-0.094 (-10.23)	0.195 (28.11)	0.237 (34.45)	0.252 (36.02)	-0.371 (-56.41)	1.000	
R/TA	-0.018 (-1.97)	0.139 (19.75)	0.148 (21.06)	0.022 (3.08)	0.062 (8.76)	0.018 (2.59)	1.000
TA	-0.210 (-23.16)	0.031 (4.45)	0.102 (14.50)	-0.309 (-44.89)	-0.011 (-1.49)	-0.030 (-4.25)	-0.129 (-18.33)

CS=Credit Spread; NI/TA=Net Quarterly Income/Total Assets; RE/TA=Retained Earnings/Total Assets; CA/CL=Current Assets / Current Liabilities; TL/TA=Total Liabilities / Total Assets; CF/TA=Net Operating Cash Flow / Total Assets; R/TA= Quarterly Revenue / Total Assets; TA=Log of Total Assets. The t-statistics are shown in parentheses.

9.3. The Relevance of Financial Accounting Variables in the Measurement of the Credit Spread

9.3.1. The Constant Coefficient Model

In order to examine the explanatory power and statistical significance of the individual ratios, the credit spread is regressed on each of them in separate univariate regressions. Table 9.3 depicts the explanatory power of the models, the magnitude of the coefficients, their t-statistics and the associated probabilities.

As expected, an increase in profitability (Net Income / Total Assets and Retained Earnings / Total Assets), operating cash flow (Net Operating Cash Flow / Total Assets) and efficiency (Revenue / Total Assets) narrows the credit spread, while an increase in leverage (Total Liabilities / Total Assets) widens it. This finding is consistent with existing empirical studies (e.g. Das, Hanouna and Sarin, 2009; Demirovic and Thomas, 2007).

The coefficient of the current ratio is positive, which, counter intuitively, indicates that an improvement in liquidity widens the credit spread. Demirovic and Thomas (2007) also obtain a positive correlation between the credit spread and the current ratio. They note that a relatively low current ratio may indicate a higher bargaining power with debtors and creditors rather than liquidity issues. In a similar vein, firms with a low current ratio may have efficient working capital management or superior access to capital markets. A negative correlation between firm size and the current ratio, as reported in Table 9.2, supports this argument. Similarly, Das, Hanouna and Sarin (2009) obtain a positive relationship between the credit default swap and the quick ratio.

The coefficient of the efficiency ratio (Revenue / Total Assets) is not statistically significant, though all other ratios are found to be statistically significant in explaining variations in the credit spread. Of the significant ratios, the profitability ratio is by far the most statistically significant, while the current ratio is the least significant. Besides exhibiting the highest statistical significance, the profitability ratio is by far the most economically significant. A one per cent increase in profitability lowers the credit spread by 39.94 basis points. The profitability ratio has much higher explanatory power than other ratios. It explains about 12 per cent of the variations in the credit spread. Past profitability, leverage and firm size also demonstrate significant explanatory power, while the R-squared statistics of the models with liquidity, efficiency and cash flow indicators as explanatory variables are all close to zero.

Table 9.3
The univariate relationship between the credit spread and the accounting ratios: the constant coefficient model

Variable	Coefficient	t-Statistic	Prob.	R-squared
Net Income / Total Assets	-3,993.70	-10.02	0.00	0.12
Retained Earnings / Total Assets	-351.55	-5.41	0.00	0.09
Current Assets / Current Liabilities	23.30	2.11	0.04	0.00
Total Liabilities / Total Assets	511.85	4.78	0.00	0.06
Net Operating Cash Flow / Total Assets	-287.55	-4.74	0.00	0.01
Revenue / Total Assets	-38.84	-0.62	0.53	0.00
Log of Total Assets	-60.25	-5.29	0.00	0.04

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338*-349; Total panel (unbalanced) observations: 11,224*-11,632; White period standard errors and covariance (d.f. corrected).

*Number of observations in the regression with the ratio of current assets to current liabilities as independent variable.

A small change in risk or any aspect of a firms' performance is expected to have a limited impact upon the credit spread of bonds issued by high-quality firms. As credit risk increases the credit spread becomes more sensitive to changes in any relevant variables. Such behaviour is predicted by the structural model of Merton (1974) and confirmed empirically in Chapter 5 as the relationship between the equity volatility and the credit spread strengthens monotonically as credit risk increases. The same should hold for the relationship between the accounting variables and the credit spread. To examine this, the univariate models presented in Table 9.3 are augmented with interaction variables which take into account the level of financial leverage when measuring the impact of accounting variables on the credit spread.

The results, which are presented in Table 9.4, are mixed. In the case of the profitability ratio (Column 1), the impact upon the credit spread increases as firms become more leveraged. The size of the interaction coefficient indicates that the economic effect of profitability increases by 0.16 basis points per one per cent increase in leverage. This implies that an improvement in profitability has a more marked impact upon the credit spread of high-risk firms. Retained earnings (Column 2) loses its statistical significance in presence of the interaction variable. Interestingly, the interaction variable is not statistically significant either. The statistical significance of the current ratio (Column 3) is substantially increased and the sign of coefficient becomes negative, implying that an improvement in liquidity leads to a decrease in the credit spread. The positive coefficient of the liquidity-leverage interaction variable implies that the impact of liquidity on the credit spread decreases as leverage increases. This is not surprising as liquidity becomes less of a positive signal to the market as leverage, and hence financial risk, increases. The same effect is present in the indicators of cash flow (Column 4) and efficiency (Column 5), that is, leverage reduces the positive impact of those two positive accounting ratios. The coefficient for firm size (Column 6) indicates that larger firms pay a lower credit spread. The positive coefficient of the size-leverage interaction variable indicates that the advantage of being larger diminishes as leverage increases.

Table 9.4
The impact of leverage on the univariate relationship between the credit spread and the accounting ratios: the constant coefficient model

	Net Income / Total Assets	Retained Earnings / Total Assets	Current Assets / Current Liabilities	Net Operating Cash Flow / Total Assets	Revenue / Total Assets	Log of Total Assets
	1	2	3	4	5	6
Variable	-2,602.93	53.11	-113.32	-520.13	-1,045.44	-92.67
	[-3.66]	[0.27]	[-4.89]	[-2.58]	[-5.30]	[-6.89]
Variable x Leverage	-1,550.39	-580.11	318.96	517.30	1,488.37	52.76
	[-2.51]	[-1.64]	[6.96]	[1.15]	[5.32]	[5.19]
Adjusted R-squared	0.12	0.11	0.07	0.01	0.04	0.09

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338*-349; Total panel (unbalanced) observations: 11,224*-11,632; White period standard errors and covariance (d.f. corrected).

*Number of observations in the regression with the ratio of current assets to current liabilities as independent variable.

The results presented in Tables 9.3 and 9.4 illustrate the relevance of individual financial accounting variables in the measurement of the credit spread. Table 9.5 presents the multivariate model with all of the selected accounting variables included as explanatory variables.

All of the variables except the efficiency ratio (Revenue / Total Assets) are statistically significant. The cash flow ratio is positive and indicates that the credit spread widens as cash flow improves. Since the cash flow coefficients are negative in the univariate models in Tables 9.3 and 9.4, this counterintuitive result is probably caused by the correlation of the cash flow ratio with other ratios used as the explanatory variables in Table 9.5. The liquidity ratio is also positive and significant in the univariate model presented in Table 9.3, so it appears that the liquidity ratio captures negative characteristics and developments such as poor working capital management and cash hoarding due to expected working capital problems. Profitability appears to be the most important determinant of credit risk. A one per cent increase in profitability lowers the credit spread by 30.57 basis, which is more than eight times of the impact of a one per cent change in the second most economically important variable (i.e. leverage). The multivariate model explains about 22 per cent of variations in the credit spread. Although not directly comparable, this is broadly comparable to the R-squared statistics reported in other studies. In bankruptcy prediction studies, Agarwal and Taffler (2008) and Campbell, Hilscher and Szilagyi (2008) obtain Pseudo R-squared statistics of 18 per cent and 26 per cent, respectively. Demirovic and Thomas (2007) manage to explain 15 per cent of changes in credit ratings, whereas Batta (2011) explains 29 per cent of the variation in the default credit swap premium. To provide some context, equity volatility explains about 39 per cent and the distance to default of Merton (1974) explains about 21 per cent of the variation in the credit spread, as presented in Chapter 5. The explanatory power of the univariate models presented in Table 9.3 implies that the major contributors to the explanatory power of the multivariate model are profitability, leverage and firm size.

Table 9.5
The multivariate relationship between the credit spread and the financial accounting ratios: the constant coefficient model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Net Income / Total Assets	-3,057.21	371.18	-8.24	0.00
Retained Earnings / Total Assets	-195.84	42.89	-4.57	0.00
Current Assets / Current Liabilities	46.74	9.55	4.90	0.00
Total Liabilities / Total Assets	367.78	81.51	4.51	0.00
Net Operating Cash Flow / Total Assets	180.22	72.21	2.50	0.01
Revenue / Total Assets	-2.38	41.98	-0.06	0.95
Log of Total Assets	-41.93	8.00	-5.24	0.00
C	408.44	92.24	4.43	0.00
R-squared	0.22	Mean dependent var		273.24
Adjusted R-squared	0.22	S.D. dependent var		344.66
S.E. of regression	304.92	Akaike info criterion		14.28
Sum squared resid	1.04E+09	Schwarz criterion		14.28
Log likelihood	-80,102.68	Hannan-Quinn criter.		14.28
F-statistic	445.95	Durbin-Watson stat		0.52
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (constant coefficient model); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338; Total panel (unbalanced) observations: 11,221; White period standard errors and covariance (d.f. corrected).

9.3.2. The Cross-sectional Fixed Effects Model

The credit spread is influenced by a number of factors in addition to financial accounting variables. The constant coefficient model assumes that the impact of those unobserved factors varies randomly in cross-section and through time. In other words, it imposes the same intercept and an error component for all firms in the sample. This is too restrictive and will bias the results if the explanatory variables are correlated with the model error. To allow for cross-sectional differences in unobserved factors, each firm in the sample is allowed to have its own intercept or fixed effect. The results are presented in Table 9.6.

In the fixed-effects model, retained earnings, liquidity and cash flow are statistically insignificant, implying that these aspects of a firm's performance are picked up by fixed effects and that their time variations are not related to variations in the credit spread. However, the efficiency indicator is statistically significant and implies that, as expected, an increase in the efficiency lowers the credit spread. The firm size indicator is significant and positive, unexpectedly indicating that the firm size is positively correlated with the credit spread. The profitability ratio remains the most economically significant variable. The coefficient size implies that a one per cent improvement in profitability lowers the credit spread by 28.23 basis points. The univariate models with fixed effects explain between 31 and 36 per cent of variations in the credit spread.

Table 9.6
The univariate relationship between the credit spread and financial accounting variables: the cross-sectional fixed effects model

Variable	Coefficient	t-Statistic	Prob.	Adj. R-sq.
Net Income / Total Assets	-2,823.24	-6.86	0.00	0.36
Retained Earnings / Total Assets	-354.46	-1.76	0.08	0.33
Current Assets / Current Liabilities	-14.10	-1.34	0.18	0.31
Total Liabilities / Total Assets	774.70	2.38	0.02	0.34
Net Operating Cash Flow / Total Assets	-13.45	-0.26	0.80	0.31
Revenue / Total Assets	-221.84	-2.91	0.00	0.31
Log of Total Assets	60.63	2.65	0.01	0.31

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338*-349; Total panel (unbalanced) observations: 11,224*-11,632; White period standard errors and covariance (d.f. corrected).

*Number of observations in the regression with the ratio of current assets to current liabilities as an independent variable.

Table 9.7 gives the results of the multivariate model which jointly considers the significance of the financial accounting variables in explaining the variations in the credit spread.

Profitability, leverage, the cash flow ratio and firm size are statistically significant in the multivariate model. The coefficient for the firm size indicator is unexpectedly positive. The profitability and leverage ratios stand out in terms of the economic significance. A one percent increase in profitability lowers the credit spread by 23.90 basis points, while a one per cent increase in leverage widens the credit spread by 6.29 basis points.

Interestingly, the adjusted R-squared statistic of 39 per cent is slightly higher than the R-squared of the univariate model with profitability as the explanatory variable. The adjusted R-squared is maximized when all variables except profitability, leverage and firm size are dropped from the model.

Table 9.7
The multivariate relationship between the credit spread and the financial accounting variables: the cross-sectional fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Net Income / Total Assets	-2,389.50	347.90	-6.87	0.00
Retained Earnings / Total Assets	-102.39	122.06	-0.84	0.40
Current Assets / Current Liabilities	23.63	16.86	1.40	0.16
Total Liabilities / Total Assets	629.36	216.77	2.90	0.00
Net Operating Cash Flow / Total Assets	113.64	44.93	2.53	0.01
Revenue / Total Assets	145.16	76.18	1.91	0.06
Log of Total Assets	98.38	13.29	7.40	0.00
C	-1,028.10	198.76	-5.17	0.00
R-squared	0.40	Mean dependent var		273.24
Adjusted R-squared	0.39	S.D. dependent var		344.66
S.E. of regression	270.11	Akaike info criterion		14.07
Sum squared resid	7.94E+08	Schwarz criterion		14.29
Log likelihood	-78,571.24	Hannan-Quinn criter.		14.14
F-statistic	21.49	Durbin-Watson stat		0.61
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338; Total panel (unbalanced) observations: 11,221; White period standard errors and covariance (d.f. corrected).

9.3.3. The Period Fixed Effects Model

The credit spread may be influenced by factors that are common in cross-section but vary through time. To control for this effect, the constant correlation panel model is augmented with period fixed effects. Similar to the cross-sectional fixed effects which capture firm specific factors, the period fixed effects are dummy variables which take the value of one if an observation is in a particular quarter and zero otherwise. The sample period covers 59 quarters, so 58 dummy variables are added to avoid the dummy variable trap. As in previous sections, the credit spread is regressed on the accounting variables individually, as well as on all of the accounting variables together in a multivariate model. The results are presented in Table 9.8.

After controlling for the time effects, liquidity and efficiency are not statistically significant, while all of the other variables are significant and have the expected sign. The profitability ratio continues to be the most economically significant variable. The estimated coefficient size implies that a one per cent increase in profitability lowers the credit spread by 34.21 basis points. The explanatory power of the models ranges from 21 per cent to 30 per cent, which is on average seven percentage points less than the explanatory power of the univariate models with cross-sectional fixed effects.

Table 9.8
The univariate relationship between the credit spread and the financial accounting variables: the period fixed effects model

Variable	Coefficient	t-Statistic	Prob.	Adj. R-sq.
Net Income / Total Assets	-3,421.17	-7.79	0.00	0.30
Retained Earnings / Total Assets	-355.40	-5.56	0.00	0.30
Current Assets / Current Liabilities	16.05	1.47	0.14	0.21
Total Liabilities / Total Assets	488.88	4.71	0.00	0.27
Net Operating Cash Flow / Total Assets	-365.85	-6.04	0.00	0.23
Revenue / Total Assets	-27.84	-0.45	0.65	0.21
Log of Total Assets	-65.76	-5.70	0.00	0.26

Dependent Variable: Credit Spread; Method: Panel Least Squares (period fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338*-349; Total panel (unbalanced) observations: 11,224*-11,632; White period standard errors and covariance (d.f. corrected).

*Number of observations in the regression with the ratio of current assets to current liabilities as the independent variable.

The multivariate model with period effects is depicted in Table 9.9.

Table 9.9
The multivariate relationship between the credit spread and the financial accounting variables: the period fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Net Income / Total Assets	-2,437.04	458.67	-5.31	0.00
Retained Earnings / Total Assets	-220.00	43.09	-5.11	0.00
Current Assets / Current Liabilities	30.39	8.89	3.42	0.00
Total Liabilities / Total Assets	284.90	81.58	3.49	0.00
Net Operating Cash Flow / Total Assets	90.46	76.84	1.18	0.24
Revenue / Total Assets	-0.32	41.36	-0.01	0.99
Log of Total Assets	-52.06	8.40	-6.19	0.00
C	582.53	96.81	6.02	0.00
R-squared	0.40	Mean dependent var		273.24
Adjusted R-squared	0.40	S.D. dependent var		344.66
S.E. of regression	266.86	Akaike info criterion		14.02
Sum squared resid	7.94E+08	Schwarz criterion		14.06
Log likelihood	-78,577.42	Hannan-Quinn criter.		14.03
F-statistic	116.31	Durbin-Watson stat		0.53
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (period fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338; Total panel (unbalanced) observations: 11,221; White period standard errors and covariance (d.f. corrected).

The multivariate model with period effects explain about 40 per cent of the variation in the credit spread, which is slightly higher than the explanatory power of the multivariate model with cross-sectional fixed effects. The period effects specification improves the model's adjusted R-squared by 18 percentage points which is a similar improvement to that obtained by augmenting the model with cross-sectional fixed effects. All of the variables except the efficiency and cash flow are significant. As in the constant coefficient model, the coefficient for liquidity is positive. The profitability ratio stands out in terms of economic significance. A one percent increase in profitability lowers the credit spread by 24.37 basis points, which is a greater impact than the combined impact of all other variables.

9.3.4. The Two-way Fixed Effects Model

To complete the examination of the univariate relationship between the credit spread and the financial accounting variables, a model with two-way effect controls (fixed and period) is estimated. This model allows that each firm and period in the sample has its own fixed effect. The results are presented in Table 9.10.

After controlling for firm and time specific fixed effects, all indicators except the indicator for efficiency are statistically significant at the 10 per cent level. The indicators of profitability, historical profitability, leverage and liquidity are significant at the five per cent level, whereas the indicators of cash flow generation and firm size are significant at the 10 per cent level. All coefficients have the expected signs.

The indicators for liquidity, leverage and cash flow generation are not statistically significant in the model with cross-sectional fixed effects, presented in Table 9.6. Therefore, adding the period control variable to the model in Table 9.6 makes these indicators statistically significant, implying that they are correlated with the period effects.

Table 9.10
The univariate relationship between the credit spread and financial accounting variables: the two-way fixed effects model

Variable	Coefficient	t-Statistic	Prob.	Adj. R-sq.
Net Income / Total Assets	-2,133.49	-4.18	0.00	0.54
Retained Earnings / Total Assets	-416.53	-2.11	0.03	0.54
Current Assets / Current Liabilities	-21.71	-2.58	0.01	0.51
Total Liabilities / Total Assets	635.61	2.00	0.05	0.53
Net Operating Cash Flow / Total Assets	-90.10	-1.83	0.07	0.52
Revenue / Total Assets	-82.25	-1.14	0.26	0.52
Log of Total Assets	-59.30	-1.79	0.07	0.52

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section and period fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338*-349; Total panel (unbalanced) observations: 11224*-11632; White period standard errors and covariance (d.f. corrected). *Number of observations in the regression with the ratio of current assets to current liabilities as independent variable.

In the multivariate model, presented in Table 9.11, which jointly considers all financial accounting indicators, only the profitability indicator is statistically significant at the five per cent level, while the indicators of historical profitability and firm size are significant at the 10 per cent level. A change in profitability has an economically meaningful impact upon the credit spread as well. The coefficient size indicates that a one per cent increase in profitability lowers the credit spread by 17.40 basis points. It is interesting to note that the leverage indicator is insignificant. This implies that the accounting based leverage indicator is a poor proxy for the firm's leverage.

Table 9.11
The multivariate relationship between the credit spread and financial accounting variables: the two-way fixed effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Net Income / Total Assets	-1,740.29	441.99	-3.94	0.00
Retained Earnings / Total Assets	-242.77	126.70	-1.92	0.06
Current Assets / Current Liabilities	7.49	14.84	0.51	0.61
Total Liabilities / Total Assets	300.88	195.66	1.54	0.12
Net Operating Cash Flow / Total Assets	21.25	44.41	0.48	0.63
Revenue / Total Assets	26.85	64.99	0.41	0.68
Log of Total Assets	-33.53	19.42	-1.73	0.08
C	440.07	178.56	2.46	0.01
R-squared	0.57	Mean dependent var		273.24
Adjusted R-squared	0.56	S.D. dependent var		344.66
S.E. of regression	229.43	Akaike info criterion		13.74
Sum squared resid	5.69E+08	Schwarz criterion		14.01
Log likelihood	-76,709.42	Hannan-Quinn criter.		13.83
F-statistic	36.08	Durbin-Watson stat		0.66
Prob(F-statistic)	0.00			

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section and period fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338; Total panel (unbalanced) observations: 11221; White period standard errors and covariance (d.f. corrected).

9.4. The Relevance of Equity Market-based Indicators of Credit Risk in the Measurement of the Credit Spread

9.4.1. The Constant Coefficient Model

Table 9.12 shows the key results of the univariate panel regressions of the credit spread on the distance to default, equity volatility and the natural logarithm of the market value of the firm's assets, which are estimated as described in Section 8.3.4. As a starting point for the analysis, the constant coefficient panel model, which forces all coefficients to be the same for all firms in the sample, is estimated.

All three variables are statistically significant and all coefficients have the expected signs. An increase in the distance to default (i.e. a decrease in credit risk) lowers the credit spread. An improvement in credit quality as measured by one distance to default narrows the credit spread by 57.72 basis points. Further, larger firms are expected to have a lower credit spread ceteris paribus. Equity volatility is positively related to the credit spread, consistent with Merton (1974). A one percentage point increase in equity volatility widens the credit spread by 9.24 basis points. The distance to default and equity volatility variables have a larger t-statistic than any of the accounting variables. Further, the market-based indicator of firm size performs better than the accounting based variable in terms of statistical significance. It is noteworthy that the univariate model with equity volatility has substantially higher explanatory power than the univariate model with the distance to default as an explanatory variable. This is unexpected as the distance to default is a far more comprehensive variable from a credit risk perspective, though the result is consistent with the results presented in Chapter 5 where equity volatility performed better in all model specifications. A possible explanation here is that the credit spread is, in addition to credit risk, driven by other factors such as liquidity which are better tracked by equity volatility.

Table 9.12
The univariate relationship between the credit spread and market-based indicators of credit risk: the constant coefficient model

Variable	Coefficient	t-Statistic	Prob.	R-squared
Distance to Default	-57.72	-12.02	0.00	0.20
Equity Volatility	924.40	12.62	0.00	0.35
Log of Market Value of Assets	-80.92	-7.79	0.00	0.09

Dependent Variable: Credit Spread; Method: Panel Least Squares; Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 349; Total panel (unbalanced) observations: 11,499-11,514*; White period standard errors and covariance (d.f. corrected).

*Number of observations in the regression with equity volatility as independent variable.

As in the analysis of the relationship between the credit spread and the financial accounting variables, in the next step the relevance of market-based measures is examined in a multivariate model. It should be noted that equity volatility and the distance to default are highly correlated (i.e. the correlation coefficient is -0.70) since equity volatility is a major determinant of the distance to default. Therefore, considering both variables as explanatory variables in a multivariate model may give rise to misleading results. To deal with this, a set of three multivariate models is estimated. The first model has equity volatility and its interaction with the distance to default as explanatory variables. The second model utilizes the distance to default and the squared distance to default to take into account nonlinearity in the relationship between the credit spread and the distance to default. The third model combines equity volatility, the distance to default and the interaction effects. In addition to these variables, all three models include the logarithm of the market value of the firm's assets as an explanatory variable. The results are presented in Table 9.13.

The equity volatility model 1 and the distance to default model 2 are very similar in that both models indicate that an increase in equity volatility and credit risk (i.e. a decrease in the distance to default) widens the credit spread. The significance of the interaction variables implies that the effect of changes in equity volatility and the distance to default is amplified by the level of credit risk. It is interesting to note that the equity volatility coefficients have substantially higher t-statistics than the distance-to-default coefficients. Furthermore, the explanatory power of equity volatility exceeds the explanatory power of the distance to default model by six percentage points.

Model 3 combines the equity volatility and the distance-to-default. Relative to model 1, the R-squared is improved by two percentage points. The high correlation between equity volatility and the distance to default causes a sharp drop in the t-statistics of the coefficients for both variables. Equity volatility retains its statistical significance while the distance to default becomes insignificant at the five per cent level.

The R-squared statistics of the models are substantially higher than the R-squared statistics of any of the accounting-based constant coefficient models. As expected, this indicates clearly that the market based indicators outperform the accounting-based indicators of credit risk. The same conclusion is reached by evaluating multiple model selection criteria, which consistently favour the model with market-based indicators.

Table 9.13
The multivariate relationship between the credit spread and market-based indicators of credit risk: the constant coefficient model

	Model 1	Model 2	Model 3
Equity Volatility	688.10		600.14
	[12.75]		[5.35]
Distance to Default		-167.57	-38.24
		[-7.22]	[-1.89]
Equity Volatility x Distance to Default	-158.03		-161.30
	[-6.01]		[-4.81]
Distance to Default^2		9.03	2.95
		[4.86]	[2.73]
Log Market Value of Assets	-36.63	-41.39	-39.09
	[-4.86]	[-5.51]	[-5.13]
Adjusted R-squared	0.40	0.34	0.41

Dependent Variable: Credit Spread; Method: Panel Least Squares; Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 349; Total panel (unbalanced) observations: 11,499; White period standard errors and covariance (d.f. corrected).

The t-statistics are shown in parentheses.

9.4.2. The Cross-sectional Fixed Effects Model

Fixed effects panel models are estimated to account for firm specific effects. As in the accounting-based model, the intercept is allowed to vary in cross section. The results are presented in Table 9.14.

All of the variables remain statistically significant after controlling for fixed effects. The statistical and economic significance of the distance to default is virtually the same as in the constant coefficient model, while the magnitude and the t-statistics of the equity volatility coefficient are reduced by about 13 per cent. The market based indicator of firm size also remains highly significant. As expected, the fixed effects specification substantially improves the model’s explanatory power. The univariate models including the equity volatility and the distance to default still outperform all of the univariate models which include accounting variables. Further, the market-based firm size indicator performs better than its accounting based alternative.

Table 9.14
The univariate relationship between the credit spread and market-based indicators of credit risk: the cross-sectional fixed effects model

Variable	Coefficient	t-Statistic	Prob.	Adj. R-sq.
Distance to Default	-53.03	-12.40	0.00	0.40
Equity Volatility	799.14	10.96	0.00	0.51
Log of Market Value of Assets	-128.14	-5.09	0.00	0.33

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 349; Total panel (unbalanced) observations: 11,499-11,514*; White period standard errors and covariance (d.f. corrected).

*Number of observations in the regression with equity volatility as the independent variable.

Table 9.15 presents a set of multivariate models with fixed effects. As in Table 9.13, three multivariate models are estimated. The first model regresses the credit spread on equity volatility, the second on the distance to default, and the third model includes both variables.

After controlling for fixed effects, the indicator of firm size is insignificant in models 1 and 3. It retains its significance in the model with the distance to default as an explanatory variable (model 2), which implies that the impact of the distance to default depends on time variations in firm size. In model 3, which combines all of the variables considered, the distance to default is insignificant. However, the squared distance to default, which captures an increasing impact of the distance to default as firms become riskier, remains significant, emphasising the importance of taking into account nonlinearities in the relationship between the credit spread and the distance to default. Further, consistent with previously reported results, this confirms that equity volatility performs better than the distance to default in explaining variations in the credit spread.

The fixed effects specification raises the model adjusted R-squared statistics by about 12 percentage points. The explanatory power of the models with market-based variables is still substantially higher than the explanatory power of the accounting-based multivariate model with fixed effects presented in Table 9.7. Other model selection criteria also give preference to the fixed effects model with market-based variables over the accounting model counterpart.

Table 9.15
The multivariate relationship between the credit spread and market-based indicators of credit risk: the cross-sectional fixed effects model

Variable	Model 1	Model 2	Model 3
Equity Volatility	550.46		501.26
	[10.63]		[5.34]
Distance to Default		-150.15	-20.66
		[-7.26]	[-1.29]
Equity Volatility x Distance to Default	-212.76		-212.72
	[-3.36]		[-3.68]
Distance to Default^2		7.88	1.57
		[4.76]	[1.98]
Log of Market Value of Assets	6.77	-37.96	7.08
	[0.37]	[-2.23]	[0.41]
Adjusted R-squared	0.52	0.46	0.52

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 349; Total panel (unbalanced) observations: 11,499; White period standard errors and covariance (d.f. corrected).

The t-statistics are shown in parentheses.

9.4.3. The Period Fixed Effects Model

In this step of the analysis of the relationship between the credit spread and market-based indicators of credit risk, the constant coefficient models presented in Table 9.12 are augmented with a set of dummy variables to control for time variations in the relationship. The results are presented in Table 9.16.

The period effects do not change the inference concerning the statistical and the economical significance of the variables. All three variables remain highly significant. The period effects improve model explanatory power substantially less than the cross-sectional fixed effects. This implies that the variables perform better in explaining the variations in the credit spread through time than in cross-section. It is interesting to note that the distance to default univariate model does not substantially outperform the best performing univariate financial accounting variable model. This implies that the distance to default is correlated with the period effects. In other words, the distance to default captures common time variations in the credit spread which gives it an edge in terms of explanatory power over the accounting variables in the constant coefficient model.

Table 9.16
The univariate relationship between the credit spread and market-based indicators of credit risk: the period fixed effects model

Variable	Coefficient	t-Statistic	Prob.	Adj. R-sq.
Distance to Default	-44.56	-10.31	0.00	0.31
Equity Volatility	876.81	9.74	0.00	0.41
Log of Market Value of Assets	-77.07	-7.58	0.00	0.29

Dependent Variable: Credit Spread; Method: Panel Least Squares (period fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 349; Total panel (unbalanced) observations: 11,499-11,514*; White period standard errors and covariance (d.f. corrected).

*Number of observations in the regression with equity volatility as the independent variable.

Table 9.17 presents the multivariate model with period fixed effects. All of the variables except the distance to default in Model 3 remain statistically significant and the period effects do not substantially change the magnitude of the coefficients. In comparison to the constant coefficient models in Table 9.13, the model adjusted R-squared statistics are improved by an average of 6.5 percentage points. The distance to default model (Model 2) performs slightly better than the multivariate accounting variables model with period effects presented in Table 9.8. The distance to default substantially outperforms the accounting variables in the constant coefficient model, but the period effects, which capture common time variations in the credit spread, improve far more the explanatory power of the accounting variables than the distance to default (19 percentage points versus 7 percentage points). This implies that the superior performance of the distance to default variable in the constant coefficient model is due to its ability to capture time variations in the credit spread which are common to all bonds.

Table 9.17
The multivariate relationship between the credit spread and market-based indicators of credit risk: the period fixed effects model

Variable	Model 1	Model 2	Model 3
Equity Volatility	616.96		592.85
	[8.63]		[4.90]
Distance to Default		-137.04	-21.29
		[-6.00]	[-1.18]
Equity Volatility x Distance to Default	-143.17		-155.25
	[-5.85]		[-4.88]
Distance to Default^2		7.46	2.13
		[4.34]	[2.34]
Log of Market Value of Assets	-40.21	-47.67	-43.96
	[-5.16]	[-5.75]	[-5.42]
Adjusted R-squared	0.46	0.41	0.47

Dependent Variable: Credit Spread; Method: Panel Least Squares (period fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 349; Total panel (unbalanced) observations: 11,499; White period standard errors and covariance (d.f. corrected).

The t-statistics are shown in parentheses.

9.4.4. The Two-way Fixed Effects Model

Table 9.18 presents the results of regressing the credit spread on individual market-based indicators with controls for cross-sectional and period fixed effects.

After jointly controlling for cross-sectional and period fixed effects, equity volatility and firm size remain highly significant, whereas the statistical and economic significance of the distance to default is sharply reduced. The distance to default is, however, statistically significant at the 10 per cent level. As revealed in Tables 9.14 and 9.16, controlling for cross-sectional and period effects separately does not substantially impact the significance of the distance to default. Considering cross-sectional and period effects jointly lowers the t-statistic of the distance to default coefficient from above 10 to 1.93. This implies that the fixed effects capture a substantial portion of the information contained in the distance to default.

Table 9.18
The univariate relationship between the credit spread and market-based indicators: the two-way fixed effects model

Variable	Coefficient	t-Statistic	Prob.	Adj. R-sq.
Distance to Default	-7.41	-1.94	0.05	0.52
Equity Volatility	612.77	6.07	0.00	0.57
Log of Market Value of Assets	-114.08	-5.14	0.00	0.52

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 349; Total panel (unbalanced) observations: 11499-11514*; White period standard errors and covariance (d.f. corrected).

*Number of observations in the regression with equity volatility as independent variable.

The multivariate models with the two-way effects are presented in Table 9.19. Model 1 includes equity volatility, the interaction between equity volatility and the distance to default as independent variables. Model 2 employs the distance to default and the squared distance to default, while Models 3 jointly considers all four variables, i.e. equity volatility, the distance to default and the two interaction variables. All three models include the natural logarithm of the market value of assets as an additional explanatory variable.

Jointly controlling for cross-sectional and period effects does not change the inference regarding the statistical significance of variables in models 1 and 2. Equity volatility and the distance to default remain highly statistically significant. The firm size indicator is not significant when jointly considered with equity volatility. This implies that equity volatility captures the size effect.

The coefficient of distance to default is statistically significant but has the incorrect (positive) sign in Model 3 which includes all variables. This is caused by a high correlation and interaction between the distance to default and equity volatility.

Table 9.19
The multivariate relationship between the credit spread and market-based indicators: the two-way fixed effects model

Variable	Model 1	Model 2	Model 3
Equity Volatility	376.16		573.29
	[5.28]		[5.41]
Distance to Default		-74.36	41.40
		[-3.92]	[3.25]
Equity Volatility x Distance to Default	-172.57		-152.73
	[-3.30]		[-2.81]
Distance to Default^2		4.73	-0.78
		[3.52]	[-1.57]
Log of Market Value of Assets	-28.06	-90.68	-40.41
	[-1.34]	[-4.49]	[-1.81]
Adjusted R-squared	0.58	0.54	0.59

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section and period fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 349; Total panel (unbalanced) observations: 11499; White period standard errors & covariance (d.f. corrected).

9.5. The Incremental Relevance of Financial Accounting Variables in the Measurement of the Credit Spread

The results presented in the previous sections indicate that both accounting and market-based variables are relevant in the measurement of the credit spread. The market-based measures appear to be superior in terms of statistical significance and explanatory power, as expected, as they are forward looking while accounting variables only reflect past performance and position. In common with other information in the public domain, the information contained within accounting data is expected to be subsumed within the market prices of securities, and therefore within market-based measures of credit risk. As a result, the accounting information is useful only if it can improve the performance of market-based measures when explaining variations in the credit spread. To examine this, a set of hybrid multivariate panel data models is estimated with all of the accounting and market-based measures as explanatory variables.

9.5.1. The Constant Coefficient Model

Table 9.20 presents results from the constant coefficient panel models which combine all of the accounting and market based measures identified above.

Model 1 includes equity volatility, its interaction with the distance to default, the natural logarithm of the market value of assets, and a set of financial accounting ratios as explanatory variables. All of the accounting variables except efficiency are statistically significant. As in the accounting model presented in Table 9.5, the coefficients of liquidity and cash flow are positive and imply that improvements in liquidity and operating cash flow widen the credit spread. The statistical and economic significance of equity volatility is similar to that in the model without the accounting variables, as presented in Table 9.13. However, the variable capturing the interaction between equity volatility and the distance to default becomes insignificant, implying that the accounting variables contain relevant information not reflected in equity volatility. As a result, they improve the model's explanatory power (adjusted R-squared) by four percentage points.

Model 2 replaces equity volatility with the distance to default. As in the previous model, all of the accounting variables except the efficiency ratio are significant. A comparison with the results presented in Table 9.13 shows that the accounting variables do not substantially reduce the statistical and economic significance of the distance to default which is the most statistically significant variable in the model. The magnitude of the coefficients and t-statistics for the accounting variables is reduced, but it should be emphasized that most of the accounting variables retain their significance. Interestingly, the accounting-based leverage ratio is significant even though the distance to default explicitly incorporates information on firm indebtedness. The accounting variables improve the model's adjusted R-squared statistic by five percentage points.

Model 3 includes equity volatility, the distance to default and the accounting ratios as explanatory variables. The distance to default and the interaction between equity volatility and the distance to default lose their significance in the presence of the accounting variables. All of the accounting variables except efficiency are significant and the explanatory power of the model is improved by four percentage points. Besides explanatory power, all other model selection criteria (Log Likelihood, Akaike, Schwartz and Hannan-Quinn) consistently indicate that the financial accounting variables improve the performance of models which include market-based measures. The results regarding the improvement in explanatory power are broadly consistent with other studies. Das, Hanouna and Sarin (2009) and Batta (2011) find that accounting variables explain an additional eight percentage points of variation in the credit default swap premium. Demirovic and Thomas (2007) report an improvement of six percentage points in explaining changes in credit ratings. It is noted that the incremental information value of accounting variables is broadly similar in explaining the credit default swap premium, the credit spread and the credit rating.

It should be emphasized that the profitability ratio has an economically significant impact upon the credit spread in all models (i.e. a one per cent increase in profitability lowers the credit spread by about 20 basis points). The economic significance of other accounting variables is limited.

Table 9.20
The incremental information value of the financial accounting variables: the constant coefficient model

Variable	Model 1	Model 2	Model 3
Equity Volatility	668.19		685.53
	[12.02]		[5.67]
Distance to Default		-140.76	-12.67
		[-7.31]	[-0.73]
Equity Volatility x Distance to Default	-70.64		-79.90
	[-1.67]		[-1.84]
Distance to Default^2		7.81	1.70
		[4.98]	[2.14]
Log of Market Value of Assets	-30.47	-34.26	-34.91
	[-4.66]	[-5.88]	[-5.12]
Net Income / Total Assets	-1,996.21	-2,108.06	-2,001.68
	[-3.53]	[-3.74]	[-3.53]
Retained Earnings / Total Assets	-96.19	-101.40	-108.50
	[-2.99]	[-2.95]	[-3.07]
Current Assets / Current Liabilities	29.19	23.67	27.64
	[4.14]	[3.44]	[3.97]
Total Liabilities / Total Assets	267.19	233.04	256.21
	[3.04]	[3.12]	[2.83]
Net Operating Cash Flow / Total Assets	223.43	249.53	199.13
	[3.59]	[3.32]	[3.75]
Revenue / Total Assets	-24.03	-24.30	-18.41
	[-0.70]	[-0.72]	[-0.57]
Adjusted R-squared	0.44	0.39	0.45

Dependent Variable: Credit Spread; Method: Panel Least Squares; Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338; Total panel (unbalanced) observations: 11,068; White period standard errors and covariance (d.f. corrected).

The t-statistics are shown in parentheses.

9.5.2. The Cross-sectional Fixed Effects Model

The models presented in Table 9.21 are augmented with cross-sectional fixed effects, that is, the regression intercept is allowed to vary across firms. The introduction of fixed effects does not affect the significance of equity volatility or the distance to default. However, most of the accounting variables, including the leverage ratio, become insignificant in all three model specifications. However, the profitability ratio is statistically and economically significant in all model specifications. Interestingly, the indicators of cash flow and liquidity are significant, but the magnitude of coefficients, which are a fraction of the profitability ratio’s coefficient, imply low economic significance.

The accounting variables improve model average explanatory power by approximately three percentage points. Other information criteria also indicate that accounting variables introduce new economically relevant information into the models with market-based measures.

Table 9.21
The incremental information value of financial accounting variables: the cross-sectional fixed effects model

Variable	Model 1	Model 2	Model 3
Equity Volatility	557.89		584.89
	[9.18]		[4.20]
Distance to Default		-135.48	-5.68
		[-7.36]	[-0.33]
Equity Volatility x Distance to Default	-155.14		-143.97
	[-2.37]		[-2.20]
Distance to Default^2		7.16	0.90
		[4.74]	[1.25]
Log of Market Value of Assets	25.29	-7.68	20.58
	[1.50]	[-0.50]	[1.37]
Net Income / Total Assets	-1,729.05	-1,867.80	-1,719.59
	[-4.01]	[-4.17]	[-3.99]
Retained Earnings / Total Assets	-138.65	-135.13	-136.24
	[-1.22]	[-1.13]	[-1.25]
Current Assets / Current Liabilities	32.41	26.82	31.79
	[2.06]	[1.67]	[2.09]
Total Liabilities / Total Assets	306.28	317.10	336.58
	[1.37]	[1.49]	[1.33]
Net Operating Cash Flow / Total Assets	120.16	126.17	114.32
	[3.03]	[2.92]	[3.19]
Revenue / Total Assets	30.21	50.06	13.70
	[0.41]	[0.65]	[0.22]
Adjusted R-squared	0.55	0.49	0.55

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338; Total panel (unbalanced) observations: 11,068; White period standard errors and covariance (d.f. corrected).

The t-statistics are shown in parentheses.

9.5.3. The Period Fixed Effects Model

To examine whether common time variations in the credit spread affect the incremental information value of accounting variables, instead of cross-sectional fixed effects the model presented in Table 9.20 is augmented with a set of time dummy variables. Each variable takes the value of one if an observation occurs in a specific quarter and zero otherwise. The results are presented in Table 9.22.

After controlling for time variation, all of the accounting variables retain their statistical significance, except the efficiency ratio, which is also insignificant in the model without period fixed effects. The accounting variables improve the explanatory power of models with period fixed effects by approximately four percentage points. Other information criteria consistently confirm that accounting variables improve the performance of the market-based variable models in explaining the credit spread.

Table 9.22
The incremental information value of financial accounting variables: the period fixed effects model

Variable	Model 1	Model 2	Model 3
Equity Volatility	585.78		688.85
	[8.63]		[5.46]
Distance to Default		-99.70	10.86
		[-5.60]	[0.67]
Equity Volatility x Distance to Default	-39.94		-56.49
	[-0.96]		[-1.32]
Distance to Default^2		5.88	0.66
		[4.39]	[1.00]
Log of Market Value of Assets	-37.50	-44.21	-44.34
	[-5.40]	[-6.63]	[-5.86]
Net Income / Total Assets	-1,790.61	-1,933.18	-1,819.32
	[-2.95]	[-3.28]	[-3.06]
Retained Earnings / Total Assets	-119.56	-145.72	-142.32
	[-3.65]	[-3.75]	[-3.75]
Current Assets / Current Liabilities	17.79	18.85	17.74
	[2.57]	[2.70]	[2.50]
Total Liabilities / Total Assets	246.62	226.42	246.24
	[2.83]	[2.97]	[2.71]
Net Operating Cash Flow / Total Assets	150.18	170.56	112.50
	[2.37]	[2.21]	[2.07]
Revenue / Total Assets	-17.66	-8.19	-7.71
	[-0.51]	[-0.24]	[-0.23]
Adjusted R-squared	0.50	0.46	0.51

Dependent Variable: Credit Spread; Method: Panel Least Squares (period fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338; Total panel (unbalanced) observations: 11,068; White period standard errors and covariance (d.f. corrected).

The t-statistics are shown in parentheses.

9.5.4. The Two-way Fixed Effects Model

In the final step of analysis, Table 9.23 depicts the incremental information value of financial accounting variables in the two-way effect model which controls for the cross-sectional and period fixed effects.

Table 9.23
The incremental information value of financial accounting variables: the two-way fixed effects model

Variable	Model 1	Model 2	Model 3
Equity Volatility	375.09		704.39
	[5.02]		[4.73]
Distance to Default		-54.55	64.97
		[-3.49]	[3.43]
Equity Volatility x Distance to Default	-119.38		-56.65
	[-2.00]		[-0.85]
Distance to Default^2		3.89	-1.72
		[3.44]	[-2.46]
Log of Market Value of Assets	-20.12	-68.36	-47.54
	[-0.96]	[-3.76]	[-2.04]
Net Income / Total Assets	-1,464.81	-1,584.33	-1,455.81
	[-2.99]	[-3.29]	[-3.16]
Retained Earnings / Total Assets	-223.03	-242.54	-218.44
	[-1.88]	[-1.91]	[-1.91]
Current Assets / Current Liabilities	15.61	8.98	10.01
	[1.08]	[0.59]	[0.72]
Total Liabilities / Total Assets	185.34	280.25	354.49
	[0.85]	[1.34]	[1.45]
Net Operating Cash Flow / Total Assets	56.89	41.13	16.38
	[1.35]	[0.92]	[0.43]
Revenue / Total Assets	80.55	32.65	-22.77
	[1.28]	[0.46]	[-0.40]
Adjusted R-squared	0.61	0.57	0.62

Dependent Variable: Credit Spread; Method: Panel Least Squares (cross-section and period fixed - dummy variables); Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338; Total panel (unbalanced) observations: 11,068; White period standard errors & covariance (d.f. corrected).

After jointly controlling for cross-sectional and period effects, the only accounting variable that remains statistically significant at the five per cent level is the profitability indicator. It has an economically significant impact upon the credit spread in all models (i.e. a one per cent increase in profitability lowers the credit spread by about 15 basis points). Additionally, the indicator of past profitability is significant at the 10 per cent level in all three specifications. The accounting variables improve the model's adjusted R-squared statistic by approximately three percentage points.

9.6. Robustness of the Results

Since a longer maturity implies a higher risk, the credit spread on bonds with longer maturities should be more sensitive to changes in the explanatory variables. The credit spread, which serves as the dependent variable, is calculated from the prices of bonds with different maturities. To examine if the maturity of the bonds influences the empirical results, a set of control variables is added to the models presented in Table 9.20, i.e. the hybrid constant coefficient models. Following King and Khang (2005), duration is used to control for maturity because it takes into account the complete set of cash flows. Another important bond characteristic which may influence the empirical results is bond liquidity. A set of four dummy variables is used to control for the logarithm of bond issue size which is a commonly used indicator of bond liquidity (e.g. Campbell and Taksler, 2003). The results are presented in Table 9.24.

The key results on the incremental information value of accounting variables are not changed after controlling for such bond characteristics. In particular, none of the variables loses its statistical significance as a result of controlling for the bond characteristics. None of the issue size dummy variables are significant, while just one variable representing bonds with the shortest duration is significant in all model specifications. As in Chapter 5, the significant bond duration variable indicates that bonds with a shorter duration have a higher credit spread. This counterintuitive result most likely captures the effect of the financial crisis in 2007 which occurred at the end of the sample period when the average credit spread was exceptionally wide and the average duration was below its peak value.

Table 9.24
The incremental information value when controlling for the bond duration and issue size

Variable	Model 1	Model 2	Model 3
Equity Volatility	653.80		674.66
	[12.12]		[5.66]
Distance to Default		-137.67	-11.90
		[-7.37]	[-0.69]
Equity Volatility x Distance to Default	-69.89		-78.75
	[-1.66]		[-1.83]
Distance to Default^2		7.65	1.66
		[5.05]	[2.14]
Log of Market Value of Assets	-28.75	-32.28	-33.74
	[-3.95]	[-4.90]	[-4.41]
Net Income / Total Assets	-1,986.96	-2,099.44	-1,992.00
	[-3.58]	[-3.80]	[-3.57]
Retained Earnings / Total Assets	-100.65	-105.99	-113.34
	[-3.02]	[-2.98]	[-3.00]
Current Assets / Current Liabilities	28.74	23.35	27.39
	[3.98]	[3.20]	[3.83]
Total Liabilities / Total Assets	256.02	221.56	245.81
	[2.95]	[3.00]	[2.74]
Net Operating Cash Flow / Total Assets	226.33	252.01	201.67
	[3.63]	[3.38]	[3.79]
Revenue / Total Assets	-25.10	-24.88	-18.56
	[-0.71]	[-0.70]	[-0.55]
Bond Value Dummy 1 (smallest)	10.92	7.81	7.03
	[0.54]	[0.36]	[0.36]
Bond Value Dummy 2	12.63	12.41	9.10
	[0.76]	[0.71]	[0.56]
Bond Value Dummy 3	1.03	-4.86	-4.36
	[0.07]	[-0.34]	[-0.32]
Bond Duration Dummy 1 (shortest)	81.55	92.29	80.73
	[4.54]	[4.81]	[4.55]
Bond Duration Dummy 2	12.55	18.74	9.72
	[0.86]	[1.22]	[0.65]
Bond Duration Dummy 3	-3.61	-4.72	-1.40
	[-0.26]	[-0.34]	[-0.11]
C	209.56	864.25	282.46
	[2.09]	[8.73]	[2.13]
Adjusted R-squared	0.45	0.40	0.46

Dependent Variable: Credit Spread; Method: Panel Least Squares; Sample (adjusted): 8/01/1996 2/01/2011; Periods included: 59; Cross-sections included: 338; Total panel (unbalanced) observations: 11,068; White period standard errors and covariance (d.f. corrected). Bond Value Dummy 1 takes the value of 1 if the bond issue value is up to $54.6 million; Dummy 2 is up to $148.41 million; Dummy 3 is up to $403.4 million; and Dummy 4, which is dropped from the model, is above $403.4 million. Bond Duration Dummy 1 takes the value of 1 if the bond duration is up to 3 years; Dummy 2 is between 3 and 6 years; Dummy 3 is between 6 and 9 years and Dummy 4, which is dropped from the model, is above 9 years. The t-statistics are shown in parentheses.

9.7. Summary

This chapter empirically examines the hypotheses formulated in Chapter 8. Financial accounting data has been traditionally used in the credit risk analysis. Accounting-based indicators of profitability, leverage and other aspects of a firm's performance are generally found to be significant in explaining and predicting corporate defaults. In line with a large body of existing literature, Hypothesis 1 states that accounting data is relevant in the measurement of the credit spread.

Alternatively, credit risk information can be extracted from the market prices of securities. Since the market prices of securities reflect all historical information as well as the expectations about future performance of firms, Hypothesis 2 states that the market-based indicators of credit risk outperform the accounting-based indicators in the measurement of the credit spread. Furthermore, since all publicly available information, including the economic information contained within accounting data is expected to be incorporated in the market price of securities, the accounting variables are relevant only if they contain information not already reflected in the market-based indicators. Consistent with the existing empirical evidence, Hypothesis 3 states that the accounting data is relevant or incrementally informative in the models containing market-based indicators.

These hypotheses are empirically tested on a sample consisting of 349 firms and over 11,000 quarterly observations. While a number of studies considers the relevance of accounting data in explaining bankruptcies, credit ratings or credit default swap premiums, this is the first study to examine the relevance of accounting data in the measurement of the credit spread on corporate bonds. The credit spread, which is used as an indicator of credit risk, is regressed on the market-based and accounting-based indicators of credit risk. The accounting variables used in this study are grouped into indicators of profitability, liquidity, leverage, cash flow generation, efficiency and firm size. Seven accounting ratios are selected form an initial set of 32, based on the strength of their correlation with the credit spread. The selected indicators are Net Income / Total Assets (profitability), Retained Earnings / Total Assets (past profitability), Current Assets / Current Liabilities (liquidity), Total Liabilities / Total Assets (leverage), Net Operating Cash Flow / Total Assets (cash flow generation), Revenue / Total Assets (efficiency), and the Logarithm of Total Assets (firm size). The market-based indicators used in this study are the distance to default of Merton (1974), equity volatility and the natural logarithm of the estimated market value of the firm’s assets.

The accounting-based profitability indicator is found to be statistically and economically significant in explaining variations in the credit spread. This result is robust to controlling for cross-sectional and period effects, as well as the bond maturity and liquidity. The indicator of leverage is also found to be significant in all model specifications except the model with two-way fixed effects, i.e. the cross-sectional and period fixed effect. The remaining results are somewhat mixed. The firm size indicator is insignificant at the five per cent level in the model with cross-sectional and period fixed effects, which implies that the effect of firm size is captured by the firm’s specific intercepts, and that the variation in firm size is not a significant determinant of the credit spread. The coefficients of the liquidity and cash flow indicators are not consistently statistically significant and, when statistically significant, are of a low economic significance. The indicator of efficiency is insignificant in all model specifications. All of the accounting-based variables taken together explain about 20 per cent of the variation in the credit spread. The cross-sectional and fixed effects increase the explanatory power to about 40 per cent. In line with Hypothesis 1, these results suggest that the accounting-based profitability and leverage indicators are relevant in credit risk modelling. However, the hypothesis that other accounting based indicators are significant determinants of the credit spread is rejected.

Unlike the accounting-based indicators which reflect the firm’s past performance, the market-based indicators capture all the information reflected in the market price of securities and therefore should be superior to the accounting-based indicators. This hypothesis is strongly confirmed in the model results. Equity volatility and the distance to default of Merton (1974) are found to be more statistically significant as well as to explain a substantially higher proportion of the variation in the credit spread when compared to the accounting indicators. Consistent with this finding, the market-based value of assets is shown to outperform its accounting-based alternative as a determinant of the credit spread.

Equity volatility is found to be a more relevant explanatory variable than the distance to default, which is surprising as the distance to default, in addition to equity volatility, incorporates information on the firm's leverage and the risk free rate. Elton et al. (2001) show that just a fraction of the credit spread is due to credit risk. Therefore, the superior performance of equity volatility is likely to be related to its ability to explain variations in other components of the credit spread.

Hypothesis 3, which states that accounting data is incrementally informative when considered in conjunction with the market-based indicators, is tested by jointly evaluating the significance of the accounting-based and the market-based variables in explaining variations in the credit spread. In line with existing empirical studies, the results lead to acceptance of this hypothesis. All accounting variables taken together improve the explanatory power of models by three to four percentage points. Other model selection criteria also indicate that the financial accounting variables improve the performance of the market-based variable models in explaining variations in the credit spread. This result is robust to controlling for cross-sectional and period effects, as well as for bond maturity and liquidity.

The profitability ratio is by far the most incrementally informative accounting variable as it is highly statistically and economically significant in all model specifications. This implies that distance to default and equity volatility do not fully incorporate information on profitability, which is found to be highly relevant in the measurement of credit risk. There is also some evidence that the leverage indicator is incrementally informative as it is found to be significant in the presence of the market-based indicators, though this result is not robust to controlling for cross-sectional fixed effects. It may seem surprising that the accounting based leverage ratio is significant in any model specification that includes the distance to default because the latter is in fact the leverage ratio scaled by the asset volatility. Consistent with Bharat and Shumway (2008), this finding implies that information on leverage is not fully captured by the structural model. Alternatively, it could be that market participants do not align their estimates of 'required' spread with the spread implied by the (rational) structural model, either because they weight leverage differently or because they depart from rationality by over-estimating the risk involved in corporate bonds. However, it should be noted that accounting based leverage may not necessarily be correlated with the distance to default precisely because the latter is scaled by other variables. So this finding may not be so surprising after all.

The next chapter summarizes the thesis findings and concludes.

CHAPTER 10

CONCLUSION

10.1. Introduction

Equity and credit risks are intrinsically related to each other and are difficult to separate (Jarrow and Turnbull, 2000). The structural model of Merton (1974) theoretically defines the relationship between the values of equity and debt securities and provides a set of empirically testable predictions. This thesis reviews the main approaches to the measurement of credit and equity risks, and conducts three studies of the relationship between equity and corporate bonds at the firm level. The first empirical study investigates the relationship between equity volatility and the credit spread. The second study examines how credit and equity risks affect the correlation between equity and bond returns, and the third study determines whether financial accounting variables are incrementally informative in explaining variations in the credit spread when considered in conjunction with theoretically grounded measures of credit risk. The empirical studies are based on a large US data sample covering more than 15 years and consisting of over 350 firms and 700,000 daily observations.

Each of the empirical studies within this thesis makes a number of contributions to the existing literature by employing a novel methodology and conducting a more thorough analysis than the extant literature due to the study of a large data sample. The results presented have some important practical implications for the integrated management of equity and credit risks.

The remainder of this chapter presents the main findings of this thesis, outlines the limitations of the empirical work, and suggests areas for further research.

10.2. Main Findings and Contributions

10.2.1. The measurement of credit risk

An improvement in a firm's prospects positively increases the value of its equity. The resulting decrease in leverage lowers the credit risk and therefore augments the value of the firm's debt. It is clear that the values of all of securities issued by a firm depend on the value of the firm's assets. This intuition is formalized in Merton (1974) who considers the values of equity and debt as derivatives written on a firm's assets, and applies the option pricing theory of Black and Scholes (1973) to price them. The value of equity equals the value of a call option, whereas the price premium on a corporate bond equals the value of a put option.

As implied by the option pricing theory, the value of assets is assumed to follow a geometric Brownian motion and the values of debt and equity depend on the difference between the market values of the firm's assets and debt, the volatility of those assets, the risk-free interest rate, and the time horizon. However, the implementation of Merton's (1974) model, referred to as the structural model, is not straightforward. First, the market value and volatility of a firm's assets are unobservable. Some studies, such as Campbell and Taksler (2003), overcome this issue by summing the market value of equity and the book value of debt. A more sophisticated approach involves a simultaneous solution of the call price equation and the hedge equation of Jones, Mason and Rosenfeld (1984). This thesis uses the latter approach as it should in principle produce a better estimate of the value of the firm's assets and their volatility. The second issue is related to the choice of the default point and the time horizon. The structural model is derived under the assumption that all firm debt is concentrated in a single zero-coupon bond issue. In this simplified case the default point is the nominal value of the bond issue and the time horizon is equal to the remaining time left before bond maturity. In practice, firms' capital structures are much more complex than this, while the maturities and other details of a firm's liabilities are not easily available. Therefore, the selection of the default point and the time horizon are to a certain degree arbitrary. In a commercial implementation of the structural model, Moody's KMV assumes that a firm defaults when the value of the firm's assets reaches the value of its short-term debt plus half of its long-term debt, and

Moody's argue that this choice adequately captures the financing constraints of firms. While a number of empirical studies follow the Moody's KMV approach, the existing literature suggests that the total value of liabilities is the most common choice for the default point. Most studies use the period of one year as the time horizon. This thesis follows the majority of studies and uses the total value of liabilities as the default point and one year as the time horizon. It should be noted, as Crosbie and Bohn (2003) point out, that the structural model is robust to the exact level of liabilities since the value of liabilities chosen as the default point is the difference between the value of equity and the value of assets. In other words, a higher value of liabilities translates into a higher value of assets, and vice versa.

Despite strong theoretical underpinning, the empirical performance of the structural model has in practice been mixed. It is commonly found that the structural model generates much lower credit spreads than those observed in the real world. This inspired a number of extensions which relax the assumptions of Merton's structural model and add features to allow for the observed properties of the credit spread. Major extensions allow for the default to occur before the maturity, stochastic interest rates, a stochastic default barrier, a mean-reverting leverage ratio, jumps in the value of assets, and stochastic volatility.

The extended structural models add an additional process to the model, and as a result are much more complex and harder to estimate than the basic Merton model. Despite this added complexity, the existing literature indicates that none of the extended structural models fully addresses the empirical weaknesses of the basic structural model. Eom, Helwege and Huang (2004) examine the performance of five structural model types and report that they all have similar empirical weaknesses. This thesis therefore utilizes the basic structural model of Merton (1974) to estimate credit risk. The distance to default or leverage relative to the volatility of assets is used as an indicator of credit risk. The value of the distance to default at the cumulative normal distribution, that is, N(-Distance to Default), gives the default probability. However, the conversion of the distance to default by means of the normal distribution yields unrealistically low default probabilities. Crosbie and Bohn (2003) note that Moody's KMV, in its commercial implementation of the structural model, uses its proprietary empirical default distribution to convert the distance to default into default probabilities. Empirical studies (e.g. Vassalou and Xing, 2004; Hillegeist et al., 2004) also avoid converting the distance to default into the default probability, and just use the distance to default as an indicator of credit risk.

10.2.2. The measurement of equity risk

Credit risk depends on the total volatility of the value of a firm's assets and hence both systematic and idiosyncratic risks should be reflected in the price of debt. However, finance theory implies that only systematic risks, which cannot be diversified away, should be priced in equity valuation. Sharpe (1964), Lintner (1965) and Mossin (1966) show that a security's exposure to systematic risks is captured by the strength of its covariance with the market portfolio. They propose a one factor model referred to as the Capital Asset Pricing Model (CAPM). Fama and French (1993) find that, in addition to the market premium, the difference in returns on the equities of big and small firms, and the difference in returns of firms with a high and low book-to-market equity, capture the exposure to systematic risk in cross-section. Due to its empirical success, the three-factor model of Fama and French has become the most widely employed model for measuring equity risk and expected equity returns.

This study utilizes both the CAPM and the Fama and French three factor model to estimate expected equity returns. A bivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is employed to estimate conditional betas and decompose equity returns into their systematic and expected components. The decomposition of equity returns enables the separation of equity volatility into its systematic and idiosyncratic components. It is well documented that equity volatility varies over time, so the estimation methods that account for the time variation are likely to provide more robust estimates. Therefore, GARCH models are used to estimate equity volatility. A symmetric GARCH model is used in the empirical analysis and an asymmetric EGARCH model, which allows for positive and negative news to impact upon volatility differentially, is utilized in the robustness analysis.

10.2.3. Empirical findings

The thesis conducts three empirical studies of the relationship between equity and credit risks. All three studies utilize the distance to default of Merton (1974) and the conditional equity volatility as risk indicators. The data sample of matched equity, bond and financial accounting data at the firm-level is thoroughly examined in a set of panel data regression models.

A. The relationship between the credit spread on corporate bonds and equity risk

The structural model implies that equity volatility and leverage are major determinants of credit risk. An increase in equity volatility increases the credit risk and therefore widens the credit spread. This study examines the empirical relationship between the credit spread and equity volatility. The existing literature is extended in several ways. Instead of focusing on the relationship between the credit spread and the volatility of equity returns in excess of the market return, hence assuming that the exposure to systematic risks of all firms is the same, this study utilizes a bivariate GARCH model to estimate the conditional sensitivity of the firm-level equity returns to systematic risk factors. Furthermore, instead of using credit ratings or the accounting leverage ratio as an indicator of credit risk, the structural model of Merton (1974) is explicitly estimated to gauge the level of credit risk. This is particularly important since the theory implies that the impact of equity volatility upon the credit spread depends on the credit risk.

Finally, the analysis is conducted on a large data sample consisting of approximately 730,000 firm-day observations covering almost 15 years. This sample is significantly larger than that used in the existing studies and enables a more thorough regression analysis, including an examination of cross-sectional and time variations in the relationship between the credit spread and equity risk.

The following hypotheses are empirically examined:

$H1_A$: The credit spread and equity volatility are positively correlated, as implied by the structural model.

Consistent with other studies, this hypothesis is strongly accepted. The relationship is both statistically and is economically significant. The results suggest that an increase in annual equity volatility of one percentage point raises the credit spread by 10.5 basis points. This is broadly consistent, although not directly comparable, with the results of Campbell and Taksler (2003). Equity volatility explains about 39 per cent of the variation in the credit spread, which also is broadly consistent with other studies (e.g. Campbell and Taksler, 2003; Ericsson, Jacobs and Oviedo, 2009; Cremers et al., 2008).

$H2_A$: The relationship between the credit spread and equity volatility is asymmetric. In other words, an increase in equity volatility has a bigger impact upon the credit spread than a decrease in volatility of a similar magnitude.

This hypothesis is rejected. The effect is found to have an unexpected negative sign implying that a positive change in volatility has a smaller rather than a larger impact upon the credit spread than an equivalent negative change in volatility. Although statistically significant, the economic significance of this effect is close to zero. The result is inconsistent with Collin-Dufresne, Goldstein and Martin (2001) who report that credit spreads respond more strongly to positive changes in the VIX index, the latter representing a weighted average of eight implied volatilities of near-the-money options on the S&P 100 index.

$H3_A$: The credit spread and the distance to default of Merton (1974) are negatively correlated.

This hypothesis is strongly accepted. The distance to default is found to have a negative impact upon the credit spread in all model specifications. As expected, this implies that an increase in credit risk widens the credit spread.

$H4_A$: The distance to default of Merton (1974) is a more economically significant determinant of the credit spread than the equity volatility.

This hypothesis is firmly rejected. The magnitude of coefficients implies that equity volatility is found to be much more economically important than the distance to default. Furthermore, equity volatility explains substantially more variation in the credit spread. This is a surprising result as the distance to default is a much more comprehensive variable than equity volatility as, besides the equity volatility, it incorporates information about the risk-free interest rate and the firm’s leverage. One possible explanation is that, as reported by Elton et al. (2001), only a fraction of the credit spread is due to the credit risk, and equity volatility captures all risks reflected in the credit spread, whereas the distance to default captures only changes in the credit risk.

$H5_A$: Idiosyncratic and systematic equity risks are equally important determinants of the credit spread.

The results for this hypothesis are mixed. The statistical significance of systematic and idiosyncratic volatility is consistently very high and similar in univariate models. Furthermore, the magnitude of the coefficients is also similar. However, in the multivariate regression, the idiosyncratic volatility coefficient is significantly larger than the corresponding coefficient of systematic volatility. A formal test strongly rejects the hypothesis that the coefficients of idiosyncratic and systematic volatility are equal in the multivariate regression.

The idiosyncratic volatility is found to explain a significantly larger portion of variations in the credit spread than the systematic volatility, which implies that credit risk is predominantly a firm-specific, rather than a systematic risk. Consistent with this finding, the cross-sectional fixed effects double the explanatory power of a model with systematic volatility.

$H6_A$: The strength of the relationship between credit spread and equity volatility is positively related to the level of credit risk.

This hypothesis is firmly accepted. The interaction variable (equity volatility x the distance to default) is found to be highly statistically and economically significant. This result is confirmed in a model with discreet control variables, that is, a set of dummy variables taking the value on one if the distance to default is within a certain range and zero otherwise.

The impact of equity volatility increases monotonically as the credit risk increases (i.e. as the distance to default shrinks). This result clearly confirms the prediction of the structural model that the credit spread becomes more sensitive to changes in equity volatility as the default probability heightens.

Importantly, Campbell and Taksler (2003) and Cremers et al. (2008) do not obtain a monotonically increasing relationship between the significance of equity volatility and credit risk when a financial accounting based leverage ratio or credit rating are used as indicators of credit risk. These inconsistent findings are clearly due to weaknesses in the accounting based leverage and the credit rating measure in proxying credit risk.

$H7_A$: Firm-specific risk measures are more important determinants of the corporate credit spread than the aggregate risk factors.

This hypothesis is accepted. The common factors (risk-free rate, market-wide volatility and returns) explain a substantially lower percentage of variations in the credit spread than the firm-level measures. Furthermore, market-wide returns and volatility are insignificant when considered jointly with their firm-level counterparts. The firm-level systematic equity volatility, which takes into account cross sectional differences in betas, outperforms the market-wide volatility. This implies that the decomposition of equity volatility into systematic and idiosyncratic components used in this thesis is useful.

Finally, the risk-free rate performs exceptionally well in explaining the variations in the credit spread. It outperforms all other variables in terms of its statistical and economic significance in the models. The magnitude of the coefficient in all specifications by far exceeds the magnitude predicted by the structural model.

B. The correlation between the equity and corporate bond returns

The structural model of Merton (1974) implies that the value of all securities issued by the firm depends on the value of firm's assets and their volatility. A change in the value of assets affects the values of equity and debt in the same manner, whereas a change in asset volatility leads to a redistribution of value between the equity and debt holders. Following the main theme of this thesis, the study examines how changes in equity volatility and credit risk affect the correlation between equity and bond returns. The existing empirical studies (e.g. Kwan, 1996; Campbell and Taksler, 2003; Cremers et al., 2008) generally investigate the unconditional correlation between the credit spread or the bond yield and the variables included in the structural model of Merton (1974). The credit spread or the bond yield are typically regressed on leverage, equity volatility and other variables in order to estimate the average impact of the explanatory variables on the credit spread or the bond yield. This study utilizes a bivariate GARCH model to estimate the conditional correlation between equity and bond returns, and then examines determinants of this correlation in the second step. Besides providing some insight into the empirical correlation between equity and bond returns, this methodological approach enables a more thorough regression analysis of the correlation determinants.

The following hypotheses are empirically examined:

$H1_B$: The correlation between the equity and bond returns is positive.

This hypothesis is accepted. Bond and equity returns are found on average to be positively correlated. Consistent with Scheicher (2009) and Belke and Gokus (2011), the conditional correlation is found to vary over time. Not unexpectedly, the correlation peaked during the recent financial crisis of 2007.

$H2_B$: Equity volatility has a positive impact upon the correlation between the equity and bond returns.

This hypothesis is accepted. Equity volatility, which is estimated from a GARCH(1,1) model, is found to have a positive effect on the correlation between the equity and bond returns. In the constant coefficient panel model, equity volatility is statistically significant and explains about 6 per cent of the variation in the correlation. The magnitude of the coefficient also implies that it is economically significant. After controlling for time variation in the correlation, the economic significance of equity volatility increases substantially. However, after controlling for the cross-sectional fixed effects, the statistical and economic significance of equity volatility is considerably reduced, implying that the effect of equity volatility strongly depends on the time-invariant firm characteristics. The structural model suggests that the level of credit risk is one of these characteristics, leading to the following two hypotheses.

$H3_B$: The strength of the correlation between the equity and bond returns depends on the credit risk.

This hypothesis is accepted. As implied by the structural model, the the equity and bond returns of more risky firms are more strongly correlated than for the less risky firms. When the level of credit risk is controlled by a set of dummy variables talking the value of one if the distance to default is within a certain range and zero otherwise, the coefficients of the dummy variables indicate that the correlation monotonically weakens as firms move away from the default point.

$H4_B$: The impact of equity volatility on the correlation between the equity and bond returns increases as the distance to default shrinks.

This hypothesis is firmly accepted. The coefficient of the interaction variable (equity volatility x distance to default) is found to be negative and highly significant. Moreover, the interaction coefficient is more statistically significant than the equity volatility coefficient. The analysis is developed by replacing the interaction variable with a set of six dummy variables which take the value of one if the distance of default is within a certain range, and zero otherwise. All of the dummy variables are highly significant. The economic significance of equity volatility monotonically decreases as firms move away from the default point (i.e. as credit risk decreases). The magnitude of the dummy variable coefficients emphasizes the importance of the interaction between equity volatility and credit risk. The effect of equity volatility on the correlation is positive for firms with a value of distance to default of up to 3, while it becomes negative for firms further away from the default point. This implies that bond and equity values for high-quality firms are driven by information related mainly to the volatility of assets. In other words, a change in equity volatility primarily affects the volatility rather than the value of the underlying firm's assets. A change in the volatility of the assets has the opposite effect on the values of its equity and bonds, hence the negative correlation between equity and bond returns.

$H5_B$: Systematic risk has a positive impact upon the correlation between equity and bond returns.

This hypothesis is accepted. Market-wide volatility, which is proxied by the volatility of the S&P 500 index, is found to have a positive effect on the correlation between the equity and bond returns. The statistical and economic significance of the market-wide volatility, however, is substantially lower than the significance of the firm-level volatility. The firm-level measure of systematic equity volatility, which takes into account the cross-sectional differences in the exposure to systematic risks (i.e. betas) performs better than S&P 500 index volatility, but the model's explanatory power remains a fraction of the explanatory power of models with total firm-level volatility and the distance to default. This implies that the correlation between equity and bond returns is primarily driven by firm-specific rather than common factors.

$H6_B$: The risk-free rate has a negative impact upon the correlation between the correlation between the equity and bond returns.

This hypothesis is firmly accepted. The structural model implies that an increase in the risk-free rate lowers credit risk. This finding is consistent with other results implying that credit and equity risks exert a positive effect on the correlation between the equity and bond returns. It should be highlighted that the economic significance of the risk-free rate by far exceeds the economic significance of all of the firm-level variables considered (such as equity volatility and the distance to default) as well as exceeding the significance of market-wide equity volatility.

C. The relevance of financial accounting data in the measurement of the credit spread

Financial accounting variables have traditionally been used in credit risk analysis. A large body of literature documents that financial accounting data contain credit sensitive information. In contrast to financial accounting data, which is by definition backward looking, market based measures of credit risk potentially take into account all available information including expectations about the future performance of firms. This makes market based measures of the credit risk superior relative to accounting measures. Moreover, the relevant information available in the accounting data should be reflected in the market price of securities and market based measures of credit risk. Therefore, an appropriate test of the relevance of financial accounting data is to determine whether accounting variables are incrementally informative when considered in conjunction with market based measures.

The existing literature focuses on examining the relevance of accounting data in equity markets. A limited number of existing studies examine the relevance of accounting data in explaining bankruptcies, credit ratings, or the credit default swap premium. This study extends the existing literature by considering the relevance of accounting data in explaining variations in the credit spread on corporate bonds. Furthermore, this study employs panel data analysis which enables a more thorough analysis of cross-sectional and time effects in the relevance of accounting data. The data sample consists of 349 firms and 11,632 quarterly observations for matched equity, bond and accounting data.

The following hypotheses are tested:

$H1_C$: The financial accounting based indicators are significantly correlated with the credit spread as follows:

Indicator	Relation with the credit spread
Profitability	Negative
Liquidity	Negative
Efficiency	Negative
Cash flow	Negative
Leverage	Positive
Firm size	Negative

This hypothesis is partially accepted. Of the financial accounting variables, only profitability, leverage and firm size are found to be significantly related to the credit spread. As hypothesized, the profitability and the firm size measures are negatively related to credit spread, whereas the relationship between leverage and the credit spread is found to be positive.

$H2_C$: Market based measures outperform financial accounting based measures in explaining variations in the credit spread.

This hypothesis is firmly accepted. Consistent with existing empirical evidence (e.g. Hillegeist et al., 2004), equity volatility and the distance to default of Merton (1974) are found to be more statistically significant and explain a substantially higher fraction of variations in the credit spread than the financial accounting variables tested. Furthermore, the market based value of a firm's assets is shown to outperform the accounting based value as a determinant of the credit spread. Consistent with the other results of this thesis, equity volatility is found to be a more important explanatory variable than the distance to default.

$H3_C$: Financial accounting variables are incrementally informative in explaining the variations in the credit spread.

This hypothesis is firmly accepted. The profitability indicator (Net Income / Total Assets) is found to be highly statistically and economically significant when considered as a dependent variable in a model together with equity volatility and the distance to default. This result is robust to controlling for cross-sectional and period effects. Some evidence indicates that the leverage ratio is also incrementally significant. It is significant in the constant coefficient model, but becomes insignificant when the model is augmented with cross-sectional fixed effects. All of the financial accounting variables improve the explanatory power of the models by about four percentage points. These results are broadly consistent with existing empirical studies and indicate that accounting data is not redundant in the measurement of the credit spread, and more broadly in the measurement of credit risk.

Overall, sixteen hypotheses have been tested in this thesis of which fourteen are accepted or partially accepted. Equity risk, measured as the volatility of equity returns, is found to be statistically and economically significant in explaining the credit spread on corporate bonds and the correlation between equity and bond returns. As predicted by the structural model, the effect of equity volatility increases as firms approach bankruptcy. Surprisingly, equity volatility strongly outperforms the distance to default in explaining the credit spread and the correlation between equity and bond returns. This finding suggests that equity volatility captures factors not related to credit risk but still important for understanding the relationship between equity and debt securities. Finally, the results suggest that equity prices do not fully reflect the information contained in financial accounting data which is relevant for the measurement of the credit spread. Therefore, accounting variables should be used in credit spread modelling alongside equity volatility and market-based credit risk measures.

10.3. Limitations of the Thesis

This study uses the basic structural model of Merton (1974) to construct a measure of credit risk. The measure, referred to as the distance to default, is shown to successfully rank firms according to their credit risk exposure. However, there is no evidence that the structural model produces the best measure of credit risk available, and empirical results may be influenced by its weaknesses. As outlined in Chapter 2, there are a number of extended structural models which arguably perform better in explaining variations in credit risk. The complexity of these models makes their estimation feasible only on a limited data sample. Therefore, the robustness of the empirical results to a change in the measure of credit risk is not examined. Furthermore, credit risk is measured over a one year horizon, taking into account a firm's total liabilities. Therefore, the maturity of a firm's liabilities is not taken into account in this thesis. Since the maturities and other details of a firms' liabilities are not readily available, this issue cannot be easily mitigated.

The credit spread is not entirely driven by credit risk. It also reflects other risks of which the most important is liquidity risk (e.g. Elton et al. 2001; Longstaff, Mithal and Neis, 2005). The smallest bonds, which are deemed the least liquid, are excluded from the sample and all results are shown to be robust to controlling for bond issue size which is an indicator of bond liquidity (e.g. Campbell and Taksler, 2003). However, the empirical results presented in this thesis may still be influenced to some extent by liquidity and other risks.

10.4. Further Research

This thesis can be extended in a number of directions. One direction for further research is to mitigate the discussed limitations of the thesis. This involves using the extended structural models and matching a model's time horizon to the average maturity of firm liabilities, which could be estimated based on information on maturities available in the notes to the financial statement in firms' annual reports.

Another direction for further research is to pursue the more striking results of this thesis. First, equity volatility is found to be a more significant determinant of the credit spread than the distance to default. This is surprising because the distance to default can be considered as the leverage ratio scaled by equity volatility. Therefore, this result is likely to be due to the correlation of equity volatility with those components of the credit spread not related to the credit risk. Second, the economic significance of the risk-free rate is by far higher than that implied by the structural model. This may be an explanation for the finding of Collin-Dufresne, Goldstein and Martin (2001) that common factors are the main drivers of the credit spread. Finally, the cross-sectional fixed effects substantially increase the explanatory power of the models in all three studies. Therefore, a detailed investigation of the firm effect may reveal interesting findings.

Finally, this thesis does not conduct any analysis taking into account industry effects. An interesting extension of this thesis, therefore, would be an examination of whether systematic variations exist across industries in the various phenomena examined in this thesis.

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Appendix

	Firm	Stock symbol	Datastream Equity Code	Datastream Bond Code
1	ASHLAND INCORPORATED	ASH	U:ASH	61487D
2	AT&T CORPORATION	T	U:T	61352P
3	AVERY DENNISON CORPORATION	AVY	U:AVY	61356V
4	BOEING COMPANY	BA	U:BA	610196
5	CARNIVAL CORPORATION	CCL	U:CCL	845587
6	CATERPILLAR INCORPORATED	CAT	U:CAT	390657
7	CORNING INCORPORATED	GLW	U:GLW	61448R
8	CSX CORPORATION	CSX	U:CSX	61443L
9	DEERE & COMPANY	DE	U:DE	597465
10	DOW CHEMICAL COMPANY (THE)	DOW	U:DOW	61410K
11	ELI LILLY & COMPANY	LLY	U:LLY	197561
12	FORTUNE BRANDS INCORPORATED	FO	U:FO	390419
13	HALLIBURTON COMPANY	HAL	U:HAL	61380N
14	INTERNATIONAL BUSINESS MACHINES CORPORATION	IBM	U:IBM	191405
15	INGERSOLL-RAND COMPANY	IR	U:IR	61392P
16	MCCORMICK & COMPANY INCORPORATED	MKC	U:MKC	61351N
17	MCDONALD'S CORPORATION	MCD	U:MCD	565728
18	NATIONAL FUEL GAS COMPANY	NFG	U:NFG	61436V
19	NEW YORK TIMES COMPANY (THE)	NYT	U:NYT	61406P
20	NEWELL RUBBERMAID INCORPORATED	NWL	U:NWL	61427H
21	NISOURCE INCORPORATED	NI	U:NI	61379X
22	PARKER-HANNIFIN CORPORATION	PH	U:PH	61367U
23	PIEDMONT NATURAL GAS COMPANY INCORPORATED	PNY	U:PNY	61395E
24	PUBLIC SERVICE ENTERPRISE GROUP INCORPORATED	PEG	U:PEG	61425Q
25	RYDER SYSTEM INCORPORATED	R	U:R	61426F
26	SOUTHWEST GAS CORPORATION	SWX	U:SWX	61377E
27	TALISMAN ENERGY INCORPORATED	TLM	U:TLM	602040
28	TEXTRON INCORPORATED	TXT	U:TXT	61521L
29	TIMKEN COMPANY	TKR	U:TKR	61369L
30	UNION PACIFIC CORPORATION	UNP	U:UNP	61495C
31	VALERO ENERGY CORPORATION	VLO	U:VLO	61411F
32	WALT DISNEY COMPANY (THE)	DIS	U:DIS	61413P
33	XEROX CORPORATION	XRX	U:XRX	61367C
34	3M COMPANY	MMM	U:MMM	81984M
35	ABBOTT LABORATORIES	ABT	U:ABT	38584V
36	AES CORPORATION (THE)	AES	U:AES	239511
37	AFFILIATED COMPUTER SERVICES INCORPORATED	ACS	U:ACS	55494J
38	AGILENT TECHNOLOGIES INCORPORATED	A	U:A	1770CQ

39	AGRIUM INCORPORATED	AGU	U:AGU	601861
40	AIR PRODUCTS AND CHEMICALS INCORPORATED	APD	U:APD	61367N
41	AK STEEL CORPORATION	AKS	U:AKS	23477F
42	ALBEMARLE CORPORATION	ALB	U:ALB	48410K
43	ALBERTO-CULVER COMPANY	ACV	U:ACV	65206E
44	ALCOA INCORPORATED	AA	U:AA	246025
45	ALLEGHENY TECHNOLOGIES INCORPORATED	ATI	U:ATI	21500K
46	ALLERGAN INCORPORATED	AGN	U:AGN	61450N
47	HONEYWELL INTERNATIONAL INCORPORATED	HON	U:HON	564017
48	AMERICAN GREETINGS CORPORATION	AM	U:AM	246871
49	AMERICAN ELECTRIC POWER COMPANY INCORPORATED	AEP	U:AEP	24241U
50	WYETH	WYE	U:WYE	217245
51	HESS CORPORATION	HES	U:HES	251986
52	AMERICAN PACIFIC CORPORATION	APFC	@APFC	1668JJ
53	AMERICAN TOWERS INCORPORATED	AMT	U:AMT	45816W
54	AMGEN INCORPORATED	AMGN	@AMGN	17875M
55	AMR CORPORATION	AMR	U:AMR	564000
56	ANADARKO PETROLEUM CORPORATION	APC	U:APC	17904C
57	ITT CORPORATION	ITT	U:ITT	243140
58	ANIXTER INCORPORATED	AXE	U:AXE	48998L
59	TIME WARNER INCORPORATED	TWX	U:TWX	17098W
60	APACHE CORPORATION	APA	U:APA	17903X
61	APPLIED MATERIALS INCORPORATED	AMAT	@AMAT	245860
62	ARCHER DANIELS MIDLAND COMPANY	ADM	U:ADM	244832
63	ARROW ELECTRONICS INCORPORATED	ARW	U:ARW	246451
64	ARVINMERITOR INCORPORATED	ARM	U:ARM	20548V
65	ATMOS ENERGY CORPORATION	ATO	U:ATO	17905F
66	AVISTA CORPORATION	AVA	U:AVA	61417V
67	AVNET INCORPORATED	AVT	U:AVT	57296N
68	AVON PRODUCTS INCORPORATED	AVP	U:AVP	252227
69	BAKER HUGHES INCORPORATED	BHI	U:BHI	252018
70	BARD (CR) INCORPORATED	BCR	U:BCR	17950J
71	BECKMAN COULTER INCORPORATED	BEC	U:BEC	19565N
72	BECTON DICKINSON & COMPANY	BDX	U:BDX	245538
73	BELDEN INCORPORATED	BDC	U:BDC	1743KE
74	BELO CORPORATION	BLC	U:BLC	245662
75	BEMIS COMPANY INCORPORATED	BMS	U:BMS	492548
76	BERRY PETROLEUM COMPANY	BRY	U:BRY	81359Q
77	BJ SERVICES COMPANY	BJS	U:BJS	72582F
78	BLACK & DECKER CORPORATION	BDK	U:BDK	18460R
79	BLOUNT INCORPORATED	BLT	U:BLT	46389R
80	BLYTH INCORPORATED	BTH	U:BTH	18003X
81	BORGWARNER INCORPORATED	BWA	U:BWA	251483
82	BOSTON SCIENTIFIC CORPORATION	BSX	U:BSX	47700P

83	BRISTOW GROUP INCORPORATED	BRS	U:BRS	2060RF
84	BROWN SHOE COMPANY INCORPORATED	BWS	U:BWS	56262C
85	BRUNSWICK CORPORATION	BC	U:BC	245557
86	BRISTOL-MYERS SQUIBB COMPANY	BMY	U:BMY	240268
87	BUCKEYE TECHNOLOGIES INCORPORATED	BKI	U:BKI	18003R
88	CALLON PETROLEUM COMPANY	CPE	U:CPE	46554R
89	CAMPBELL SOUP COMPANY	CPB	U:CPB	240278
90	CARDINAL HEALTH INCORPORATED	CAH	U:CAH	16420U
91	CARLISLE COMPANIES INCORPORATED	CSL	U:CSL	79031F
92	CENTERPOINT ENERGY INCORPORATED	CNP	U:CNP	24812U
93	CENTURYTEL INCORPORATED	CTL	U:CTL	245990
94	CENVEO CORPORATION	CVO	U:CVO	46313P
95	CHURCH & DWIGHT COMPANY INCORPORATED	CHD	U:CHD	56761J
96	CIMAREX ENERGY COMPANY	XEC	U:XEC	93510X
97	CINTAS CORPORATION	CTAS	@CTAS	21398F
98	CISCO SYSTEMS INCORPORATED	CSCO	@CSCO	63275C
99	FRONTIER COMMUNICATIONS CORPORATION	FTR	U:FTR	17433F
100	CLOROX COMPANY	CLX	U:CLX	16420K
101	COMPUTER SCIENCES CORPORATION	CSC	U:CSC	251531
102	CON-WAY INCORPORATED	CNW	U:CNW	252270
103	COCA-COLA BOTTLING COMPANY CONSOLIDATED	COKE	@COKE	251649
104	COCA-COLA ENTERPRISES INCORPORATED	CCE	U:CCE	219960
105	COLEMAN CABLE INCORPORATED	CCIX	@CCIX	57887P
106	COLGATE-PALMOLIVE COMPANY	CL	U:CL	61424F
107	COMMERCIAL METALS COMPANY	CMC	U:CMC	18219X
108	CA INCORPORATED	CA	@CA	477003
109	COMSTOCK RESOURCES INCORPORATED	CRK	U:CRK	38875H
110	CONAGRA FOODS INCORPORATED	CAG	U:CAG	245554
111	CONSTELLATION BRANDS INCORPORATED	STZ	U:STZ	20107D
112	CONVERGYS CORPORATION	CVG	U:CVG	481083
113	COOPER TIRE & RUBBER COMPANY	CTB	U:CTB	244836
114	COORS BREWING COMPANY	TAP	U:TAP	21182R
115	CORN PRODUCTS INTERNATIONAL INCORPORATED	CPO	U:CPO	234894
116	COSTCO WHOLESALE CORPORATION	COST	@COST	85600Q
117	COTT CORPORATION	COT	U:COT	21407T
118	CRANE COMPANY	CR	U:CR	72515X
119	CROWN HOLDINGS INCORPORATED	CCK	U:CCK	240596
120	CUMMINS INCORPORATED	CMI	U:CMI	18158U
121	CVS CAREMARK CORPORATION	CVS	U:CVS	468891
122	CYTEC INDUSTRIES INCORPORATED	CYT	U:CYT	25113Q

123	DANAHER CORPORATION	DHR	U:DHR	1842L5
124	DARDEN RESTAURANTS INCORPORATED	DRI	U:DRI	61437T
125	DEAN FOODS COMPANY	DF	U:DF	66291F
126	DELL INCORPORATED	DELL	@DELL	246343
127	DELUXE CORPORATION	DLX	U:DLX	23289F
128	DEVON ENERGY CORPORATION	DVN	U:DVN	20951C
129	HEWLETT-PACKARD COMPANY	HPQ	U:HPQ	55527H
130	DILLARDS INCORPORATED	DDS	U:DDS	246909
131	DOVER CORPORATION	DOV	U:DOV	246465
132	DTE ENERGY COMPANY	DTE	U:DTE	17464R
133	DUPONT (EI) DE NEMOURS AND COMPANY	DD	U:DD	245977
134	DUN & BRADSTREET CORPORATION (THE)	DNB	U:DNB	64318R
135	EASTMAN CHEMICAL COMPANY	EMN	U:EMN	240618
136	EATON CORPORATION	ETN	U:ETN	18257M
137	ECOLAB INCORPORATED	ECL	U:ECL	18261R
138	EL PASO CORPORATION	EP	U:EP	18739L
139	ELIZABETH ARDEN INCORPORATED	RDEN	@RDEN	21081T
140	EMBARQ CORPORATION	EQ	U:EQ	66303U
141	EMERSON ELECTRIC COMPANY	EMR	U:EMR	251560
142	ENBRIDGE INCORPORATED	ENB	U:ENB	48954T
143	ENSCO INTERNATIONAL INCORPORATED	ESV	U:ESV	18262P
144	EOG RESOURCES INCORPORATED	EOG	U:EOG	18260H
145	ESTEE LAUDER COMPANIES INCORPORATED (THE)	EL	U:EL	20145V
146	EXELON CORPORATION	EXC	U:EXC	55585P
147	FEDEX CORPORATION	FDX	U:FDX	17770H
148	FIRSTENERGY CORPORATION	FE	U:FE	19541V
149	FORD MOTOR COMPANY	F	U:F	237010
150	FREEPORT-MCMORAN COPPER & GOLD INCORPORATED	FCX	U:FCX	23670V
151	FTI CONSULTING INCORPORATED	FCN	U:FCN	63476W
152	GANNETT COMPANY INCORPORATED	GCI	U:GCI	20734H
153	GAP INCORPORATED (THE)	GPS	U:GPS	21332X
154	GENERAL DYNAMICS CORPORATION	GD	U:GD	70640T
155	GENERAL ELECTRIC COMPANY	GE	U:GE	1833QL
156	GENENTECH INCORPORATED	DNA	U:DNA	56524W
157	GENERAL MILLS INCORPORATED	GIS	U:GIS	61406Q
158	GOODRICH CORPORATION	GR	U:GR	61429R
159	GOODYEAR TIRE & RUBBER COMPANY (THE)	GT	U:GT	18249J
160	GREAT PLAINS ENERGY INCORPORATED	GXP	U:GXP	1716J9
161	GREENBRIER COMPANIES INCORPORATED (THE)	GBX	U:GBX	58775T
162	HARRIS CORPORATION	HRS	U:HRS	18425T
163	HASBRO INCORPORATED	HAS	U:HAS	18428D

164	HEALTH MANAGEMENT ASSOCIATES INCORPORATED	HMA	U:HMA	65473R
165	HEARST-ARGYLE TELEVISION INCORPORATED	HTV	U:HTV	245978
166	HEINZ (HJ) COMPANY	HNZ	U:HNZ	246817
167	HERMAN MILLER INCORPORATED	MLHR	@MLHR	18430V
168	HERSHEY COMPANY (THE)	HSY	U:HSY	245632
169	HILL-ROM HOLDINGS INCORPORATED	HRC	U:HRC	18431U
170	HOME DEPOT INCORPORATED	HD	U:HD	485613
171	HORMEL FOODS CORPORATION	HRL	U:HRL	17613K
172	HOSPIRA INCORPORATED	HSP	U:HSP	45960K
173	HOST HOTELS AND RESORTS INCORPORATED	HST	U:HST	45893L
174	ILLINOIS TOOL WORKS INCORPORATED	ITW	U:ITW	251496
175	INTERPUBLIC GROUP OF COMPANIES INCORPORATED	IPG	U:IPG	20602L
176	IRON MOUNTAIN INCORPORATED	IRM	U:IRM	16924R
177	ITC HOLDINGS CORPORATION	ITC	U:ITC	25279L
178	JAMES RIVER COAL COMPANY	JRCC	@JRCC	55326X
179	JO-ANN STORES INCORPORATED	JAS	U:JAS	46256K
180	JOHNSON & JOHNSON	JNJ	U:JNJ	241302
181	JOHNSON CONTROLS INCORPORATED	JCI	U:JCI	18445F
182	KENNAMETAL INCORPORATED	KMT	U:KMT	21635W
183	KIMBERLY-CLARK CORPORATION	KMB	U:KMB	246838
184	KINDER MORGAN ENERGY PARTNERS LP	KMP	U:KMP	251406
185	KOHL'S CORPORATION	KSS	U:KSS	251941
186	KRAFT FOODS INCORPORATED	KFT	U:KFT	19428V
187	KROGER COMPANY	KR	U:KR	247657
188	MCCLATCHY COMPANY (THE)	MNI	U:MNI	241314
189	LABORATORY CORPORATION OF AMERICA HOLDINGS	LH	U:LH	23742C
190	ENBRIDGE ENERGY LP	EEP	U:EEP	18483P
191	LAS VEGAS SANDS CORPORATION	LVS	U:LVS	56844Q
192	LEGGETT & PLATT INCORPORATED	LEG	U:LEG	61415M
193	LIN TELEVISION CORPORATION	TVL	U:TVL	19714T
194	LOCKHEED MARTIN CORPORATION	LMT	U:LMT	243366
195	LOUISIANA-PACIFIC CORPORATION	LPX	U:LPX	235434
196	LUBRIZOL CORPORATION (THE)	LZ	U:LZ	247612
197	MAGELLAN MIDSTREAM PARTNERS LP	MMP	U:MMP	45721L
198	MANITOWOC COMPANY INCORPORATED	MTW	U:MTW	22147M
199	MARATHON OIL CORPORATION	MRO	U:MRO	21578J
200	MARRIOTT INTERNATIONAL INCORPORATED	MAR	U:MAR	251949
201	MARTIN MARIETTA MATERIALS INCORPORATED	MLM	U:MLM	251585
202	MASCO CORPORATION	MAS	U:MAS	241329
203	MATTEL INCORPORATED	MAT	U:MAT	61391T

204	MCGRAW-HILL COMPANIES INCORPORATED (THE)	MHP	U:MHP	1782R2
205	MCKESSON CORPORATION	MCK	U:MCK	18681X
206	MCMORAN EXPLORATION COMPANY	MMR	U:MMR	1798EF
207	MEDTRONIC INCORPORATED	MDT	U:MDT	57887Q
208	MERCER INTERNATIONAL INCORPORATED	MERC	@MERC	48784T
209	MERCK & COMPANY INCORPORATED	MRK	U:MRK	247614
210	MOHAWK INDUSTRIES INCORPORATED	MHK	U:MHK	20863D
211	MOSAIC COMPANY (THE)	MOS	U:MOS	82413C
212	MUELLER INDUSTRIES INCORPORATED	MLI	U:MLI	47520L
213	MURPHY OIL CORPORATION	MUR	U:MUR	241094
214	ACUITY BRANDS INCORPORATED	AYI	U:AYI	252444
215	NATIONAL SEMICONDUCTOR CORPORATION	NSM	U:NSM	97839K
216	NAVISTAR INTERNATIONAL CORPORATION	NAV	U:NAV	45817C
217	NCR CORPORATION	NCR	U:NCR	21501P
218	NEWFIELD EXPLORATION COMPANY	NFX	U:NFX	18622T
219	NEWS CORPORATION	NWSA	U:NWSA	252028
220	NEXEN INCORPORATED	NXY	U:NXY	20767T
221	NEXSTAR BROADCASTING INCORPORATED	NXST	@NXST	46064E
222	NIKE INCORPORATED	NKE	U:NKE	61454C
223	NOBLE ENERGY INCORPORATED	NBL	U:NBL	244845
224	NOBLE CORPORATION	NE	U:NE	251562
225	NORDSTROM INCORPORATED	JWN	U:JWN	246248
226	NORTHROP GRUMMAN CORPORATION	NOC	U:NOC	246196
227	NUCOR CORPORATION	NUE	U:NUE	18620V
228	NVR INCORPORATED	NVR	U:NVR	24919J
229	OCCIDENTAL PETROLEUM CORPORATION	OXY	U:OXY	246292
230	OFFICE DEPOT INCORPORATED	ODP	U:ODP	72082N
231	OGE ENERGY CORPORATION	OGE	U:OGE	47648N
232	OLIN CORPORATION	OLN	U:OLN	19781N
233	ONEOK INCORPORATED	OKE	U:OKE	18598R
234	ORACLE CORPORATION	ORCL	@ORCL	62093Q
235	OVERSEAS SHIPHOLDING GROUP INCORPORATED	OSG	U:OSG	38803V
236	OWENS-ILLINOIS INCORPORATED	OI	U:OI	217281
237	PACKAGING CORPORATION OF AMERICA	PKG	U:PKG	25337E
238	PAETEC HOLDING CORPORATION	PAET	@PAET	2025K5
239	PALL CORPORATION	PLL	U:PLL	221945
240	ENCANA CORPORATION	ECA	U:ECA	19440L
241	PANTRY INCORPORATED (THE)	PTRY	@PTRY	46088D
242	PENNEY (JC) COMPANY INCORPORATED	JCP	U:JCP	241670
243	PENTAIR INCORPORATED	PNR	U:PNR	241628
244	PEPCO HOLDINGS INCORPORATED	POM	U:POM	22434Q

245	PEPSICO INCORPORATED	PEP	U:PEP	96533F
246	PFIZER INCORPORATED	PFE	U:PFE	239458
247	ALTRIA GROUP INCORPORATED	MO	U:MO	18646U
248	CONOCOPHILLIPS COMPANY	COP	U:COP	390015
249	PHILLIPS VAN HEUSEN CORPORATION	PVH	U:PVH	18642W
250	PINNACLE ENTERTAINMENT INCORPORATED	PNK	U:PNK	36523C
251	PITNEY BOWES INCORPORATED	PBI	U:PBI	22663F
252	POLYONE CORPORATION	POL	U:POL	22349Q
253	PORTLAND GENERAL ELECTRIC COMPANY	POR	U:POR	61473N
254	PPG INDUSTRIES INCORPORATED	PPG	U:PPG	18641W
255	PRAXAIR INCORPORATED	PX	U:PX	20747H
256	PROCTER & GAMBLE COMPANY	PG	U:PG	243176
257	PROGRESS ENERGY INCORPORATED	PGN	U:PGN	16526Q
258	PULTE HOMES INCORPORATED	PHM	U:PHM	18653W
259	QUEST DIAGNOSTICS INCORPORATED	DGX	U:DGX	17699K
260	RAYTHEON COMPANY	RTN	U:RTN	245619
261	RENT-A-CENTER INCORPORATED	RCII	@RCII	72188V
262	REPUBLIC SERVICES INCORPORATED	RSG	U:RSG	251716
263	RITE AID CORPORATION	RAD	U:RAD	242147
264	ROCK-TENN COMPANY	RKT	U:RKT	18161D
265	ROCKWELL AUTOMATION INCORPORATED	ROK	U:ROK	246022
266	ROHM & HAAS COMPANY	ROH	U:ROH	667455
267	RYLAND GROUP INCORPORATED (THE)	RYL	U:RYL	48279C
268	SAFEWAY INCORPORATED	SWY	U:SWY	251937
269	SAKS INCORPORATED	SKS	U:SKS	247620
270	SARA LEE CORPORATION	SLE	U:SLE	18659K
271	SBA COMMUNICATIONS CORPORATION	SBAC	@SBAC	17594W
272	SCANA CORPORATION	SCG	U:SCG	17319W
273	SCHERING-PLOUGH CORPORATION	SGP	U:SGP	37456W
274	SCHOLASTIC CORPORATION	SCHL	@SCHL	25263C
275	SEACOR HOLDINGS INCORPORATED	CKH	U:CKH	18730U
276	SEALED AIR CORPORATION	SEE	U:SEE	251703
277	SEMPRA ENERGY	SRE	U:SRE	252249
278	SENSIENT TECHNOLOGIES CORPORATION	SXT	U:SXT	18800W
279	SHAW COMMUNICATIONS INCORPORATED	SJR	U:SJR	19709F
280	SMITH INTERNATIONAL INCORPORATED	SII	U:SII	16488K
281	SNAP-ON INCORPORATED	SNA	U:SNA	18358P
282	SONOCO PRODUCTS COMPANY	SON	U:SON	18726Q
283	SOUTHERN COMPANY	SO	U:SO	84337E
284	SOUTHERN UNION COMPANY	SUG	U:SUG	242174
285	SOUTHWEST AIRLINES COMPANY	LUV	U:LUV	18728M
286	SPRINT NEXTEL CORPORATION	S	U:S	242177
287	SPX CORPORATION	SPW	U:SPW	23410D

288	STANDARD PACIFIC CORPORATION	SPF	U:SPF	21022R
289	STANLEY WORKS COMPANY (THE)	SWK	U:SWK	72239L
290	STAPLES INCORPORATED	SPLS	@SPLS	24446K
291	STARBUCKS CORPORATION	SBUX	@SBUX	1659LR
292	STARWOOD HOTELS & RESORTS WORLDWIDE INCORPORATED	HOT	U:HOT	24534C
293	STEELCASE INCORPORATED	SCS	U:SCS	78605X
294	STEINWAY MUSICAL INSTRUMENTS INCORPORATED	LVB	U:LVB	63448M
295	STERICYCLE INCORPORATED	SRCL	@SRCL	18733R
296	STEWART ENTERPRISES INCORPORATION	STEI	@STEI	74845L
297	SOUTHWESTERN ENERGY COMPANY	SWN	U:SWN	61410J
298	STONERIDGE INCORPORATED	SRI	U:SRI	21779R
299	SUNCOR ENERGY INCORPORATED	SU	U:SU	37486D
300	SUNOCO INCORPORATED	SUN	U:SUN	245438
301	SUPERVALU INCORPORATED	SVU	U:SVU	252085
302	SPEEDWAY MOTORSPORTS INCORPORATED	TRK	U:TRK	24634U
303	SWIFT ENERGY COMPANY	SFY	U:SFY	45998X
304	SYSCO CORPORATION	SYY	U:SYY	246875
305	TCI COMMUNICATIONS INCORPORATED	TCII	@TCII	243090
306	TECO ENERGY INCORPORATED	TE	U:TE	21249R
307	TEEKAY CORPORATION	TK	U:TK	19034N
308	TELEPHONE & DATA SYSTEMS INCORPORATED	TDS	U:TDS	49604P
309	TEMPLE-INLAND INCORPORATED	TIN	U:TIN	251507
310	PACTIV CORPORATION	PTV	U:PTV	252239
311	TEREX CORPORATION	TEX	U:TEX	45893D
312	THERMADYNE HOLDINGS CORPORATION	THMD	@THMD	38487D
313	THERMO FISHER SCIENTIFIC INCORPORATED	TMO	U:TMO	55327C
314	THOMAS & BETTS CORPORATION	TNB	U:TNB	18764N
315	THOMSON REUTERS CORPORATION	TRI	U:TRI	45612N
316	TJX COMPANIES INCORPORATED	TJX	U:TJX	252122
317	TOREADOR RESOURCES CORPORATION	TRGL	@TRGL	58864U
318	TORO COMPANY (THE)	TTC	U:TTC	18763X
319	TRANSALTA CORPORATION	TAC	U:TAC	37413R
320	TRANSOCEAN INCORPORATED	RIG	U:RIG	244861
321	YUM BRANDS INCORPORATED	YUM	U:YUM	17090V
322	TYSON FOODS INCORPORATED	TSN	U:TSN	246361
323	UNISYS CORPORATION	UIS	U:UIS	24242E
324	UNITED PARCEL SERVICE INCORPORATED	UPS	U:UPS	1910UV
325	UNITED STATES STEEL CORPORATION	X	U:X	96533H
326	UNIVERSAL CORPORATION	UVV	U:UVV	61432V
327	UNIVERSAL HEALTH SERVICES INCORPORATED	UHS	U:UHS	19482F

328	URS CORPORATION	URS	U:URS	224759
329	UNITED STATES CELLULAR CORPORATION	USM	U:USM	23016Q
330	US CONCRETE INCORPORATED	RMIX	@RMIX	46370H
331	IAC INTERACTIVECORP	IACI	@IACI	24298F
332	USEC INCORPORATED	USU	U:USU	18800T
333	VF CORPORATION	VFC	U:VFC	18803R
334	VALASSIS COMMUNICATIONS INCORPORATED	VCI	U:VCI	18801K
335	NATIONAL OILWELL VARCO INCORPORATED	NOV	U:NOV	18506Q
336	VERIZON COMMUNICATIONS INCORPORATED	VZ	U:VZ	91528V
337	CBS CORPORATION	CBS	U:CBS	243167
338	VULCAN MATERIALS COMPANY	VMC	U:VMC	1842ME
339	W&T OFFSHORE INCORPORATED	WTI	U:WTI	97716L
340	WAL-MART STORES INCORPORATED	WMT	U:WMT	398635
341	WEATHERFORD INTERNATIONAL INCORPORATED	WFT	U:WFT	19551C
342	WENDY'S/ARBY'S GROUP INCORPORATED	WEN	U:WEN	18796T
343	MEADWESTVACO CORPORATION	MWV	U:MWV	18799P
344	WEYERHAEUSER COMPANY	WY	U:WY	242687
345	WHIRLPOOL CORPORATION	WHR	U:WHR	243473
346	WISCONSIN ENERGY CORPORATION	WEC	U:WEC	19585R
347	FOOT LOCKER INCORPORATED	FL	U:FL	610847
348	WORTHINGTON INDUSTRIES INCORPORATED	WOR	U:WOR	18804W
349	INTEGRYS ENERGY GROUP INCORPORATED	TEG	U:TEG	23158W
350	WEIGHT WATCHERS INTERNATIONAL INCORPORATED	WTW	U:WTW	668431
351	XCEL ENERGY INCORPORATED	XEL	U:XEL	66988K
352	XTO ENERGY INCORPORATED	XTO	U:XTO	21079H

- The results presented in Chapter 5 are based on the dataset consisting of all above data items
- The results presented in Chapter 7 are based on the dataset consisting of all above data series except the item 305
- The results presented in Chapter 9 are based on the dataset consisting of all above data series except the item 305, 330 and 331